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REVIEW

A Comprehensive Review of Archimedes Optimization Algorithm with its Theory, Variants, Hybridization, and Applications

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Abstract

The Archimedes Optimization Algorithm (AOA) is a recent physics-based metaheuristic inspired by Archimedes' principle. Since its introduction by Hashim et al. in 2021, it has gained significant attention and has been applied to various real-world optimization problems. Its popularity stems from its simple structure, adaptability, ease of implementation, and satisfactory convergence. This paper presents a comprehensive review of the AOA algorithm, including its modified, multi-objective, and hybrid variants, and examines its applications in several domains such as classification, feature selection, parameter tuning, scheduling, photovoltaic systems, wireless networks, and clustering. The performance of the AOA algorithm is evaluated against some well-known metaheuristic algorithms, including Genetic Algorithm (GA), Differential Evolution (DE), Tabu Search (TS), Firefly Algorithm (FA), Bat Algorithm (BA), Whale Optimization Algorithm (WOA), Grey Wolf Optimizer (GWO), Sine Cosine Algorithm (SCA), and Marine Predators Algorithm (MPA), and results demonstrates its superiority in most cases (72,22%) with stable dispersion in box-plot analyses. Finally, future research directions for improving the effectiveness and applicability of the AOA algorithm are outlined.

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Abbreviations

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ADS	Advanced Design System
AFT	Ali Baba and the Forty Thieves
AGTO	Artificial Gorilla Troops Optimizer
AHO	Archerfish Hunting Optimizer
AMA	Artificial Meerkat Algorithm
AM-GNN	Auto-Metric Graph Neural Networks AO Aquila Optimizer
AOA	Archimedes Optimization Algorithm
AOA-GA	Archimedes Optimization Algorithm - Genetic Algorithm
AOA-GWO	Archimedes Optimization Algorithm - Grey Wolf Optimizer AOABSA AOA with Bird Swarm Algorithm
APBC	Average Percentage of Branch Coverage APFD Average Percentage of Faults Detected
ARX	AutoRegressive with eXogenous input
AVR	Automatic Voltage Regulation
AVO	African Vultures Optimization
AVOA-AOA	African Vultures Optimization Algorithm - Archimedes Optimization Algorithm
BA	Bat Algorithm
BAOA	Binary Archimedes Optimization Algorithm BBO Biogeography-Based Optimizer
BBBC	Big-Bang Big-Crunch
BMA	Boxing Match Algorithm
BSO	Brain Storm Optimization
CAOA	Chaotic Archimedes Optimization Algorithm
CBIR	Content-Based Image Retrieval
CFO	Central Force Optimization
CHIO	Coronavirus Herd Immunity Optimizer
COA	Coyote Optimization Algorithm
CST	Computer Simulation Technology (CST Studio Suite)
CNN	Convolutional Neural Network
DA	Dragonfly Algorithm
DAOA	Developed Archimedes Optimization Algorithm
DE	Differential Evolution
DHL	Dynamic Hunting Leadership
DSC	Dice Similarity Coefficient
DLO	Draco Lizard Optimizer
EDLSTM	Encoder-Decoder Long Short-Term Memory
EHO	Elephant Herding Optimization
ELO	Eurasian Lynx Optimizer
EMA	Exchange Market Algorithm
EP	Evolutionary Programming
EVO	Energy Valley Optimizer
FA	Firefly Algorithm
FBI	Forensic-Based Investigation
FGIA	Football Game Inspired Algorithm
FHO	Fire Hawk Optimization
FWA	Fireworks Algorithm
GA	Genetic Algorithm
GEO	Golden Eagle Optimizer
GL S	Guided Local Search
GOA	Grasshopper Optimization Algorithm
GP	Genetic Programming
GRASP	Greedy Randomized Adaptive Search Procedure
GSA	Gravitational Search Algorithm
GWO	Grey Wolf Optimizer
HBA	Honey Badger Algorithm
HCAOA	Hybrid Chaotic Archimedes Optimization Algorithm
HDAO	Hybrid Dwarf Archimedes Optimization
HESS	Hybrid Energy Storage System
HGSO	Henry Gas Solubility Optimization
HGSO-AOA	Henry Gas Solubility Optimization - Archimedes Optimization Algorithm
HHO	Harris Hawks Optimization
HSS	Hyper-Spherical Search
HWAO	Hybrid Whale-Archimedes Optimization
IAOA	Improved Archimedes Optimization Algorithm
ICA	Imperialist Competitive Algorithm
ILS	Iterated Local Search
JI	Jaccard Index
KH	Krill Herd Algorithm
LA	Lichtenberg Algorithm
LCA	League Championship Algorithm
LPBO	Learner Performance-Based Behavior Optimization
LPSP	Loss of Power Supply Probability
LSA	Lightning Search Algorithm
LSO	Light Spectrum Optimizer
LSTM	Long Short-Term Memory
MA	Memetic Algorithm
MAE	Mean Absolute Error
MAOA	Modified Archimedes Optimization Algorithm
MBA	Mine Blast Algorithm
MFO	Moth-Flame Optimization
MPA	Marine Predators Algorithm
MPPT	Maximum Power Point Tracking
MRI	Magnetic Resonance Imaging
MSE	Mean Squared Error
MVO	Multi-Verse Optimizer

NPC	Net Present Cost
NRO	Nuclear Reaction Optimization
OBL	Opposition-Based Learning
PAOA	Parallel Archimedes Optimization Algorithm
PBS	Peripheral Blood Smears
PGO	Plasma Generation Optimization
PO	Political Optimizer
PRO	Poor and Rich Optimization
PSNR	Peak Signal-to-Noise Ratio
PSO	Particle Swarm Optimization
PV	Photovoltaic
PVS	Passing Vehicle Search
QANA	Quantum-based Avian Navigation Algorithm
QAOA	Quantum Archimedes Optimization Algorithm
RNN	Recurrent Neural Network
RMSE	Root Mean Squared Error
RSO	Rhinopithecus Swarm Optimization
SA	Simulated Annealing
SCA	Sine Cosine Algorithm
SCO	Single Candidate Optimizer
SFS	Stochastic Fractal Search
SIO	Sonar Inspired Optimization
SLS	Stochastic Local Search
SMO	Starling Murmuration Optimizer
SRS	Special Relativity Search
SSA	Salp Swarm Algorithm
SSIM	Structural Similarity Index Measure
StD	Standard Deviation
STOA	Sooty Tern Optimization Algorithm
SVM	Support Vector Machine
SPBO	Student Psychology Based Optimization
TEO	Thermal Exchange Optimization
TLBO	Teaching-Learning-Based Optimization
TOC	Tornado Optimizer with Coriolis force
UFLP	Uncapacitated Facility Location Problem
UFLS	Under-Frequency Load Shedding
VNS	Variable Neighborhood Search
VPSA	Vibrating Particles System Algorithm
VSA	Vortex Search Algorithm
VSWR	Voltage Standing Wave Ratio
WAOA	Waterwheel Archimedes Optimization Algorithm
WEO	Water Evaporation Optimization
WOA	Whale Optimization Algorithm
WSM	Weighted Sum Method
WSN	Wireless Sensor Network
WSO	White Shark Optimizer

1 Introduction

Optimization is the process of determining the best possible value of a fitness function while adhering to multiple constraints. It has recently emerged as one of the most interesting issues for solving several real-world problems across various domains. Optimization techniques can generally be divided into two main categories: traditional optimization methods and meta-heuristic optimization methods. Traditional optimization methods, also referred to as conventional optimization techniques, are known for their fast convergence and potential to yield highly accurate optimal solutions. However, they typically require stringent conditions, including fully defined constraints and continuously differentiable objective functions. In practice, many real-world problems are complex and nonlinear, making traditional methods susceptible to getting trapped in local optima. Furthermore, these methods often struggle with high-dimensional problems and complex search spaces, where they may fail to find the global optimum.

To address the limitations of traditional optimization methods, researchers have increasingly turned to meta-heuristic algorithms. Meta-heuristics are intelligent, computer-based techniques that tackle complex optimization problems using iterative search strategies inspired by natural behaviors, biological processes, physical phenomena, or social interactions. These algorithms simulate such mechanisms to guide the search toward optimal or near-optimal solutions. Unlike traditional methods, meta-heuristics do not rely on gradient information or require the objective function to be differentiable. Owing to their adaptability and robustness, they have gained popularity among researchers and have been successfully applied to a wide range of complex optimization problems. Meta-heuristics can be categorized into two main classes: those based on a single solution and those based on a population of solutions, as shown in Fig. 1.

Single-based meta-heuristics, also referred to as trajectory methods, start from an initial solution and iteratively refine it, creating a search trajectory through the solution space. These methods utilize a neighborhood mechanism to improve the current solution. Some well-known and widely used single-based meta-heuristics include: Simulated Annealing (SA) [1], Tabu Search (TS) [2], Greedy Randomized Adaptive Search Procedure (GRASP) [3], Variable Neighborhood Search (VNS) [4], Single Candidate Optimizer (SCO) [5], Vortex Search algorithm (VSA) [6], Guided Local Search (GLS) [7], Stochastic Local Search (SLS) [8], Iterated Local Search (ILS) [9], and their variants.

Unlike single-based meta-heuristics, population-based meta-heuristics work with a group of solutions rather than just one. They start with an initial population and generate new candidate solutions in each iteration. These candidates

Fig. 1 Classification of meta-heuristic algorithms

are then incorporated into the population using selection mechanisms. The iterative process continues until a predefined stopping condition is satisfied. Population-based meta-heuristics are commonly classified into four main categories based on the source of their inspiration, which includes evolutionary processes, swarm intelligence, human behavior, and physical phenomena.

Evolutionary Algorithms (EAs), a subset of Evolutionary Computation (EC), are inspired by the principles of natural evolution. They operate using four fundamental mechanisms such as selection, reproduction, mutation, and recombination. Some well-regarded EAs are: Genetic Algorithm (GA) [10], Evolutionary Strategies (ES) [11], Stochastic Fractal Search (SFS) algorithm [12], Lightning Search Algorithm (LSA) [13], Genetic Programming (GP) [14], Bull Optimization Algorithm (BOA) [15], Evolutionary Programming (EP) [16], Memetic Algorithm (MA) [17], Probability-Based Incremental Learning (PBIL) [18], Differential Evolution (DF) [19], Clonal Selection Algorithm (CSA) [20], Biogeography-Based Optimizer (BBO) [21], and Scatter search (SS) [22].

Swarm-based algorithms simulate the collective behavior of animals during movement and hunting, typically drawing inspiration from natural phenomena such as bird flocks, insect colonies, and animal herds. Particle Swarm Optimization (PSO) [23] and Ant Colony Optimization (ACO) [24] are the first introduced swarm intelligence algorithms. Other optimization algorithms that come from analogies with natural biological phenomena have been proposed. Among the most significant we cite the Firefly Algorithm (FA) [25], Cuckoo Search (CS) [26], Ant Bee Colony (ABC) [27], Bat Algorithm (BA) [28], Krill Herd Algorithm (KH) [29], Grey Wolf Optimizer (GWO) [30], Moth Flame Optimization (MFO) [31], Elephant Herding Optimization (EHO) algorithm [32], Social Spider (SS) algorithm [33], Whale Optimization Algorithm (WOA) [34], Crow Search Algorithm (CSA) [35, 36], Dragonfly Algorithm (DA) [37, 38], Salp Swarm Algorithm (SSA) [39], Coyote Optimization Algorithm (COA) [40], Grasshopper Optimization Algorithm (GOA) [41, 42], Harris Hawks Optimization (HHO) algorithm [43], Seagull Optimization Algorithm (SOA) [44], chimp Optimization Algorithm (ChOA) [45], Marine Predators Algorithm (MPA) [46], Woodpecker Mating Algorithm (WMA) [47–51], Manta Ray Foraging Optimization (MRFO) algorithm [52, 53], Aquila Optimizer (AO) [54, 55], African Vultures Optimization (AVO) [56], Honey Badger Algorithm (HBA) [57], White Shark Optimization (WSO) algorithm [58], Artificial Gorilla Troops Optimizer (AGTO) [59], Golden Eagle Optimizer (GEO) [60], Snake Optimizer (SO) [61], Starling Murmuration Optimizer (SMO) [62], Shrimp and Goby association search Algorithm (ShGA) [63], Termite Life Cycle Optimizer (TLCO) algorithm [64], Sooty Tern Optimization Algorithm (STOA) [65], Fire Hawk Optimization (FHO) algorithm [66], Dynamic Hunting Leadership (DHL) algorithm [67], Artificial Meerkat Algorithm (AMA) [68], Rhinopithecus Swarm Optimization (RSO) algorithm [69], Eurasian Lynx Optimizer (ELO) [70], Salamander Optimization Algorithm (SOA) [71], Rabbit and Turtle Algorithm (RTS) [72], Red-Crowned Crane Optimization (RCO) [73], Starfish optimization algorithm (SFOA) [74], and Draco Lizard Optimizer (DLO) [75].

Human-based algorithms (HMAs) simulate human behavior within communities, focusing on aspects such as social interaction, decision-making, and cooperation. Some of the most well-known human-based algorithms are: Harmony Search (HS) [76], Imperialist Competitive Algorithm (ICA) [77], Seeker Optimization Algorithm (SOA) [78], Fire Work Algorithm (FWA) [79], Teaching Learning-Based Algorithm (TLBA) [80], League Championship Algorithm (LCA) [81], Brain Storm Optimization (BSO) algorithm [82], Soccer League Competition (SLC) algorithm [83], Mine Blast Algorithm (MBA) [84], Passing Vehicle Search (PVS) algorithm [85], Student Psychology Based Optimization (SPBO) algorithm [86], Ali Baba and the Forty Thieves (AFT) [87], Forensic-Based Investigation (FBI) algorithm [88], Boxing Match Algorithm (BMA) [89], Political Optimizer (PO) [90], Football Game Inspired Algorithm (FGIA) [91], Poor and Rich Optimization (PRO) algorithm [92], Exchange Market Algorithm (EMA) [93], Coronavirus Herd Immunity Optimizer (CHIO) [94], Singer Optimization Algorithm (SOA) [95], Social Rumor Propagation Optimization (SRPO) [96], Motorbike Courier Optimization (MCO) [97], Court and Judge Algorithm (CJA) [98], Community-Based Crisis Management Algorithm (CCMA) [99], Perfumer Optimization Algorithm (POA) [100], Program Manager Optimization Algorithm (PMOA) [101], Negotiators Algorithm (NA) [102], and Farmer and Seasons Algorithm (FSA) [103].

Math-based Algorithms (MAs) draw inspiration from mathematical rules and fundamentals (i.e.: mathematical operators, mathematical programming processes, numerical techniques, and others). Some of the most well-known MAs are: Radial Movement Optimization (RMO) algorithm [104], Hyper-Spherical Search (HSS) algorithm [105], Stochastic Fractal Search (SFS) [12], Sine Cosine Algorithm (SCA) [106–110], Spherical Search Optimizer (SSO) [111], Golden Ratio Optimization Method (GROM) [112], Arithmetic Optimization Algorithm (AOA) [113], and RUNge Kutta Optimizer (RUN) [114].

Physics-based algorithms (PAs) are inspired by physical laws observed in the real world, modeling phenomena such as motion, energy, gravity, wave propagation, thermodynamics, and so on. Some of the most popular PAs algorithms are: Central Force Optimization (CFO) [115], Gravitational Search Algorithm (GSA) [116], and Big-Bang Big-Crunch (BBBC) [117]. Other recently developed algorithms are: Ray Optimization (RO) algorithm [118], Magnetic Charged System Search (MCSS) [119], Intelligent Water Drops (IWD) algorithm [120], Colliding Bodies Optimization (CBO) algorithm [121], Optics Inspired Optimization (OIO) algorithm [122], Electromagnetic Field Optimization (EFO) algorithm [123], Multi-Verse Optimizer (MVO) [124], Water Evaporation Optimization (WEO) [125], Thermal Exchange Optimization (TEO) algorithm [126], Sonar Inspired Optimization (SIO) algorithm [127], Nuclear Reaction Optimization (NRO) algorithm [128], Quantum-based Avian Navigation Optimizer Algorithm (QANA) [129], Vibrating Particles System Algorithm (VPSA) [130], Equilibrium Optimizer (EO) [131], Henry Gas Solubility Optimization (HGSO) algorithm [132], Plasma Generation Optimization (PGO) algorithm [133], Solar System Algorithm (SSA) [134], Lichtenberg Algorithm (LA) [135], Light Spectrum Optimizer (LSO) [136], Special Relativity Search (SRS) algorithm [137], Energy Valley Optimizer (EVO) [138], Thunderstorm and Cloud Algorithm (TCA) [139], Tornado Optimizer with Coriolis force (TOC) [140], and Archimedes Optimization Algorithm (AOA) [141].

Despite this growth in the field of metaheuristics, the No Free Lunch (NFL) Theorem [142] establishes that no single metaheuristic can solve all optimization problems effectively. Algorithms that perform well on benchmark functions may fail in real-world applications, and vice versa. With the emergence of increasingly complex optimization challenges, the limitations of existing metaheuristics become apparent. Consequently, enhancing current methods for specific problem domains, developing innovative strategies to address common shortcomings, and designing entirely new metaheuristics are crucial directions for advancing the field.

The Archimedes Optimization Algorithm (AOA) is a recently Physic-based meta-heuristic optimization algorithm introduced by Hashim et al. [141] in 2021. It mimics the physical laws of Archimedes principle. The AOA algorithm demonstrates its efficiency and robustness in addressing complex real-world optimization problems, outperforming several well-known optimization algorithms. As a result, the AOA algorithm was successfully applied to a wide range of problems, including feature selection, image processing, optimal parameter control, economic load dispatch, classification, wireless networks, robotics, and more.

To gather relevant AOA-related publications, we consider reputable academic publishers such as Elsevier, Springer, IEEE, MDPI, Wiley, and others. Furthermore, we use Google Scholar with specific search strings to construct a database of articles related to the AOA algorithm, with the relevant keywords:

- Archimedes Optimization Algorithm
- Improved Archimedes Optimization Algorithm
- Modified Archimedes Optimization Algorithm
- Enhanced Archimedes Optimization Algorithm
- Binary Archimedes Optimization Algorithm
- Adaptive Archimedes Optimization Algorithm
- Multi-Objective Archimedes Optimization Algorithm
- Hybridized Archimedes Optimization Algorithm
- Applications of Archimedes Optimization Algorithm
- Archimedes Optimization Algorithm survey
- Archimedes Optimization Algorithm review
- Archimedes Optimization Algorithm overview

As shown in Fig. 2, the collected papers were carefully screened to include only credible and original studies published in reputable journals (WoS Q1–Q4). To ensure a rigorous and objective selection process, this survey excludes those that meet the following criteria:

- Published by predatory journals;
- Less than four pages in length;

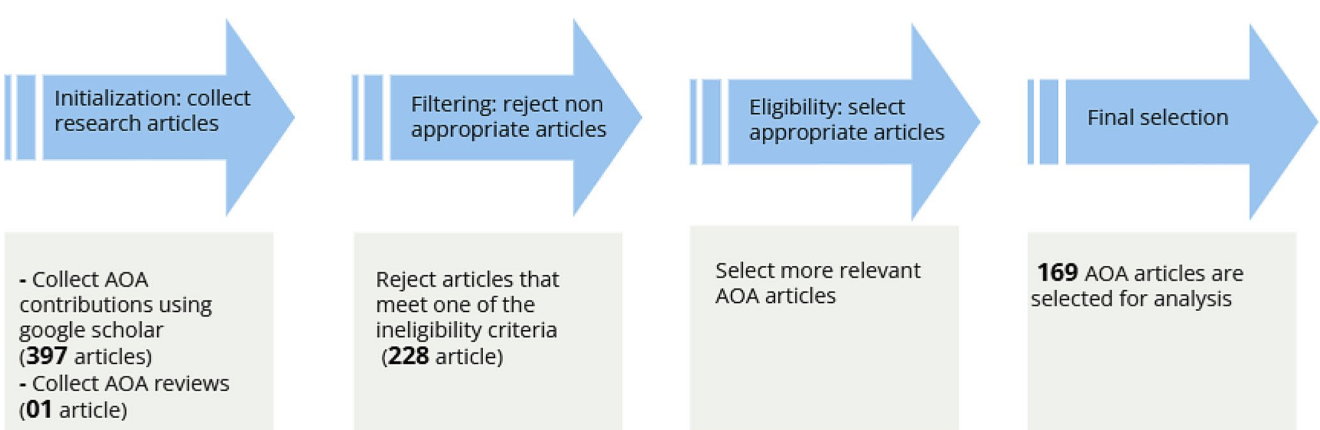


Fig. 2 Diagram illustrating the AOA paper collection process

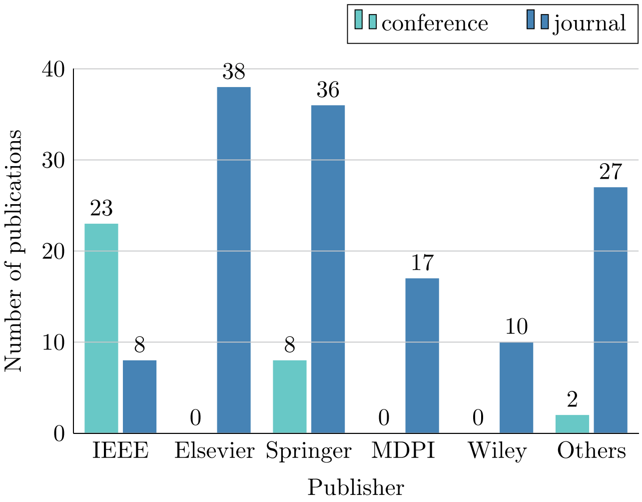


Fig. 3 Number of AOA related publications per database

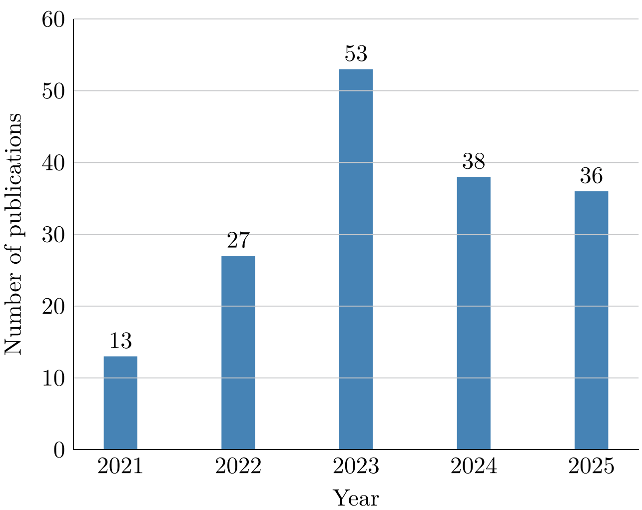


Fig. 4 Number of AOA algorithm related publications per year

Table 1 Top 10 countries ranked by number of AOA publications

Country	Rank	Number of publications
India	1	53
China	2	36
Egypt	3	19
Turkey	4	12
Malaysia	5	8
Algeria	6	7
Saudi Arabia	7	5
Iraq	7	5
Morocco	8	4
Tunisia	9	3

Table 2 Top 10 AOA co-cited articles

Studies	Rank	Number of citations
Hashim et al. [141]	1	1105
Houssein et al. [144]	2	108
Moustafa and Elsheikh [145]	3	104
Zhang et al. [146]	4	102
Ali et al. [147]	5	98
Fathy et al. [148]	6	84
Akdag [149]	7	75
Kharich et al. [150]	8	65
Janamala and Rani [151]	9	54
Desuky et al. [152]	10	49

- Not written in English;
- Incomplete (when multiple versions of an article exist, only the most complete version is considered).

The findings of our study are presented in the following figures. Figure 3 shows the distribution of AOA-related publications by publisher and publication type, with Elsevier, Springer, and IEEE emerging as the most prominent sources. Figure 4 illustrates the yearly trend in AOA publications, revealing a marked increase in interest over the past four years, peaking in 2023. Since the algorithm's introduction in 2021, more than 160 related works have been published, highlighting its growing influence in the field.

Table 1 provides an overview of the geographical distribution of AOA research, highlighting the top 10 contributing countries. India and China stand out as the most active contributors, followed by Egypt, Turkey, Malaysia, Algeria, Saudi Arabia, Iraq, Morocco, and Tunisia. The most frequently co-cited AOA articles are presented in Table 2.

To the best of our knowledge, there is only one AOA survey developed by Dhal et al. [143] which analyzed only 39 AOA articles. Our recent AOA survey, on the other hand, provides a more comprehensive review covering over 160 articles published between 2021 and the end of September 2025. The performance of the AOA algorithm is assessed using 18 IEEE CEC benchmark functions (categorized into three groups: unimodal, multimodal, and fixed-dimension numerical optimization problems). This makes our survey different from the aforementioned survey, offering a broader and more up-to-date look into AOA research.

The primary contributions of our survey are as follows.

1. **Comprehensive survey**: This work synthesizes research on the AOA algorithm and its various enhancements, covering modified, multi-objective, and hybrid adaptations.
2. **Diverse Applications**: We highlight and analyze the applications of the AOA algorithm in several domains, such as image processing, feature selection, wireless

sensor networks, optimal control of parameters, and photovoltaic energy systems.

3. **Comparative Analysis**: The AOA algorithm's performance was evaluated on 18 IEEE CEC benchmark functions against eight meta-heuristic algorithms, demonstrating its competitive results.
4. **Strengths and Limitations Analysis**: This study critically assesses the AOA algorithm, outlining its key strengths and notable limitations.
5. **Future research directions**: The paper outlines potential research directions and development opportunities for the AOA algorithm, encouraging its continued evolution.

The structure of this paper is given as follows. Sect. 2 outlines the fundamental design of the AOA algorithm. Sect. 3 provides an in-depth review of modified, multi-objective, and hybridized variants of the AOA algorithm. Sect. 4 discusses the algorithm's practical applications across various domains. Comparisons and results of the AOA algorithm with some well-regarded optimization meta-heuristics are given in Sect. 5. Sect. 6 offers a detailed discussion, including insights and recommendations for future research. Finally, Sect. 7 concludes the paper.

2 Archimedes Optimization Algorithm

The Archimedes Optimization Algorithm (AOA), introduced by Hashim et al. [141] in 2021, is a physics-based metaheuristic optimization algorithm inspired by the fundamental physical law known as Archimedes' principle. The principle states that the buoyancy force experienced by an object immersed in a fluid is equal to the weight of the fluid displaced by the object. This relationship can be mathematically expressed by the following equation:

$$F_b = W_o \tag{1}$$

where F_b and W_o represent the buoyancy force and the weight of the object, respectively. We can express this equality in terms of density (p), volume (v), and acceleration (a):

$$p_b v_b a_b = p_o v_o a_o \tag{2}$$

where the subscripts b and o denote the fluid and the immersed object, respectively. This equation represents the object's effort to reach equilibrium and can be rearranged as follows:

$$a_o = \frac{p_b v_b a_b}{p_o v_o} \tag{3}$$

An object immersed in a fluid moves towards the surface if its density is lower than that of the fluid; if higher, it sinks to the bottom; and if equal, it remains suspended. In AOA, each candidate solution in the search space is treated as an object immersed in a fluid. The algorithm enables each object to move toward the global optimal solution by adjusting its density, volume, and acceleration.

2.1 Mathematical Formulation of the AOA Algorithm

The AOA algorithm relies on the idea of generating an initial population and iteratively updating this population in accordance with predetermined rules, just as other population-based metaheuristic algorithms. The algorithm's mathematical rule-based steps can be represented as follows:

Step 1: Initialization

The algorithm starts with a population consisting of N objects (population size). The position of each object is initialized at a random point in the search space using:

$$O_i = lb_i + rand \times (ub_i - lb_i),\ i = 1, 2, \ldots, N \tag{4}$$

where O_i represents the position of the i-th object, lb_i and ub_i represent the lower and upper bounds of the search space, and $rand$ represents a uniformly distributed random variable in [0, 1].

The density and volume of each i-th object are randomly initialized as follows:

$$\begin{aligned} den_i &= rand \\ vol_i &= rand \end{aligned} \tag{5}$$

The acceleration of the i-th object is also randomly initialized as follows:

$$acc_i = lb_i + rand \times (ub_i - lb_i) \tag{6}$$

This initial population is evaluated to determine the object with the best fitness value x_{best} and its associated parameters den_{best} vol_{best}, acc_{best}.

Step 2: Densities and volumes update

In each iteration, the density and volume values of the objects are updated toward the values of the best object:

$$\begin{aligned} den_i^{t+1} &= den_i^t + rand \times (den_{best} - den_i^t) \\ vol_i^{t+1} &= vol_i^t + rand \times (vol_{best} - vol_i^t) \end{aligned} \tag{7}$$

where t represents the current iteration. These updates ensure that the population converges toward the known best solution.

Step 3: Transfer Function and Density Decreasing Factor The AOA algorithm has two important parameters (i.e.: Transfer Function (TF) and Density Decreasing Factor (d)) that facilitate the transition between exploration and exploitation phases. Initially, collisions occur between objects, and over time, the system tends to move toward an equilibrium state. In the AOA algorithm, this process is modeled using the transfer operator (TF), which facilitates the transition from exploration to exploitation. The TF operator is defined as follows:

$$TF = \exp\left(\frac{t - t_{max}}{t_{max}}\right) \tag{8}$$

Where TF increases progressively over time until it reaches a value of 1. Here, t and t_max represent the current iteration number and the maximum iteration number, respectively.

Similarly, the density decreasing factor (d) also contributes to the transition from a global search to a local search. The value of this parameter decreases as iterations progress using the following equation:

$$d^{t+1} = \exp\left(\frac{t_{max} - t}{t_{max}}\right) - (\frac{t}{t_{max}}) \tag{9}$$

Step 4.1: Exploration Phase ($TF \leq 0.5$)

During this stage, a collision occurs between objects, and the acceleration of the i-th object is updated according to the following equation based on its interaction with another randomly selected object *mr*.

$$acc_i^{t+1} = \frac{den_{mr} + vol_{mr} \times acc_{mr}}{den_i^{t+1} \times vol_i^{t+1}} \tag{10}$$

where acc_i, den_i, and vol_i are acceleration, density, and volume of object i, respectively. Whereas acc_{mr}, den_{mr}, and vol_{mr} represent acceleration, density, and volume of random material. It is important to note that setting $TF \leq 0.5$ ensures exploration during approximately one third of the iterations. Using a value different from 0.5 will alter the balance between exploration and exploitation.

Step 4.2: Exploitation Phase (TF > 0.5)

In this step, there is no collision between objects, and the acceleration of the i-th object is updated according to the following equation based on the parameters of the best object:

$$acc_i^{t+1} = \frac{den_{best} + vol_{best} \times acc_{best}}{den_i^{t+1} \times vol_i^{t+1}} \tag{11}$$

Step 4.3: Acceleration normalization

Following the acceleration updates in respective phases, a normalization procedure is executed to establish proportional step percentages for each object, which is mathematically represented by:

$$acc_{i\text{-norm}}^{t+1} = u \times \frac{acc_i^{t+1} - \min(acc)}{\max(acc) - \min(acc)} + l \tag{12}$$

where u and l are parameters that determine the normalization range and are typically set as u=0.9 and l=0.1. min(acc) and max(acc) represent the smallest and largest acceleration values in the population. If an object is far from the global optimum, its acceleration value becomes high, and the exploration phase occurs. Otherwise, the exploitation phase occurs.

Step 5: Position Update Step 5 (Position Update): The positions of objects are updated differently in exploration and exploitation phases.

Step 5.1: Exploration Phase ($TF \leq 0.5$) The position of the i-th object is updated using the following equation:

$$x_i^{t+1} = x_i^t + C_1 \times rand \times acc_{i\text{-norm}}^{t+1} \times d \times (x_{rand} - x_i^t) \tag{13}$$

where C_1 is a constant typically set to 2, and x_{rand} is the position of a randomly selected object from the population.

Step 5.2: Exploitation Phase (TF > 0.5) In this case, the position of the i-th object is updated according to the following equation:

$$x_i^{t+1} = x_{best}^t + F \times C_2 \times rand \times acc_{i-norm}^{t+1} \times d \times (T \times x_{best} - x_i^t) \tag{14}$$

where C_2 is a constant typically set to 6, T is a parameter calculated by the formula $T = C_3 \times TF$ and increases over time, and F is a flag that determines the direction of movement:

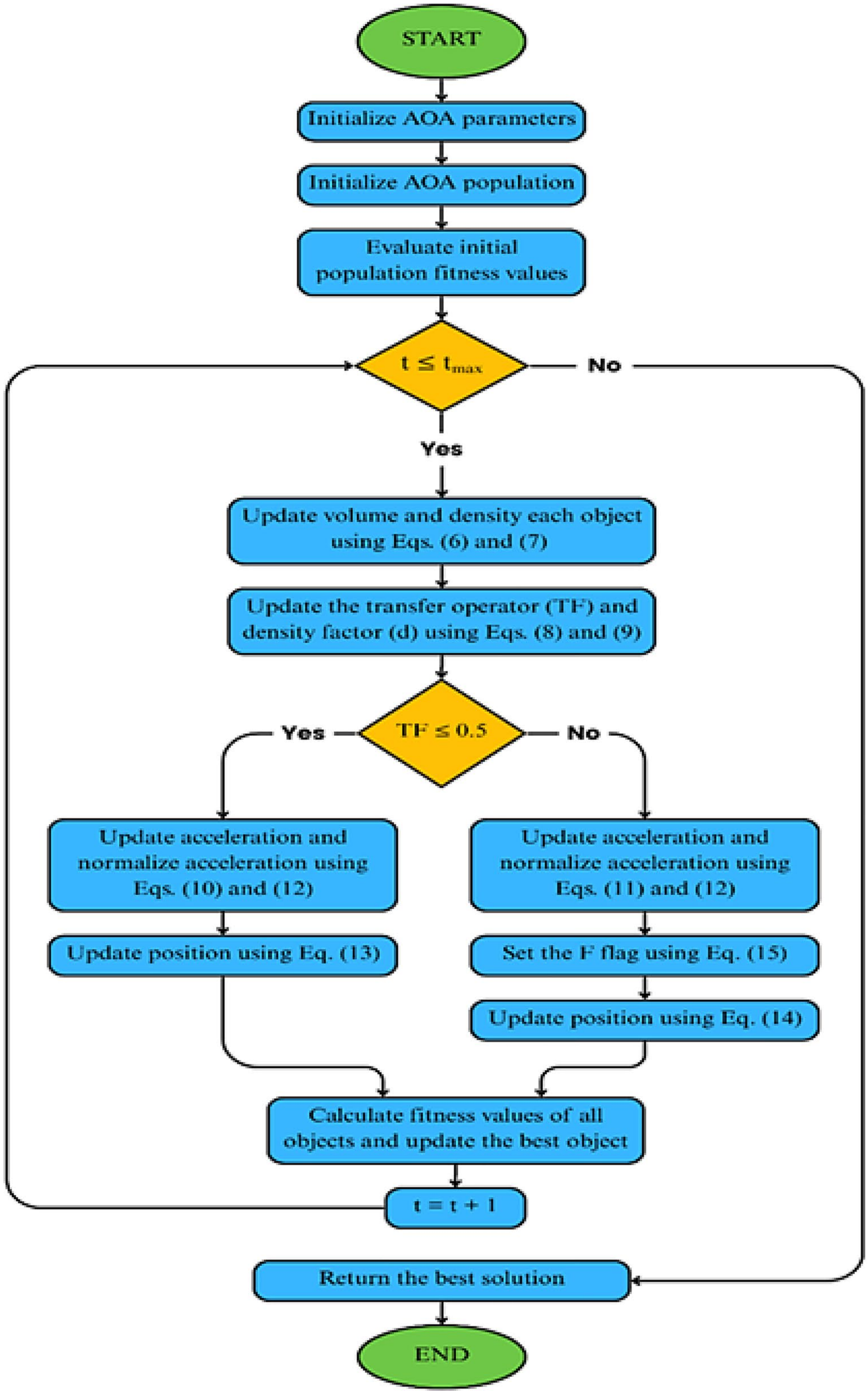
$$F = \begin{cases} +1 & \text{if } P \leq 0.5 \\ -1 & \text{if } P > 0.5 \end{cases} \tag{15}$$

where P is calculated by the formula $P = 2 \times rand - C_4$, and C_4 is typically set to 0.5.

Step 6: Evaluation and Termination of Iteration In each iteration, the fitness values of all objects are calculated, and the best solution x_best, den_best, vol_best, acc_best is updated. The algorithm terminates when the maximum number of iterations is reached or when a specific termination criterion is satisfied.

The pseudo-code of the AOA algorithm is presented in Algorithm 1, and its flowchart is illustrated in Fig. 5.

Fig. 5 Flowchart of the AOA algorithm



Algorithm 1 Pseudo-code of the AOA Algorithm

Initialize AOA parameters: Population size N, Maximum iterations T, Constants C_1, C_2, C_3, C_4, Dimension D, etc.
Initialize population of objects: X_i for $i = 1, 2, \ldots, N$
Initialize density (den_i), volume (vol_i), and acceleration (acc_i) for each object
Evaluate initial population and determine best solution x_{best}
while $t \leq T$ **do**
    Update den_i and vol_i using Eqs. (6) and (7), respectively
    Update the transfer operator (TF) using Eq. (8)
    Update the density factor (d) using Eq. (9)
    for $i = 1$ to N **do**
        if $TF \leq 0.5$ **then**
            Update acc_i using Eq. (10) and normalize using Eq. (12)
            Update X_i using Eq. (13)
        else
            Update acc_i using Eq. (11) and normalize using Eq. (12)
            Compute F flag using Eq. (15)
            Update X_i using Eq. (14)
        end if
        Evaluate fitness values of all objects
    end for
    $t = t + 1$
end while
Return the best solution X_{best} and its fitness value

3 Recent Variants of the Archimedes Optimization Algorithm

In this section, variants of the AOA algorithm proposed in the literature, classified into modified, multi-objective, and hybridized versions, are presented as illustrated in Fig. 6

3.1 Modified Versions of Archimedes Optimization Algorithm

In the following, different modified versions of the AOA algorithm are highlighted and their summary is given in Table 3.

3.1.1 Binary Archimedes Optimization Algorithm

Çınar [153] proposed the first comprehensive study on binary variants of the AOA algorithm for solving the uncapacitated facility location problem, a classical NP-hard discrete optimization problem. The study introduced 17 binary AOA variants (BAOA1–BAOA17) by applying different stationary and non-stationary transfer functions (TF1–TF17) to map continuous values to binary values. Experimental evaluations on 15 well-known Uncapacitated Facility Location Problem (UFLP) benchmarks, ranging from 16 to 100 dimensions, demonstrated that the non-stationary transfer functions, particularly TF9 used in BAOA9, produce superior solutions compared to their stationary counterparts. The BAOA9 variant achieves the best performance in terms of mean GAP, significantly outperforming conventional binary optimization algorithms.

Amine et al. [154] introduced a binary AOA algorithm (BAOA) for feature selection in regression problems. The original AOA algorithm was adapted to a binary search space using a transfer function, enabling it to effectively select relevant feature subsets while discarding redundant or noisy ones. Simulation results on benchmark regression datasets demonstrated that the BAOA algorithm achieves lower prediction error, fewer selected features, and better generalization compared to other existing binary meta-heuristic approaches.

Fang et al. [155] proposed a Binary AOA algorithm (BAOA) for solving discrete optimization problems, including feature selection, medical image segmentation, and 0–1 knapsack problems. The BAOA algorithm incorporates a V-shaped transfer function to effectively handle binary search spaces, addressing the limitations of the classical AOA algorithm in discrete optimization contexts. Experiments showed the robustness and computational efficiency of the proposed BAOA algorithm compared to some well-regarded binary meta-heuristics such as BPSO, BGOA, BWOA, and BGWO algorithms.

Rosli et al. [156] proposed a binary AOA algorithm (BAOA) combined with the Weighted Sum Method (WSM) for Under-Frequency Load Shedding (UFLS) in islanded distribution systems. The proposed BAOA algorithm was tested on 11 kV Malaysian distribution network considering four criteria such as load priority, load category, stability index, and load size. Experiments demonstrated that the BAOA algorithm provides significant improvements in frequency response and voltage stability compared to conventional methods, achieving 73.3% better performance in islanding events and 60% better performance in overloading events.

Mohamed et al. [157] proposed a binary AOA algorithm (BAOA) for solving the Dominant Metric Dimension

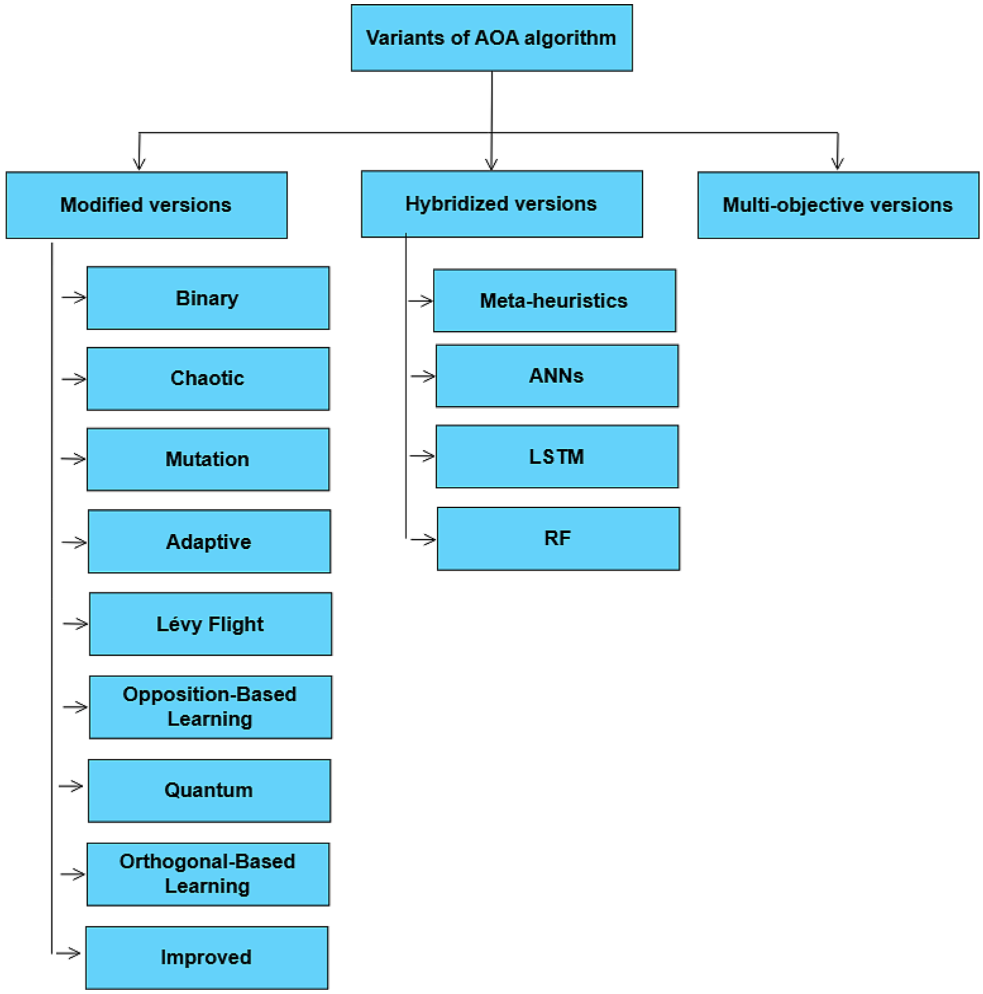


Fig. 6 Variants of AOA algorithm

(DMD) problem in graph theory. The BAOA algorithm adapts the continuous AOA algorithm to a binary search space, enabling efficient selection of dominant metric vertices that uniquely identify all other vertices in a graph. Results showed that the BAOA algorithm achieves more accurate solutions, faster convergence, and better scalability compared to BPSO and BWOA meta-heuristics.

3.1.2 Chaotic Archimedes Optimization Algorithm

Akdag [149] proposed an enhanced version of the AOA algorithm, named as IAOA, to address both single and multi-objective Optimal Power Flow (OPF) problems. The IAOA incorporated a chaotic strategy and a dynamic weight adjustment mechanism to enhance the exploration and exploitation capabilities of the standard AOA algorithm. The proposed IAOA algorithm was tested on IEEE 30-bus and 118-bus systems, as well as on a practical 300-bus power system, considering various objective functions such as minimizing fuel cost, emission levels, and transmission losses. Results indicated that the IAOA algorithm outperforms the original AOA algorithm and several other state-of-the-art optimization algorithms including PSO, DE, and GA, in terms of convergence speed and solution quality.

Lydia et al. [158] proposed an enhanced AOA algorithm (EAOA) for clustered wireless sensor networks (WSNs). The chaos concept was incorporated into the original AOA algorithm to enhance its exploration and exploitation capabilities. The performance of the EAOA algorithm was validated on three distinct conditions dependent upon the placement of base stations. Simulation results revealed the superiority of the EAOA algorithm compared to the standard AOA algorithm and other clustering algorithms by obtaining longer network lifetime, higher packet delivery ratio, and lower energy usage.

Cheng et al. [159] proposed a modified AOA algorithm, termed as MAOA, for the localization accuracy of nodes in WSNs. The concept of chaos was integrated into the original AOA algorithm to enhance the initial population diversity and improve the global convergence speed. The MAOA algorithm was evaluated in four different network environments, demonstrating superior localization speed

Table 3 Modified versions of the AOA algorithm

Variant	Name	Application	Author	Year
Binary AOA	BAOA	Uncapacitated facility location problem	Çınar [153]	2022
	BAOA	Feature selection problem	Amine et al. [154]	2022
	BAOA	Feature selection, medical image segmentation, and 0–1 knapsack problems	Fang et al. [155]	2023
	BAOA	Under-frequency load shedding (UFLS) in islanded distribution systems	Rosli et al. [156]	2023
	BAOA	Dominant Metric Dimension problem in graph theory	Mohamed et al. [157]	2023
Chaotic AOA	IAOA	Optimal power flow problem	Akdag [149]	2022
	EAOA	Clustered wireless sensor networks	Lydia et al. [158]	2022
	MAOA	Localization accuracy of nodes in wireless sensor networks	Cheng et al. [159]	2022
	CAOA	Nonlinear ARX model identification	Mehmood et al. [160]	2023
	CAOA	Regression test case selection in software testing	Verma et al. [161]	2023
	CAOA	Network reconfiguration in power distribution systems	Adegoke et al. [183]	2024
	CAO	Signal feature extraction	Bencherqui et al. [162]	2024
Adaptive AOA	IAOA	Parameter identification of solar cells	Krishnan et al. [163]	2023
	IAOA	Rayleigh surface wave inversion	Yao et al. [164]	2023
	CAOA	Global optimization problems	Ding et al. [165]	2023
	MTO-AO	Lung cancer detection and classification	Chowdary and Purushotaman [184]	2024
	IAOA	Data-driven modeling of continuous-time Hammerstein models	Islam et al. [166]	2024
	MDAOA	Global optimization problems	Nurmuhammed et al. [167]	2024
Lévy Flight AOA	LAO	Optimal design of microstrip patch antennas	Singh and Kaur [168]	2022
	HCAOA	Global optimization problems	Zhang et al. [169]	2023
	HAOA	Network reconfiguration in power distribution systems	Adegoke et al. [170]	2024
	IAOA	DC microgrids with hybrid photovoltaic storage systems	Han et al. [171]	2025
	MAoA	Resources allocation in multicell D2D communications	Patil and Hendre [185]	2025
	IAOA	Parameter estimation of fractional-order system	Chen et al. [186]	2025
Opposition-Based AOA	IAOA	Global optimization problems	Wang et al. [172]	2023
	DAOA	Early detection of skin cancer from dermoscopic images	Ding et al. [173]	2024
Orthogonal-Based AOA	I-AOA	Parameter identification of polymer electrolyte membrane fuel cells	Houssein et al. [144]	2021
Quantum-Based AOA	QAOA	Underdetermined blind source separation problem	Gao et al. [174]	2023
	QMQAOA	hybrid-load autonomous guided vehicle scheduling problem	Zhou et al. [175]	2023
Gaussian AOA	MAOA	Global optimzation problems	Zhan et al. [176]	2023
Improved AOA	AOA-LS	Power system harmonics estimation	Apon et al. [177]	2021
	FDB-AOA	Design optimization of induction motor	Yenipinar et al. [187]	2021
	A-FAOA	Photovoltaic parameter identification	Yousri et al. [178]	2022
	KSAOA	Ridge regression	Song et al. [188]	2022
	IAOA-Quadratic	Energy demand estimation problem	Aslan [179]	2023
	IAOA	Design of hybrid renewable energy systems	Kharrich et al. [150]	2023
	IAOA	Global optimization problems	Ahmad et al. [180]	2023
	PAOA	Variable pitch control in wind turbines	Jiang et al. [181]	2023
	HFA	Distributed task scheduling in mobile edge computing	Kumaresan et al. [189]	2023
	AoA-DCT	Remote sensing image watermarking	Bodke and Chaudhari [182]	2024
	FBIAOA	Fast-charging stations for electric vehicles with grid integration	Singh and Kumar [190]	2024
	DAOA	Melanoma detection and diagnosis	Gao et al. [191]	2024
	IAOA	Identification of continuous-time Hammerstein model	Islam et al. [192]	2024
	H-AOA	Molten iron allocation in steel production	Hu et al. [193]	2024

and accuracy compared to DE and BOA algorithms. Results showed that the proposed MAOA algorithm reduces localization errors by 35% to 71% compared to DE and by 3% to 7% compared to the BOA algorithm.

Mehmood et al. [160] developed a chaotic AOA algorithm (CAOA) for nonlinear ARX model identification with key term separation. The chaotic map was incorporated into the standard AOA algorithm to improve its exploration capabilities and avoid premature convergence. The proposed CAOA algorithm was evaluated on several benchmark problems including the AutoRegressive eXogenous (ARX) and Nonlinear Input ARX (NI-ARX) models, LD-Didactic temperature process plants, and electrically stimulated muscle models. Results proved that the CAOA algorithm outperforms conventional AOA and competing metaheuristics such as RSA, SCA, HHO, and WOA in terms of convergence speed and solution accuracy across varying noise levels and population sizes.

Verma et al. [161] proposed a chaotic AOA algorithm (CAOA) for efficient regression test case selection in software testing. The chaos concept was integrated into AOAs initialization and parameter updates to enhance population diversity and avoid premature convergence. Simulation results showed that the CAOA algorithm provides higher fault detection rates, reduced testing time, and better selection efficiency compared to the standard AOA algorithm, BA, and AO algorithms.

Bencherqui et al. [162] proposed a chaotic AOA (CAO) algorithm for solving real-world engineering problems and signal feature extraction. Ten distinct chaotic maps were used to replace random sequences in the three essential components of the classical AOA algorithm (i.e.: position update, initialization, and parameter update) to improve population diversity and avoid premature convergence. Experimental results showed that the proposed CAO algorithm provides faster convergence, higher solution accuracy, and better robustness compared to the standard AOA algorithm and other optimization metaheuristics.

3.1.3 Adaptive Archimedes Optimization Algorithm

Krishnan et al. [163] proposed an improved AOA algorithm (IAOA) for parameter identification of solar cells. The IAOA algorithm integrates adaptive parameter control and augmented density decreasing strategies to obtain better exploration-exploitation balance and reduce local optima issues. Experiments on benchmark and real datasets showed the superiority of the proposed IAOA algorithm compared to the standard AOA algorithm and other optimization techniques by achieving lower Root Mean Square Error (RMSE), faster convergence, and more accurate parameter estimation.

Yao et al. [164] introduced an adaptive AOA algorithm (IAOA) to Rayleigh surface wave inversion for geophysical exploration. The IAOA algorithm integrates the adaptive strategy into the original AOA algorithm to improve convergence speed and solution accuracy in estimating subsurface shear-wave velocity profiles. The performance of the IAOA algorithm was assessed using measured data taken from the Wyoming area of the United States and results showed that the IAOA algorithm achieves higher accuracy, better stability, and faster convergence compared to the original AOA algorithm and PSO.

Ding et al. [165] introduced the Corrected AOA algorithm (CAOA) based on the adaptive iterative update mechanism for solving global optimization problems. The performance of the CAOA algorithm was evaluated using CEC2017 benchmark functions in 30 and 50 dimensions and two practical engineering problems. Results demonstrated that the CAOA algorithm achieves comprehensive scores ranking first among all compared algorithms such as BOA, GA, Archerfish Hunting Optimizer (AHO), PSO, Transient search algorithm (TSO), and Dynamic Differential Annealed Optimization (DDAO) algorithm.

Islam et al. [166] proposed an adaptive AOA (IAOA) algorithm for data-driven modeling of continuous-time Hammerstein models. Two strategies including adaptive parameter control and modified density factor were incorporated into the original AOA algorithm to improve search balance and convergence. Experimental validation on systems with incomplete data demonstrated that the IAOA algorithm achieves higher identification accuracy, better robustness to missing samples, and faster convergence compared to traditional optimization techniques and the standard AOA algorithm.

Nurmuhammed et al. [167] developed an enhanced version of the AOA algorithm (MDAOA) for solving global optimization problems. Adaptive parameter control and dimension learning strategies were incorporated into the original AOA algorithm to improve its performance. The efficiency of the MDAOA algorithm was assessed on 13 standard benchmark functions, 29 CEC 2017 benchmark functions, and five real-life engineering problems. Statistical results demonstrated that the proposed MDAOA algorithm achieves faster convergence, higher solution accuracy, and better performance across diverse optimization scenarios.

3.1.4 Lévy Flight-Based Archimedes Optimization Algorithm

Singh and Kaur [168] introduced an enhanced AOA algorithm (LAO) for improving the design of microstrip patch antennas. The Lévy flight strategy was incorporated into the original AOA algorithm to achieve a better balance between exploration and exploitation and escape local optima. The LAOs performance was evaluated using 29 benchmark functions from the CEC2017 test suite and four different antenna design problems, with simulations conducted using MATLAB-R2018a linked to Computer Simulation Tool (CST) and Keysight Advanced Design System (ADS) software. Experimental results indicated that the LAO algorithm outperforms other metaheuristics in key antenna performance metrics, including gain, return loss, directivity, efficiency, bandwidth, Voltage Standing Wave Ratio (VSWR), and reflection coefficient.

Zhang et al. [169] proposed an improved AOA algorithm (HCAOA) for solving global optimization problems. Levy flight and orthogonal learning mechanisms were incorporated into the original AOA algorithm to improve convergence speed and avoid local optima. The HCAOA algorithm was benchmarked using the CEC 2017 test suite and four engineering design problems, demonstrating superior performance compared to the conventional AOA and other advanced metaheuristic algorithms in terms of optimization speed and solution quality.

Adegoke et al. [170] introduced an enhanced version of the AOA algorithm (HAOA) for network reconfiguration in power distribution systems. The Lévy flight mechanism was integrated into the original AOA algorithm to enhance convergence speed and solution quality. The performance of the HAOA algorithm was assessed using the IEEE 33 and 69 bus systems. Simulation results demonstrated that the HAOA algorithm achieves lower power losses, better voltage stability, and improved load distribution compared to standard AOA and other optimization techniques.

Han et al. [171] proposed a control strategy optimization for DC microgrids with hybrid photovoltaic storage systems using an improved AOA algorithm (IAOA). The study focuses on enhancing system stability by minimizing voltage fluctuations through optimized control parameters for the inverter. The proposed IAOA algorithm integrates Lévy flight and Gaussian variation strategies to improve convergence speed and accuracy. The optimization method was applied to a DC microgrid system with a Hybrid Energy Storage System (HESS) consisting of lithium-ion batteries and supercapacitors, demonstrating a 1.6% to 6.98% reduction in voltage fluctuation amplitude under sudden load disturbances compared to conventional optimization methods.

3.1.5 Opposition-Based Archimedes Optimization Algorithm

Wang et al. [172] proposed an improved version of the AOA algorithm (IAOA) for solving global optimization problems. Three strategies including Opposition-based learning, simplex method, and ajustment factor were integrated into the original AOA algorithm to enhance its convergence performance. The effectiveness of the IAOA algorithm was validated on CEC2013 benchmark functions and results showed that the IAOA algorithm has significant advantages compared to the original AOA algorithm and the four most excellent meta-heuristics algorithms in terms of accuracy, convergence speed, and stability.

Ding et al. [173] proposed a Developed AOA algorithm (DAOA) for the early detection of skin cancer from dermoscopic images. Three mechanisms were incorporated into the original AOA algorithm including opposition-based learning (OBL), dynamic transfer operator, and chaotic map to enhance its convergence and provide a good balance between exploitation and exploration. The DAOA algorithm was validated on the American Cancer Society dataset, and experiments showed its high performance among five well-known methods by achieving an accuracy of 88%, sensitivity of 96%, precision of 97%, specificity of 81%, and F-measure of 97% in melanoma classification.

3.1.6 Orthogonal-Based Archimedes Optimization Algorithm

Houssein et al. [144] proposed an enhanced AOA algorithm (I-AOA) for parameter identification of polymer electrolyte membrane fuel cells. Orthogonal learning and local escaping operator strategies were integrated into the original AOA algorithm to address its limitations such as slow convergence and unbalanced exploration-exploitation phases. The I-AOA algorithm was validated on the CEC'2020 benchmark suite and three engineering design problems, including the tension/compression spring, pressure vessel, and rolling element bearing design problems. Comparative evaluations demonstrated that the I-AOA algorithm outperforms several well-known optimization algorithms such as WOA, MFO, SCA, PSO, HHO, and the original AOA algorithm.

3.1.7 Quantum-Based Archimedes Optimization Algorithm

Gao et al. [174] introduced a quantum AOA algorithm (QAOA) for solving the underdetermined blind source separation problem. A quantum theory was incorporated into the original AOA algorithm to enhance its performance and provide a good counterbalance between exploitation and exploration. Simulation results demonstrated that the proposed QAOA algorithm outperforms the standard AOA algorithm and other existing optimization methods by providing higher separation accuracy.

Zhou et al. [175] introduced a quantum-inspired AOA algorithm (QMQAOA) to address the hybrid-load autonomous guided vehicle scheduling problem in mixed-model automotive assembly lines. Quantum rotation gate initialization and Q-learning-based neighborhood search were integrated into the original AOA algorithm to enhance solution quality and convergence speed. Experimental results demonstrated the QMQAOAs superiority over traditional methods, achieving higher degrees of Pareto optimality, better solution evenness, and lower inverted generational distance in 90/90, 77/90, and 90/90 cases, respectively.

3.1.8 Gaussian Mutation Archimedes Optimization Algorithm

Zhan et al. [176] proposed a multi- strategy fusion improved AOA algorithm (MAOA) for solving global optimization problems. Three strategies including Gaussian mutation, chaotic mapping, and reverse learning were incorporated into the original AOA algorithm to provide a stronger balance between global and local search, avoid premature convergence, and adapt more effectively to complex landscapes. Simulation results demonstrated that the MAOA algorithm delivers higher solution accuracy, faster convergence, and better robustness compared to the standard AOA algorithm and other metaheuristics.

3.1.9 Other Improved Archimedes Optimization Algorithm

Apon et al. [177] proposed an improved AOA technique (AOA-LS) for power system harmonics estimation. The least square (LS) method was incorporated into the standard AOA algorithm to enhance its efficiency. The proposed AOA-LS algorithm was evaluated using a voltage waveform obtained from a standard testing module under both uniform and Gaussian noise conditions. Results indicated that the AOA-LS technique consistently outperforms other conventional approaches, including PSOPC-LS, ABC-LS, and FA-LS in terms of estimation accuracy and computational efficiency across all noise levels. Specifically, the AOA-LS algorithm demonstrated superior performance in reducing estimation error while maintaining faster convergence time.

Yousri et al. [178] proposed an enhanced AOA algorithm (A-FAOA) for photovoltaic parameter identification, addressing the challenges of accurate model estimation under partial shading conditions. The fractional calculus mechanism was integrated into the standard AOA algorithm to enhance its memory effect and dynamic search capability. The proposed A-FAOA algorithm was validated on single diode, double diode, and triple diode PV models, which capture the complex nonlinear current-voltage characteristics of PV cells. Simulation results showed superior performance of the A-FAOA algorithm compared to several state-of-the-art optimization algorithms such as PSO, HHO, and SMA in terms of RMSE, Mean Absolute Error (MAE), and convergence speed.

Aslan [179] proposed six variants of the AOA algorithm to estimate Turkey's long-term energy demand from 2021 to 2050. These variants include AOA-Linear, AOA-Quadratic, AOA-Exponential, and their improved counterparts (IAOA-Linear, IAOA-Quadratic, IAOA-Exponential) that integrate linear, quadratic, and exponential models with the AOA algorithm. Utilizing a newly compiled dataset spanning 1997 to 2020, which includes observed energy demand, population, Gross Domestic Product (GDP), export, and import data, the study conducted sensitivity analyses to fine-tune algorithmic parameters. Among the models, the IAOA-Quadratic variant demonstrated superior performance in terms of solution quality and robustness.

Kharrich et al. [150] proposed an improved AOA Algorithm (IAOA) for the design of Hybrid Renewable Energy Systems (HRES) in isolated regions of Farafra, Egypt. The proposed IAOA aims to minimize the Net Present Cost (NPC) of HRES while considering technical and economic constraints, including the renewable fraction index, loss of power supply probability (LPSP), and availability. The IAOA algorithm was benchmarked against several established optimization algorithms such as EO, GWO, HHO, AEF, and the original AOA algorithm. Simulation results revealed the performance of the IAOA algorithm in minimizing NPC while ensuring high system reliability and efficiency.

Ahmad et al. [180] proposed an improved version of the AOA algorithm (IAOA) for solving global optimization problems. Two key strategies such as modified density decreasing factor and game theory-inspired safe updating mechanism were integrated into the original AOA algorithm to obtain good balance between exploration and exploitation phases. The IAOA algorithm was evaluated on 23 benchmark functions and results demonstrated its superior performance when compared to other algorithms like MVO, GOA, SCA, and ALO.

Jiang et al. [181] proposed a Parallel AOA algorithm (PAOA) for variable pitch control in wind turbines. The Taguchi mechanism was integrated into the original AOA algorithm to improve its convergence speed and optimization accuracy. The proposed PAOA algorithm was validated on a three MW variable pitch wind turbine model, where the objective was to minimize power fluctuation and maximize energy capture under varying wind speeds. The PAOA algorithm demonstrated superior performance compared to conventional optimization algorithms including PSO, WOA, and the original AOA, achieving significant reductions in overshoot and steady-state error.

Bodke and Chaudhari [182] proposed an improved AOA algorithm (AoA-DCT) for remote sensing image watermarking. The Discrete Cosine Transform (DCT) model was integrated into the AOA algorithm to enhance its performance. The proposed AoA-DCT algorithm was evaluated on Pavia University, Kennedy Space Center, and Cuprite datasets, considering Mean Square Error (MSE), Structural Similarity Index Measure (SSIM), and Peak Signal-to-Noise Ratio (PSNR) metrics. Simulation results showed superior robustness and perceptual quality of the AoA-DCT algorithm, achieving PSNR of 31.59, 31.50, and 31.79, and SSIM values of 0.97, 0.91, and 0.92, respectively, demonstrating superior robustness and perceptual quality compared to conventional optimization techniques.

3.2 Multi-Objective Versions of Archimedes Optimization Algorithm

Zhang et al. [146] proposed a multi-objective AOA algorithm (MOAOA) for optimizing the accuracy and reliability of wind speed forecasting. The MOAOA algorithm used archive and roulette-wheel selection strategies to improve global and local search capabilities. The proposed MOAOA approach was validated on hourly wind speed datasets from the Shandong Peninsula in China, demonstrating superior performance compared to conventional ensemble methods, particularly in capturing complex wind speed dynamics.

Eid and El-Kishky [194] introduced a Multi-Objective AOA algorithm (MO-AOA) based on the Pareto Optimal Front strategy for the placement of photovoltaic-based distributed generation units within electrical distribution networks. Utilizing the IEEE 33-bus test system, the MO-AOA algorithm aimed to minimize both total power losses and voltage deviations. Comparative analyses demonstrated the performance and robustness of the MO-AOA algorithm compared to PSO and ASO algorithms.

El-Afifi et al. [195] proposed a multi-objective AOA algorithm (MOAOA) for demand-side management in smart buildings, focusing on optimizing energy consumption and reducing power costs while maintaining user comfort. The MOAOA effectively balances energy loads across peak and off-peak hours, minimizing the peak-to-average power ratio and enhancing overall energy efficiency. Simulation results with a 95% confidence interval demonstrated that the MOAOA significantly reduced power costs and improved energy distribution compared to conventional methods.

Kazemi et al. [196] proposed a multi-objective AOA algorithm (MOAOA) for sentiment analysis, to improve the accuracy and speed of opinion mining from large volumes of unstructured text. The MOAOA approach includes a novel feature extraction phase, where all ironic sentences were grouped into a specific class to address the challenge of irony detection, a critical issue in sentiment analysis. The MOAOA was evaluated on benchmark datasets, achieving a classification accuracy of 96.7%, significantly outperforming conventional sentiment analysis methods.

Khaledian et al. [197] introduced a two-stage task scheduling approach, termed as TS-MOAOA, for fog-cloud computing environments. In the first stage, the multi-criteria decision-making method ranks tasks based on multiple criteria such as deadline, priority, and resource requirements. In the second stage, a Multi-Objective AOA algorithm (MOAOA) optimizes task allocation to fog and cloud nodes, balancing objectives like execution time minimization, energy efficiency, and cost reduction. Experiments showed that the proposed TS-MOAOA algorithm outperforms traditional scheduling methods by achieving faster task completion and lower energy consumption.

Kushwaha et al. [198] proposed a multi-objective AOA algorithm (MLEAO) for workflow scheduling in cloud computing. The performance of the MLEAO algorithm was assessed using scientific workflows as benchmarks considering the metrics of cost, energy consumption, improved makespan, and resource utilization. Experimental results showed that the MLEAO algorithm achieves shorter execution time, lower operational cost, and better load balancing compared to other optimization methods.

3.3 Hybridized Versions of Archimedes Optimization Algorithm

In this section, the hybridization of the AOA algorithm with other optimization algorithms are given as shown in Table 4

3.3.1 Hybridization with Genetic Algorithm

Moharram and Sundaram [201] developed a hybrid algorithm (AOA-GA) based on the hybridization of AOA and GA algorithm for spectral-spatial hyperspectral image classification. The efficiency of the AOA-GA algorithm was assessed using two classifiers (i.e.: Random Forest and Support Vector Machine) on three benchmark hyperspectral datasets such as Indian Pines, Salinas, and Pavia University. Experimental results demonstrated that the proposed AOA-GA algorithm delivers higher classification accuracy, better noise robustness, and improved spatial coherence compared to state-of-the-art optimization methods.

3.3.2 Hybridization with Ant Colony Optimization Algorithm

Yao et al. [202] proposed a combined approach (IAOA) based on the combination of AOA and ACO algorithms to address the challenges of limited node energy and short network lifetime in WSNs. The main objective is to construct the shortest transmission path to the sink node, thereby

Table 4 Multi-objective versions of the AOA algorithm

	Name	Application	Author	Year
Multi-objective	MOAOA	Wind speed forecasting	Zhang et al. [146]	2021
AOA	MO-AOA	Placement of photovoltaic-based distributed generation units	Eid and El-Kishky [194]	2021
	MOIAOA	MIMO radar orthogonal waveform design	Wanf et al. [199]	2023
	MOAOA	Demand-side management in smart buildings	El-Afifi et al. [195]	2023
	MOAOA	Sentiment analysis	Kazemi et al. [196]	2024
	TS-MOAOA	Task scheduling	Khalediian et al. [197]	2025
	MLEAO	Workflow scheduling in cloud computing	Kushwaha et al. [198]	2025
	MOAGT	Power system economic emission dispatch	Xiong et al. [200]	2025

reducing the energy consumption of long-distance transmissions. The proposed IAOA approach effectively balances energy consumption and prolongs network lifetime, outperforming traditional protocols such as LEACH, E-LEACH, LEACH-ANT, and MAXLEACH, achieving a network lifetime improvement of up to 140.55%, 107.09%, 99.24%, and 96.76%, respectively.

3.3.3 Hybridization with Grey Wolf Optimizer

Hannon et al. [203] proposed a hybrid approach (AOA-GWO) based on the hybridization of AOA with GWO algorithms to enhance the Maximum Power Point Tracking (MPPT) control strategy in photovoltaic systems. The AOA component enables rapid global search, while the GWO component refines the local optimization, resulting in reduced overshoot and oscillation. Simulation results in MATLAB/Simulink demonstrated a maximum efficiency of 99.62% for the proposed hybrid AOA-GWO, significantly outperforming conventional and other heuristic-based approaches.

3.3.4 Hybridization with Whale Optimization Algorithm

Raman and Chelliah [204] combined AOA and WOA algorithms for soil nutrient classification and pH prediction. The performance of the proposed HWAO algorithm was assessed using Marathwada datasets considering various measuring units such as accuracy, precision, MSE, Area Under Curve, specificity, G-mean, and sensitivity. Simulation results highlighted a significant advantage of the proposed HWAO algorithm over existing state-of-the-art optimization methods.

3.3.5 Hybridization with Sine Cosine Algorithm

Neggaz et al. [205] proposed a hybrid algorithm (scAOA) based on the hybridization of AOA and SCA algorithms for gender classification in facial analysis. This variant integrated sine-cosine operators into the standard AOA algorithm to improve its convergence speed, enhance its local search capability, and escape getting into local optima. The efficiency of the scAOA algorithm was evaluated on the Brazilian FEI and Georgia Tech Face (GT) datasets in comparison with ALO, SSA, GWO, Simple Genetic Algorithm (SGA), GOA, and PSO algorithms. Experimental results demonstrated the superiority of the scAOA algorithm in terms of accuracy, F-score, and statistical significance.

3.3.6 Hybridization with Arithmetic Optimization Algorithm

Sheik Dawood et al. [206] proposed a hybrid Archimedes Arithmetic Optimization approach (HYB-AO-AOA) for cluster head selection and multipath routing in WSNs. The hybridization combines AOAs strong exploration with the AO Algorithm's exploitation capabilities to optimally choose energy-efficient cluster heads and establish reliable multipath routes. Experimental results showed that the proposed HYB-AO-AOA approach achieves longer network lifetime, higher packet delivery ratio, and lower energy consumption compared to some existing optimization techniques.

3.3.7 Hybridization with Jaya Optimization Algorithm

Sugave et al. [207] proposed a hybrid approach (Jaya-AOA) based on the hybridization of AOA and JA algorithms for fault-aware test case prioritization in software testing. The hybrid Jaya-AOA approach combined Jaya's fast convergence with AOAs balanced exploration-exploitation to reorder test cases based on fault detection potential. The Jaya-AOAs performance was evaluated considering two function objectives such as Average Percentage of Fault

Table 5 Hybrid versions of the AOA algorithm

Variant	Name	Application	Author	Year
AOA+GA	AOA-GA	Spectral-spatial hyperspectral image classification	Moharram and Sundaram [201]	2025
AOA+ACO	IAOA	Limited node energy and short network lifetime in WSNs	Yao et al. [202]	2022
AOA+GWO	SGOA	Maximum power point tracking control strategy in photovoltaic systems	Hannon et al. [203]	2023
AOA+WOA	HWAO	Soil nutrient classification and pH prediction	Raman and Chelliah [204]	2023
AOA+SCA	scAOA	Gender classification in facial analysis	Neggaz et al. [205]	2023
AOA+AO	HYB-AO-AOA	Cluster head selection and multipath routing in WSNs	Sheik Dawood et al. [206]	2025
AOA+JAYA	Jaya-AOA	Fault-aware test case prioritization in software testing	Sugave et al. [207]	2025
AOA+AVOA	AVOA-AOA	Global optimization problems	Mostafa et al. [208]	2024
AOA+HGSO	HGSO-AOA	Data classification tasks	Yu et al. [209]	2023
AOA+chOA	AOA-chOA	Channel estimation in OFDM systems	Mydhili et al. [210]	2024
AOA+FHO	AFHO	Combinatorial optimization problems	Rani et al. [211]	2024
AOA+BSA	AOABSA	Global optimization problems	Hashim et al. [212]	2023
AOA+HGS	HGSAO	Multiclass plant disease detection	Gajmal et al. [213]	2024
AOA+SOS	MAOA	Global optimization problems	Altay [214]	2023
AOA+WSO	AOA-WSO	Automated arrhythmia detection	Sahoo et al. [215]	2025
AOA+DAO	HDAO	Secure data in cloud computing environments	Alandjani [216]	2024
AOA+LSTM	HDL-AOA	Soybean plant disease classification	Annrose et al. [217]	2021
	AOA-EDLSTM	Intelligent Operation and Maintenance	Wei et al. [218]	2023
	AOA-LSTM	Prediction accuracy of underground gas gush quantity	Huang and Xu [239]	2023
	WAOA-RCBiLSTM	Secure and efficient data aggregation in IoT-based healthcare systems	Shetty and Raghu [219]	2025
AOA+RF	AOA-RF	Detection accuracy of modulation types in underwater acoustic communication signals	Wang et al. [220]	2023
AOA+ANNs	DBN-IAOA	Optimal estimation of Proton-Exchange Membrane Fuel Cells	Sun et al. [221]	2021
	AAOA-DBN	Mobile network traffic prediction in 5 G cellular networks	Selvamanju and Shalini [222]	2022
	IAOA-DLFD	Reliable fall detection in healthcare applications	Alluhaidan et al. [223]	2022
	HCLAOA	Parameter identification in fuel cells	Fathy et al. [224]	2022
	IAOA-DBN	Survival prediction of patients with esophageal squamous cell carcinoma	Wang et al. [240]	2022
	MOAOA-FDL	Brain tumor diagnosis and classification	Devanathan et al. [225]	2023
	AOA-QDCNN	Road network extractions	Khan et al. [226]	2023
	BAOML	Drug supply chain management for pharmaceutical sector	Shanti and Venkatesh [241]	2023
	ASRNN-AOA	Detection of COVID-19 patients	Kannan et al. [227]	2023
	NNMPC-AOA	Robot manipulators	Aouaichia et al. [228]	2023
	AOADLB	Prostate cancer classification	Ragab et al. [229]	2023
	AOAEDL	Drug supply chain management	Rathor et al. [242]	2023
	ACOA	Web data classification	Ramesh and Mohanasundaram [243]	2023
	AOAMLP	Prediction of joint characteristics in laser-welded polymeric lap joints	Moustafa and Elsheikh [145]	2023
	AO-HRCNN	Detection and classification of diabetic retinopathy	Krishnamoorthy et al. [244]	2023
	AOADL-CBIRH	Content-based image retrieval in the healthcare sector	Issaoui et al. [230]	2024
	AOA-AM-GNN	Health monitoring	Arumugam et al. [231]	2024
	AOA-ANN	Estimate at completion predictions	Mhady et al. [245]	2024
	SCAOA_DenseNet	Multilevel brain tumor classification	Geetha et al. [246]	2024
	MSSAO-ERNN	Detection of post-traumatic stress disorder	Singh et al. [232]	2024
	MLBF-ArOA	Single-region committed emission prediction	Kumar et al. [233]	2024
	AOA-QDCNNRE	Road extraction in remote sensing images	Sundarapandi et al. [234]	2024
	TAOA-BPNN	Power and resource allocation in Non-Orthogonal Multiple Access for 5 G cellular systems	Thakre and Pokle [235]	2024
	MLBF-AOA	Securing resource constrained environments in IoT ecosystem	Kannaiah et al. [236]	2024
	HCC-PCGAN-AO	Preserving and innovating Huizhou carving culture	Geng [237]	2024

Table 5 (continued)

Variant	Name	Application	Author	Year
	FAOA_LeNet	Diabetic retinopathy detection	Kundan and Sangaralingam [238]	2025
	AOA-ML	Heart disease prediction	Elgendy et al. [247]	2025
	AOA-RL	Robot path planning	Islam et al. [248]	2025

Detected (APFD) and Average Percentage of Branch Coverage (APBC). Experimental results demonstrated that the Jaya-AOA algorithm achieves higher fault detection rates, shorter fault detection times, and better prioritization efficiency compared to traditional optimization methods.

3.3.8 Hybridization with African Vultures Optimization Algorithm

Mostafa et al. [208] introduced a hybrid optimization algorithm (AVOA-AOA)that combined AOA with AVOA for solving global optimization problems. The integration aims to address AVOAs limitations in exploration and tendency toward premature convergence by incorporating AOAs dynamic search capabilities. The hybrid algorithm was evaluated on twenty-nine CEC2017 benchmark functions and nineteen feature selection datasets, demonstrating its superior performance on 15 out of 19 datasets in terms of accuracy and convergence speed.

3.3.9 Hybridization with Henry Gas Solubility Optimization Algorithm

Yu et al. [209] developed a combined approach (HGSO-AOA) based on the combination of AOA with HGSO algorithms for optimizing Support Vector Machine (SVM) parameters for data classification tasks. The HGSO-AOAs performance was validated using four datasets of breast cancer in UCI datasets (i.e.: Strip surface defect datasets, Wisconsin datasets, Iris datasets, and Wine datasets). Experiments demonstrated that optimizing SVM parameters using the HGSO-AOA algorithm can effectively enhance the classification accuracy.

3.3.10 Hybridization with Chimp Optimization Algorithm

Mydhili et al. [210] proposed a hybrid algorithm (AOA-ChOA) based on the hybridization of AOA with ChOA algorithms for channel estimation in OFDM systems. The performance of the AOA-ChOA was conducted using network simulator (NS2) tool considering computational cost, bit error rate, and mean square error metrics. Simulation results revealed that the AOA-chOA algorithm achieves lower computational cost, lower estimation error, improved robustness to noise, and better bit error rate performance compared to conventional channel estimation techniques.

3.3.11 Hybridization with Fire Hawk Optimization Algorithm

Rani et al. [211] combined AOA with FHO algorithms for network intrusion detection. The performance of the proposed AFHO algorithm was tasked with selecting the most relevant features from network traffic data, retaining salient attributes while eliminating noise. Simulation results demonstrated the robustness of the AFHO algorithm by achieving the accuracy, recall, and F-measure of 93.7%, 97.7%, and 95.6%, respectively.

3.3.12 Hybridization with Bird Swarm Algorithm

Hashim et al. [212] proposed a hybrid optimization algorithm (AOABSA), integrating the AOA algorithm with the Bird Swarm Algorithm (BSA) for solving global optimization problems. The performance of the AOABSA algorithm was tested on 29 functions from the CEC2017 benchmark suite and seven real-world engineering problems. Experiments demonstrated that the AOABSA algorithm obtained competitive results when compared to ten well-known optimization methods.

3.3.13 Hybridization with Hunger Game Search Algorithm

Gajmal et al. [213] proposed a combined model (HGSAO) based on the combination of the AOA algorithm with the Hunger Game Search Algorithm (HGS) for multiclass plant disease detection. The efficiency of the HGSAO algorithm was validated using plant leaf images. Simulation results showed the robustness of the HGSAO algorithm achieving the accuracy, true positive rate, true negative rate, false negative rate, and false positive rate of 0.972, 0.963, 0.951, 0.936, and 0. 942, respectively.

3.3.14 Hybridization with Symbiotic Organism Search Algorithm

Altay [214] introduced a hybrid approach (MAOA) based on the hybridization of AOA and SOS algorithms for solving global optimization problems. The performance of the proposed MAOA algorithm was assessed on standard benchmark functions from the CEC'17 test suite, and various engineering design problems. Experiments demonstrated that the MAOA algorithm outperforms AOA, SOS, and other contemporary metaheuristic algorithms in terms of global search performance and convergence speed. Additionally, the MAOA algorithm showed superior performance in feature selection tasks across nine benchmark datasets.

3.3.15 Hybridization with War Search Optimization Algorithm

Sahoo et al. [215] developed a hybrid approach (AOA-WSO) based on the hybridization of AOA algorithm with War Search Optimization (WSO) algorithm for automated arrhythmia detection. The proposed AOA-WSO algorithm was validated using three publicly available ECG databases taken from the Physio Net health center server (i.e.: BIDMC Congestive Heart Failure, MIT-BIH normal sinus rhythm, and MIT-BIH Arrhythmia). Experiments revealed the superiority of the AOA-WSO algorithm compared to some well-regarded optimization methods in terms of accuracy, precision, sensitivity, F1-score, and Area Under the Curve (AUC).

3.3.16 Hybridization with Dwarf Optimization Algorithm

Alandjani [216] proposed a novel hybrid approach (HDAO) based on the hybridization of AOA and Dwarf Optimization Algorithm (DOA) for secure data in cloud computing environments. The HDAO was employed for optimal key generation, data sanitization, and restoration, with performance evaluated on five diverse datasets, including genome, protein, general text, English text, and rand128. Experimental results demonstrated that the HDAO algorithm significantly improves encryption time, decryption time, and the avalanche effect.

3.3.17 Hybridization with Long Short-Term Memory Networks

Annrose et al. [217] proposed a hybrid approach (HDL-AOA) based on the combination of the AOA algorithm with Long Short-Term Memory (LSTM) networks model for soybean plant disease classification. The proposed HDL-AOA algorithm addresses the challenges of high computational complexity, noise, and feature dimensionality. It was evaluated on the Soybean (Large) dataset, achieving 98.23% accuracy, 97.13% specificity, 98.01% sensitivity, 98.45% precision, 99.12% recall, and 99.45% F-score, outperforming conventional deep learning models like Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and LSTM in bean disease classification.

Wei et al. [218] proposed a hybrid neural anomaly detection model based on the hybridization of the AOA algorithm with the Encoder-Decoder LSTM network for Intelligent Operation and Maintenance. The AOA-EDLSTM model focuses on optimizing critical model parameters, including learning rate, batch size, and training epochs, to improve anomaly detection accuracy. The optimized model demonstrated significant performance gains, achieving a 3.47% increase in accuracy, a 7.12% boost in precision, and a 8.02% reduction in MSE.

Shetty and Raghu [219] proposed a Waterwheel AOA algorithm (WAOA) combined with a Resilient Consensus BiLSTM model, termed as WAOA-RCBiLSTM, for secure and efficient data aggregation in Internet of Things (IoT)-based healthcare systems. The WAOA variant improves intensification-diversification balance for optimal clustering and routing, improving energy efficiency and communication reliability. On the other hand, the Resilient Consensus BiLSTM detects and discards malicious nodes and corrupted packets by analyzing temporal and spatial patterns in aggregated healthcare data. Experimental results showed that the proposed WAOA-RCBiLSTM algorithm provides maximum data Packet Delivery Rate (PDR) of 84.322%, trust of 74.860, detection rate as 86.802%, energy of 0.439 J, delay of 0.362 ms.

3.3.18 Hybridization with Random Forest

Wang et al. [220] introduced a hybrid classification method (AOA-RF) combining the AOA algorithm with the Random Forest model for the detection accuracy of modulation types in underwater acoustic communication signals. Seven distinct modulation types were selected as recognition targets to assess the efficiency of the proposed AOA-RF method. Simulation results showed that the AOA-RF algorithm provides superior accuracy and consistent performance compared to other classification optimization techniques.

3.3.19 Hybridization with Artificial Neural Networks

Sun et al. [221] proposed a novel approach (DBN-IAOA) based on the combination of AOA algorithm with Deep Belief Network (DBN) model for the optimal estimation of Proton-Exchange Membrane Fuel Cells. The proposed DBN-IAOA approach was tested on Nafion 117 PEM fuel cell datasets against some well-known optimization algorithms such as GA, PSO, and the standard AOA. Experimental results demonstrated the efficiency of the DBN-IAOA algorithm providing a significant reduction in maximum relative error during both training and testing phases (3.25 V to 3.11 V in training, 34.0879 V to 28.5016 V in testing).

Selvamanju and Shalini [222] combined the AOA algorithm with the DBN model for mobile network traffic prediction in 5 G cellular networks. The proposed AOA-DBN method follows a 3-stage process namely prediction, pre-processing, and hyperparameter tuning. Simulation results proved the superiority of the AOA-DBN method compared to some well-known optimization algorithms achieving the minimum average MAPE of 0.034 and running time of 0.1373s.

Alluhaidan et al. [223] proposed a hybrid approach (IAOA-DLFD) based on the hybridization of the AOA algorithm with the Deep Learning Fall Detection (DLFD) model for reliable fall detection in healthcare applications. The performance of the IAOA-DLFD approach was validated using URFD and Multiple Cameras Fall datasets. Results revealed that the IAOA-DLFD approach achieves higher detection accuracy and faster convergence compared to some conventional deep learning approaches.

Fathy et al. [224] proposed a hybrid approach (HCLAOA) based on the hybridization of the AOA algorithm with the heterogeneous comprehensive learning model for parameter identification in fuel cells, specifically for Proton Exchange Membrane Fuel Cells (PEMFC) and Solid Oxide Fuel Cells (SOFC). The HCLAOA approach was validated using PEMFC stacks (250 W and 500 W) and SOFC models under various temperature and pressure levels. Results indicated that the proposed HCLAOA algorithm outperforms the standard AOA algorithm and other well-regarded metaheuristics, by achieving faster convergence and higher parameter accuracy for both static and dynamic fuel cell models.

Devanathan et al. [225] proposed a Multi-objective AOA algorithm with Fusion-based Deep Learning (MOAOA-FDL) framework for brain tumor diagnosis and classification. The effectiveness of the proposed MOAOA-FDL algorithm was validated on publicly available brain MRI datasets as benchmarks. Simulation results showed that the MOAOA-FDL algorithm outperforms standard Deep Learning models and other optimization methods in terms of sensitivity, specificity, and F-score, demonstrating its effectiveness in early brain tumor detection.

Khan et al. [226] developed a combined approach (AOA-QDCNN) based on the combination of the AOA algorithm with the Quantum Dilated Convolutional Neural Network model (QDCNN) for road network extractions. The efficiency of the AOA-QDCNN approach was conducted on the Massachusetts road dataset covering a wide variety of urban, suburban, and rural regions. Experiments showed the superiority of the AOA-QDCNN approach compared to more recent methods achieving precision of 87.54%, Mean Intersection over Union (MIoU) of 95.19%, F1 of 90.85%, and recall of 94.41%.

Kannan et al. [227] proposed a hybrid approach (ASRNN-AOA) based on combining the AOA algorithm with the Attention Segmental Recurrent Neural Network model (ASRNN) for the detection of COVID-19 patients. The proposed ASRNN-AOA approach was validated using Ultra-Low-Dose Computed Tomography (ULDCT) images to capture critical radiomic features such as morphological, grayscale statistical, and Haralick texture features. The proposed ASRNN-AOA approach demonstrated superior accuracy and precision, achieving 22.08% to 45.86% better performance across multiple metrics compared to DenseNet-HHO-ULDCT, ELM-DNN-ULDCT, EDL-ULDCT, ResNet 50-ULDCT, SDL-ULDCT, CNN-ULDCT, and DRNN-ULDCT.

Aouaichia et al. [228] proposed a hybrid model (NNMPC-AOA) based on the hybridization of the AOA algorithm with the Neural Network model for robot manipulators. The NNMPC-AOAs performance was evaluated considering the control of the model of the two degrees-of-freedom robot manipulator. Simulation results showed that the proposed NNMPC-AOA model achieves faster response, lower tracking error, and better constraint handling compared to some well-known optimization-based techniques.

Ragab et al. [229] combined the AOA algorithm with a deep learning model for prostate cancer classification. The performance of the proposed AOADLB algorithm was evaluated using a benchmark Magnetic Resonance Imaging (MRI) dataset. Experimental results demonstrated that the AOA-DLB model achieves higher diagnostic accuracy, better sensitivity and specificity, and faster convergence compared to some well-regarded optimization-based approaches.

Issaoui et al. [230] combined the AOA algorithm with deep learning for Content-Based Image Retrieval (CBIR) in the healthcare sector. The evaluation of the AOADL-CBIRH algorithm was tested using four benchmark image datasets including TCIA-CT (604 Images), EXACT09-CT (675 Images), NEMA-CT (315 Images), and OASIS-MRI (421 Images). Experimental results revealed that the AOADL-CBIRH algorithm achieves higher retrieval precision, better robustness, and faster search performance compared to other optimization-based algorithms.

Arumugam et al. [231] proposed an enhanced health monitoring framework for IoT-based healthcare systems based on the hybridization of the AOA algorithm with the Auto-Metric Graph Neural Networks (AM-GNN). The AOA-AM-GNN approach relationships between IoT medical devices and patient data, enabling adaptive feature learning for health status assessment. Simulation results showed that the AOA-AM-GNN achieves higher diagnostic accuracy, reduced latency, and better scalability compared to some well-known optimization-based techniques.

Singh et al. [232] developed a hybrid model (MSSAO-ERNN) based on the hybridization of the Multi-Strategy Seeker AOA algorithm with Elman Recurrent Neural Network (ERNN) for the detection of post-traumatic stress disorder. The efficiency of the MSSAO-ERNN was validated using three clinical and behavioral datasets such as NNE, FME hosptial, and TIMIT. Experimental results demonstrated that the proposed model outperforms conventional models achieving higher diagnostic accuracy, faster convergence, and reduced overfitting.

Kumar et al. [233] proposed a hybrid method (MLBF-ArOA) based on the combination of the AOA algorithm with Multi-Lead-Branch Fusion Network (MLBF) model for Single-Region Committed Emission prediction. The performance of the proposed MLBF-ArOA algorithm was assessed using data taken from the N-BaIoT dataset considering five metrics such as accuracy, precision, recall, F-measure, and specificity. Simulation results showed that the MLBF-ArOA method provides higher accuracy, higher recall, lower prediction error, and faster convergence compared to other optimization methods.

Sundarapandi et al. [234] developed a hybrid approach (AOA-QDCNNRE) based on combining the AOA algorithm with Quantum Dilated Convolutional Neural Network (QDCNN) for road extraction in remote sensing images. The performance of the AOA-QDCNNRE approach was validated on two high-resolution remote sensing datasets namely Massachusetts Road and GF-2 Road Datasets taking into account five metrics such as accuracy, precision, recall, F1-score, and IoU. Experiments showed the suitability of the proposed AOA-QDCNNRE approach for complex and irregular road network extraction compared to some recent optimization algorithms.

Thakre and Pokle [235] proposed a hybrid approach, termed as TAOA-BPNN, for power and resource allocation in Non-Orthogonal Multiple Access (NOMA) for 5G cellular systems. The proposed TAOA-BPNN is based on the hybridization of the Transit AOA algorithm (TAOA) with the Back Propagation Neural Network (BPNN) model. The analytic parameters used to assess the performance of the proposed TAOA-BPNN are throughput, energy efficiency, achievable rate, and sum rate. Experiments demonstrated that the proposed TAOA-BPNN approach offers good results compared to conventional optimization and deep learning methods.

Kannaiah et al. [236] proposed a combined approach (MLBF-AOA) based on combining the AOA algorithm with Multi-Lead-Branch Fusion Network (MLBFN) model for Securing Resource Constrained Environments (SRCE) in the IoT ecosystem. This combination ensures rapid convergence to the global optimum and provides a good balance between exploitation and exploration. The proposed MLBF-ArOA approach was evaluated against some existing approaches and results demonstrated its significant performance improvements, including 33% higher precision, 23.5% higher F-measure, 13.86% better recall, and 29.86% higher accuracy.

Geng [237] proposed a combined method (HCC-PCGAN-AO) based on the combination of the AOA algorithm with the Progressive Conditional Generative Adversarial Network (PCGAN) model for preserving and innovating Huizhou carving culture. The HCC-PCGAN-AO approach integrates three-dimensional data scanning for cultural artifact digitization with a PCGAN framework, where the AOA is used to optimize the classifier, reducing design errors and enhancing carving precision. The proposed HCC-PCGAN-AO method demonstrated superior performance, achieving 22.13%, 19.46%, and 30.65% lower RMSE compared to conventional methods such as IPTA-CH-DMT, RID-TCC-HICHC, and RID-HCC-NCAP, respectively.

Kundan and Sangaralingam [238] proposed a fractional AOA algorithm-based deep learning model (FAOA_LeNet) for diabetic retinopathy detection. The efficiency of the proposed FAOA_LeNet model was analyzed using the digital retinal images for vessel extraction dataset and the Indian diabetic retinopathy image dataset. Simulation results showed the effectiveness of the FAOA_LeNet model by achieving an accuracy of 0.954, sensitivity of 0.938, and specificity of 0.974.

4 Applications of the Archimedes Optimization Algorithm

Applications of the AOA algorithm in diverse fields are discussed in the next section, while their summary is outlined in Table 6.

4.1 Engineering

Ali et al. [147] used the AOA algorithm to determine the optimal distributed generation locations, sizes, and Soft Open Points placements. The performance of the AOA algorithm was assessed based on IEEE 33-node distribution network, IEEE 69-node network, 59-node Egyptian distribution network, and 135-node Brazilian distribution network. Results demonstrated that the AOA algorithm achieves improved system performance, lower losses, and better voltage stability compared to conventional planning and reconfiguration optimization techniques.

Janamala and Rani [151] applied the AOA algorithm to address the optimal allocation of solar Photovoltaic (SPV)

Table 6 Applications of the AOA algorithm

Class	Problem	Research Works
Engineering	Optimizing proportional resonant controller parameters for an active arc suppression device	Haque et al. [276]
	optimization of tuned mass dampers in structural control	Ayadin et al. [277]
	Welded beam design problem, Tension/compression spring design problem	Hashim et al. [141]
	Optimal distributed generation locations	Ali et al. [147]
	PID speed control of DC motor	Acharya et al. [278]
	UAV path planning	Basil et al. [279]
	Workflow scheduling in cloud	Kushwaha and Singh [280]
	Blockchain based privacy preserving IoT with smart cities	Pillai et al. [281]
	Optimal allocation of solar photovoltaic systems	Janamala and Rani [151]
	Generalized Discrete Cost Multicommodity Network Design Problem	Mejri et al. [249]
	PID controller	Saklani et al. [250]
	Load frequency control in interconnected power systems	Hemeida et al. [251]
	Placement of unknown nodes in underwater sensor networks	Kaliraj et al. [252]
	Optimizing PID controller for an electric wheelchair's DC motor	Kmich et al. [253]
	Tracking of the global maximum power point in photovoltaic systems	Sajid et al. [254]
	Maximum power point tracking in photovoltaic systems	Hannon et al. [255]
	Structural engineering optimization problems	Aydin et al. [256]
	Parameters tuning of power system stabilized based proportional integral derivative controller	Osheba et al. [257]
	Fault diagnosis of rotating machines	Das [282]
	Optimal load distribution in fog computing	Premkumar and Santhosh [258]
	Parameter extraction of photovoltaic models	Hussain et al. [259]
	Parameter identification in Proton Exchange Membrane Fuel Cells	Caliskan and Percin [260]
	Resource allocation in 5 G mobile communications	Zaidi et al. [261]
	PID controller design of buck converter	Ahmad et al. [283]
	Fault diagnosis in rolling bearings	Wang et al. [284]
	Placement and sizing of capacitor problem in distribution system	Kaushik et al. [285]
	Optimizing the control of Medical Defense Nanorobots	Marhoon et al. [286]
	Optimum relay coordination in microgrid and combined overhead/cable distribution network	Kudkelwar et al. [287]
Power and Energy	Optimizing the distributed generation (DG) placement in electrical grids	Ivanov et al. [264]
	Optimizing the energy hub system	El-Afifi et al. [288]
	Energy management in microgrid systems	Fawzy et al. [289]
	Reactive power dispatch for hybrid Wind-Solar power system	Megantoro et al. [290]
	Optimum power dispatch	Patel et al. [291]
	Optimal sizing and placement of electric vehicle charging stations	Zaki et al. [262]
	Wind energy conversion systems	Abdelbadie et al. [263]
	Bid-based dynamic economic load dispatch problem in power systems	Rani et al. [268]
	Optimal power flow problem in power systems	Zhu et al. [265]
	Energy management in smart interconnected microgrids	Al-Gazzar et al. [267]
	Demand side management in smart grid environments	Lakshmi and Queen [266]
	Pitch angle control in wind energy systems	Perçin and Çalışkan [292]
	Energy recovery in cooling systems	Abaas et al. [293]
	Short-term photovoltaic power prediction	Li et al. [294]
	Optimal power flow in hybrid AC-DC power system	Patel et al. [295]
	Maximum power point tracker for wind energy generation system	Fathy et al. [148]
Image Processing	COVID-19 diagnosis	Chen and Rezaei [269]
	Multi-focus image fusion	Çakıroğlu et al. [296]
	Intensity-based image registration	Kmish et al. [270]
	Noisy image segmentation	Dhal et al. [143]
	Color medical encryption and compression images	Bencherqui et al. [297]
	Hyperspectral remote sensing image watermarking	Bodkle and Chaudhari [271]
	DNA motif discovery and optic disc detection	Hashim et al. [272]
	Preprocessing steps in multichannel EEG data	Srinivasan and Johnson [298]
	Precise medical image segmentation	Balaha et al. [299]

Table 6 (continued)

Class	Problem	Research Works
Classification	Biomedical data classification	Ragab and Hamed [300]
	Feature Selection	Neggaz and Fizazi [273], Desuky et al. [151]
	Optimal data classification	Khrissi et al. [274]
	Automatic leukemia classification	Shaban et al. [275]

systems in electrical distribution networks. The authors aimed to minimize grid dependency and greenhouse gas emissions by identifying optimal SPV locations and sizes. The AOA algorithm was tested on three practical distribution feeders: a 22-bus agricultural feeder, a 28-bus rural feeder, and an IEEE 85-bus urban feeder. Results indicated that the AOA algorithm outperforms other nature-inspired algorithms, achieving lower distribution losses, improved voltage profiles, and reduced GHG emissions.

Mejri et al. [249] used the AOA algorithm for solving the Generalized Discrete Cost Multicommodity Network Design Problem (GDCMNDP). The GDCMNDP, a complex variant of the traditional Network Design Problem (NDP), aims to optimize total network costs while adhering to multiple design constraints, making it a particularly challenging NP-hard problem. The experimental results demonstrated that the AOA algorithm effectively reduced network costs while satisfying multiple constraints, outperforming conventional approaches in terms of computational efficiency and solution quality.

Saklani et al. [250] employed the AOA algorithm to design a Proportional Integral Derivative (PID) controller for Load Frequency Control of the single area power system. The performance of the AOA algorithm was validated using Integrated Time-weighted Absolute Error (ITAE) as an objective function to quickly and accurately restore frequency after load disturbances. Simulation results demonstrated that the AOA algorithm performs better concerning settling time and ITAE over the other four optimization meta-heuristics such as GWO, PSO, ALO, and MFO.

Hemeida et al. [251] applied the AOA algorithm to optimally tune a Proportional-Integral (PI) controller for two-area load frequency control (LFC) in interconnected power systems. The AOAs performance was evaluated in comparison with other optimization algorithms like Learner Performance-Based Behavior Optimization (LPBO) algorithm and MPSO in similar multi-area LFC+Automatic Voltage Regulation (AVR) contexts. Simulation results demonstrated that the AOA algorithm provides enhanced performance in regulating frequency and mitigating tie-line power deviations.

Kaliraj et al. [252] applied the AOA algorithm for localizing unknown nodes in underwater sensor networks. The AOA algorithm optimizes nodes position by minimizing localization errors caused by signal propagation delays, Doppler effects, and environmental noise. Simulation results revealed that the AOA algorithm provides higher positioning accuracy, lower error variance, and better robustness compared to PSO and WOA algorithms.

Kmich et al. [253] employed the AOA algorithm to enhance the performance of a PID controller for an electric wheelchair's DC motor. The effectiveness of the AOA algorithm was assessed using ITAE as the objective function. Experimental results demonstrated greater effectiveness and robustness of the AOA algorithm when compared to two other popular metaheuristics such as SMA and SCA in terms of convergence speed, stability, and overall response.

Sajid et al. [254] used the AOA algorithm for accurate tracking of the Global Maximum Power Point (GMPP) in photovoltaic systems operating under partial and complex shading conditions. The AOA algorithm was validated using the Typhoon Hardware-in-the-Loop (HIL)-402 emulator and compared against conventional algorithms including PSO, Jaya, and Adaptive Jaya (A-Jaya). Experimental results demonstrated that the AOA algorithm significantly improves tracking efficiency, achieving 99.89% in uniform shading and 99.92% in moderate shading under diverse shading conditions.

Hannon et al. [255] applied the AOA algorithm in an extremum seeking control framework for MPPT in photovoltaic systems. The AOA algorithm dynamically tunes controller parameters to rapidly and accurately track the maximum power point under varying irradiance and temperature conditions. Experimental results showed that the AOA algorithm provides an efficiency of up to 99.65%.

Aydin et al. [256] applied the AOA algorithm for solving structural engineering optimization problems. The performance of the AOA algorithm was tested on benchmark trusses (i.e.: 10-bar truss, 25-bar truss, and 72-bar space truss) considering stress and displacement constraints. Results indicated that the AOA algorithm achieves competitive outcomes compared to TLBO and FPA algorithms demonstrating its efficacy in structural optimization tasks.

Osheba et al. [257] used the AOA algorithm to tune parameters of power system stabilized based proportional integral derivative (PSS-PID) controller. The efficiency of the AOA algorithm was validated using two types of disturbances (i.e.: electrical three phase short circuit fault at generator terminals and a mechanical disturbance on the rotor shaft). Simulation results demonstrated that the AOA algorithm achieves good performance compared to conventional tuning methods, making it effective for maintaining stability in dynamic operating conditions.

Premkumar and Santhosh [258] applied the AOA algorithm for optimal load distribution in fog computing. The performance of the AOA algorithm was validated considering resource utilization and response time parameters while ensuring secure user authentication to prevent unauthorized access. Simulation results demonstrated the robustness of the AOA algorithm compared to conventional optimization approaches by achieving lower latency, balanced resource utilization, and strong security.

Hussain et al. [259] used the AOA algorithm for parameter extraction of photovoltaic (PV) models. The AOAs performance evaluations were conducted using the sum of individual absolute errors (SIAE) and a novel RMSE parameter. Results demonstrated that the AOA algorithm achieves lower RMSE, lower SIAE, more accurate parameter estimation, and better predictive performance compared to conventional optimization techniques.

Caliskan and Percin [260] applied the AOA algorithm for parameter identification in Proton Exchange Membrane Fuel Cells (PEMFCs). The performance of the AOA algorithm was assessed on two commercial PEMFC systems (i.e.: 250 W fuel cell stack and 500 W BCS stack). Experiments demonstrated the superior performance of the AOA algorithm outperforming other meta-heuristic algorithms such as GWO, Emperor Penguin Optimizer (EPO), and MRFO. Voltage and power curves obtained using the AOA closely matched experimental data, confirming the algorithm's robustness and precision in parameter estimation.

Zaidi et al. [261] used the AOA algorithm for resource allocation in 5 G mobile communications. The performance of the AOA algorithm was validated taking into account user mobility in the cell, channel conditions, and different types of services. Experimental results demonstrated that the AOA algorithm achieves better user fairness, higher throughput, and lower interference compared to conventional optimization algorithms.

4.2 Power and Energy

Zaki et al. [262] employed the AOA algorithm to determine the optimal sizing and placement of electric vehicle charging stations. The robustness of the AOA algorithm was validated using the IEEE 33-bus testing network system considering the objective of minimization of real power loss. Results showed that the AOA provides lower operational costs and improved service coverage compared to PSO and CS algorithms.

Abdelbadie et al. [263] used the AOA algorithm to optimally configure superconducting magnetic energy storage systems for stability enhancement of wind energy conversion systems. Simulation experiments were carried out utilizing real-world wind data under various operating conditions. Simulation results showed the superiority of the AOA algorithm compared to GA and PSO algorithms.

Ivanov et al. [264] applied the AOA algorithm for optimizing the Distributed Generation (DG) placement in electrical grids. The study aimed to minimize active power losses by optimally placing DG units in the IEEE 30-bus test system. The performance of the AOA algorithm in comparison with PSO and the Tiki-Taka Algorithm (TTA) algorithms was benchmarked under identical initial conditions, including population size, iteration count, and parameter tuning. Results demonstrated that while PSO achieved a 100% success rate with the lowest average fitness, AOA exhibited superior convergence in complex, high-dimensional search spaces, achieving comparable best fitness values but requiring significantly more iterations. The TTA, although faster in finding optimal solutions, exhibited a lower overall success rate. The findings highlight the potential of AOA for solving large-scale DG placement problems, offering a promising alternative to conventional metaheuristic approaches.

Zhu et al. [265] employed the AOA algorithm for solving the optimal power flow problem in power systems. The AOA algorithm optimizes control variables such as generator outputs, voltage levels, and transformer tap settings to minimize objectives like fuel cost, power losses, and emissions while satisfying operational constraints. Tests on standard IEEE bus systems demonstrated that the AOA algorithm provides lower operating costs, reduced losses, and better constraint handling compared to some well-regarded optimization metaheuristics.

Lakshmi and Queen [266] applied the AOA algorithm for demand side management in smart grid environments. The AOA algorithm optimizes energy consumption scheduling to reduce peak demand and electricity costs while maintaining user comfort. Simulation results demonstrated that the AOA algorithm generates substantial cost savings and significant reductions in peak load demand.

Authors in [267] applied the AOA algorithm for energy management in smart interconnected microgrids. The performance of the AOA algorithm was validated using different types of distributed generation units (micro-turbine, solar photovoltaic, and wind turbine) to achieve the minimization of total power generation cost as the main objective function. Simulation results demonstrated that the AOA algorithm achieves lower energy costs, better renewable energy utilization, and improved power balance compared to the PSO algorithm.

Rani et al. [268] applied the AOA algorithm to solve the bid-based dynamic economic load dispatch problem in power systems. The performance of the AOA algorithm was validated on a power system with five conventional power plants (one virtual power plant and two flexible loads). Statistical analysis showed the superiority of the AOA algorithm when compared with contemporary optimization methods.

4.3 Image Processing

Chen and Rezaei [269] used the AOA algorithm for Coronavirus (COVID-19) diagnosis chest X-ray images. The performance of the AOA algorithm was validated using three different datasets provided by the Renmin Hospital of Wuhan University and two affiliated hospitals (the Third Affiliated Hospital and Sun Yat-sen Memorial Hospital) of Sun Yat-sen University in Guangzhou. Experimental results revealed that the AOA algorithm achieves higher diagnostic accuracy, sensitivity, and specificity compared to four conventional deep learning methods.

Kmish et al. [270] used the AOA algorithm for intensity-based image registration. The efficiency of the AOA algorithm was validated using medical and remote sensing images. Simulation results revealed superior performance of the AOA algorithm compared to the SCA and EO algorithms in terms of both registration accuracy and computation time.

Bodkle and Chaudhari [271] applied the AOA algorithm for hyperspectral remote sensing image watermarking. The Discrete Wavelet Transform (DWT) decomposes hyperspectral images for embedding robust watermarks, while the AOA optimizes watermarking parameters to balance imperceptibility, robustness, and capacity. Experiments demonstrated the superiority of the AOA algorithm compared to traditional optimization approaches achieving high watermark imperceptibility, strong resistance to attacks, and reliable forensic traceability.

Hashim et al. [272] applied the AOA algorithm for solving complex biomedical problems, specifically DNA motif discovery and optic disc detection. The AOA algorithm was evaluated against some well-established tools, demonstrating superior performance in detecting motifs within both real and synthetic datasets. For optic disc detection, the AOA algorithm achieved remarkable accuracy, attaining a 100% success rate on DRIVE and DRIONS-DB datasets, and over 98% on DIARETDB0 and DIARETDB1, surpassing existing state-of-the-art methods.

4.4 Classification

Neggaz and Fizazi [273] introduced a wrapper-based feature selection method for gender recognition using the AOA algorithm. The study divided facial images into subregions, extracting features via handcrafted techniques such as Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), and Gray-Level Co-occurrence Matrix (GLCM). The AOA algorithm was then employed to select the most informative regions for classification. Evaluated on the Georgia Tech Face, Brazilian FEI, and Gallagher's uncontrolled datasets, the AOA-based LBP approach achieved a 96.08% accuracy on the Gallagher dataset, surpassing state-of-the-art deep convolutional neural networks.

Khrissi et al. [274] used the AOA algorithm for optimal data classification. The AOA algorithm was evaluated on 16 benchmark datasets taken from the UCI repository and compared with other widely used metaheuristic algorithms, including SCA, WOA, Butterfly Optimization Algorithm (BAO), and MFO. Experimental results demonstrated that the AOA algorithm achieves superior classification accuracy and requires fewer features.

Shaban et al. [275] applied the AOA algorithm for automatic leukemia classification. The performance of the AOA algorithm was assessed using 3256 Peripheral Blood Smears (PBS) images collected from 89 patients at Taleqani Hospital in Tehran. Experimental results demonstrated that the AOA performs better than other competitor optimization classifications methods in terms of accuracy, precision, specificity, recall, F-measure, Dice Similarity Coefficient (DSC), and Jaccard Index (JI), providing 99.2%, 90.5%, 89.9%, 89%, 90%, 98%, and 96.6%, respectively.

5 Results and Comparison

This section evaluates and validates the performance of the AOA under the parameter settings summarized in Table 10. We benchmark AOA on three categories: unimodal 7, multimodal 8, and fixed-dimension multimodal 9. AOA is compared against nine well-known metaheuristics: SCA, WOA, BA, GWO, MPA, DE, FA, GA, and TS.

Unless stated otherwise, each algorithm uses a population of 30 search agents and runs for 500 iterations. For every benchmark function, we perform 30 independent runs and report the *Best*, *Worst*, *Mean*, and *Standard Deviation (StD)* of the final fitness values; we also provide the rank of each algorithm. The detailed numerical results are summarized in Tables 11 and 12, while the distribution of final scores and the mean convergence behaviors are shown in Fig. 6 and Fig. 7, respectively.

Table 7 Unimodal benchmark functions

Function	Description	Dimension	Range	$f_{\min}$
F1	$f(x)=\sum_{i=1}^{n} x_i^2$	10	$[-100, 100]$	0
F2	$f(x)=\sum_{i=0}^{n} \lvert x_i\rvert+\prod_{i=0}^{n} \lvert x_i\rvert$	10	$[-10, 10]$	0
F3	$f(x)=\sum_{i=1}^{d}\left(\sum_{j=1}^{i} x_j\right)^2$	10	$[-100, 100]$	0
F4	$f(x)=\max_i\{\lvert x_i\rvert : 1\leq i\leq n\}$	10	$[-100, 100]$	0
F5	$f(x)=\sum_{i=1}^{n-1}\left[100\left(x_i^2-x_{i+1}\right)^2+(1-x_i)^2\right]$	10	$[-30, 30]$	0
F6	$f(x)=\sum_{i=1}^{n}(\lvert x_i+0.5\rvert)^2$	10	$[-100, 100]$	0
F7	$f(x)=\sum_{i=0}^{n} i x_i^4+\mathrm{random}[0, 1)$	10	$[-1.28, 1.28]$	0

Table 8 Multimodal benchmark functions

Function	Description	Dimension	Range	$f_{\min}$
F_8	$f(x)=\sum_{i=1}^{n}\left(-x_i\sin(\sqrt{\lvert x_i\rvert})\right)$	10	$[-500, 500]$	$-418.9829\times n$
F_9	$f(x)=\sum_{i=1}^{n}\left[x_i^2-10\cos(2\pi x_i)+10\right]$	10	$[-5.12, 5.12]$	0
F_{10}	$f(x)=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right)$	10	$[-32, 32]$	0
F_{11}	$f(x)=1+\frac{1}{4000}\sum_{i=1}^{n} x_i^2-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)$ $+\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right)+20+e$	10	$[-600, 600]$	0
F_{12}	$f(x)=\sum_{i=1}^{n-1}(y_i-1)^2\left[1+10\sin^2(\pi y_1)\right]+\sum_{i=1}^{n} u(x_i, 10, 100, 4)$, where $y_i=1+\frac{x_i+1}{4}$	10	$[-50, 50]$	0
F_{13}	$f(x)=0.1\left[\sin^2(3\pi x_1)+\sum_{i=1}^{n-1}(x_i-1)^2\left(1+\sin^2(3\pi x_{i+1})\right)\right]$ $+(x_n-1)^2\left(1+\sin^2(2\pi x_n)\right)+\sum_{i=1}^{n} u(x_i, 5, 100, 4)$, $u(x_i, a, k, m)=\begin{cases} k(x_i-a)^m, & x_i>a, \\ 0, & -a\leq x_i\leq a, \\ k(-x_i-a)^m, & x_i<-a\end{cases}$	10	$[-50, 50]$	0

Table 9 Fixed-dimension multi-modal benchmark functions

Function	Description	Dimension	Range	$f_{\min}$
F_{14}	$f(x)=\left(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i-a_{ij})}\right)^{-1}$	2	$[-65, 65]$	1
F_{15}	$f(x)=\sum_{i=1}^{11}\left[a_i-\frac{x_1(b_i^2+b_i x_2)}{b_1^2+b_i x_3+x_4}\right]^2$	4	$[-5, 5]$	0.00030
F_{16}	$f(x)=-\sum_{i=1}^{5}\left[(X-a_i)(X-a_i)^\top+c_i\right]^{-1}$	4	[10]	−10.1532
F_{17}	$f(x)=-\sum_{i=1}^{7}\left[(X-a_i)(X-a_i)^\top+c_i\right]^{-1}$	4	[10]	−10.4028
F_{18}	$f(x)=-\sum_{i=1}^{10}\left[(X-a_i)(X-a_i)^\top+c_i\right]^{-1}$	4	[10]	−10.5363

Table 10 Parameter setting of the evaluated optimization algorithms

Parameter(s)	Value(s)
Common settings	
Population size	30
Max iterations	500
Independent runs per function	30
AOA	
MOA (math optimizer acceleration)	linearly increases $0.2 \rightarrow 1$
α (MOP exponent)	5
C_3	1
C_4	2
SCA	
Control parameter $r_{\max}$	2
Control parameter $r_{\min}$	0
Auxiliary factors r_2, r_3, r_4	$\mathcal{U}(0,1)$
FA	
Randomness α	1.0
Attractiveness β_0	1.0
Absorption coefficient γ	0.01
Reduction factor θ	0.97
WOA	
a (encircling)	linearly decreases $2 \rightarrow 0$
b (log-spiral coefficient)	1
p (exploit/explore switch)	$\mathcal{U}(0,1)$
l (spiral shape)	$\mathcal{U}([-1,1])$
GA	
Selection	Roulette-wheel
Crossover operator	Single-point
Crossover probability p_c	0.8
Mutation probability p_m	$1/\mathrm{dim}$
BA	
Frequency min $f_{\min}$	0
Frequency max $f_{\max}$	2
Loudness constant	0.5
Initial loudness A_0	Random
GWO	
Control parameter a	linearly decreases $2 \rightarrow 0$
$A = 2ar_1 - a, C = 2r_2$	$r_1, r_2 \sim \mathcal{U}(0,1)$
DE	
Crossover factor CR	0.7
Mutation factor F	0.8
Mutation/crossover strategy	`DE/rand/1/bin`
MPA	
FADs probability	0.2
Phase switch P	0.5
Lévy exponent β	1.5
Step coefficient (CF)	0.2
TS	
Neighborhood size (k_{local})	$\max(6, \min(12, \lfloor 0.3\,\mathrm{dim} \rfloor))$
Tabu tenure (dimension-level)	6
Patience (no-improve)	8
Step factor (initial)	0.2 of variable range

From Table 11 and 12, AOA achieves superior and more stable results on **4 of the 7** unimodal functions (F1–F4). This suggests that AOA provides stronger *exploitation* capability than the competing methods. On the multimodal set (F8–F13), AOA attains the best performance on F8 and F10, indicating competitive *exploration* behavior. Finally, on the fixed-dimension multimodal functions (F14–F18), AOA generally outperforms SCA, WOA, GA, GWO, DE, and BA on most cases, showing improved resilience to local optima and a balanced exploration-exploitation trade-off.

Figure 6 presents the box plots for the AOA algorithm and competing algorithms across all functions. In most cases, AOA exhibits narrower boxes (lower variability) and comparable or lower medians, which reflects more stable final solutions.

Figure 7 shows the *mean* convergence curves over 30 runs. Across many functions, AOA converges faster and more stably than SCA, WOA, GA, GWO, DE, and BA. While TS often shows signs of premature convergence, AOA maintains a smoother transition from exploration to exploitation. MPA is competitive on fixed-dimension multimodal cases but may plateau earlier on others. FA can stagnate in complex landscapes, whereas AOA adapts effectively to reach better optima. Overall, AOA avoids stagnation more reliably on multimodal landscapes and reaches high-quality solutions efficiently in unimodal landscapes.

To provide a fair and rigorous comparison among the ten optimization algorithms and to evaluate the performance consistency of the **AOA algorithm**, the non-parametric **Friedman test** was applied to the obtained fitness values across all 18 benchmark functions. The Friedman test is suitable for analyzing multiple algorithms over several datasets without assuming data normality. The detailed statistical results are summarized in Table 13.

As observed from the table, the descriptive statistics reveal significant variability in the performance of all algorithms. The AOA algorithm exhibits competitive results across several benchmarks. It maintains a strong position, ranking among the top performing algorithms in most cases.

The results report a **Chi-square** value of 90.24 with **9 degrees of freedom**, and an asymptotic significance level (p-**value**) < **0.001**. This significance level is below the **5%** threshold, indicating that the null hypothesis H_0, which assumes that all algorithms perform equally, can be rejected. Consequently, the observed differences among the algorithms are statistically significant.

Overall, the Friedman test confirms that there are meaningful performance differences among the compared metaheuristic algorithms, and that the AOA algorithm demonstrates competitive and statistically validated performance.

Table 11 Optimization results all algorithms across 18 benchmark functions

Function	Metric	AOA	SCA	WOA	BA	GWO	MPA	DE	FA	GA	TS
F_1	Min	6.31E-145	6.99E-19	2.04E-86	2.49E+03	1.05E-60	1.45E-32	2.80E-20	4.61E+03	4.34E-05	1.70E-01
	Max	1.25E-97	1.27E-09	3.53E-77	1.61E+04	9.00E-56	9.63E-30	5.40E-19	1.20E+04	1.04E-03	6.73E-01
	Mean	4.17E-99	4.39E-11	2.39E-78	9.75E+03	8.39E-57	2.90E-30	1.99E-19	8.67E+03	4.42E-04	3.48E-01
	Std	2.28E-98	2.33E-10	8.92E-78	3.43E+03	2.01E-56	3.07E-30	1.41E-19	1.69E+03	2.71E-04	1.22E-01
	Rank	1	6	2	10	3	4	5	9	7	8
F_2	Min	1.72E-72	1.35E-12	1.57E-59	1.56E+01	1.29E-34	3.04E-18	2.88E-12	8.89E-06	1.06E-03	8.35E-02
	Max	1.17E-51	1.65E-08	1.34E-51	4.96E+01	5.12E-32	2.82E-16	1.91E-11	1.99E-05	1.10E-02	2.61E-01
	Mean	4.30E-53	2.11E-09	9.38E-53	3.33E+01	3.88E-33	5.34E-17	7.38E-12	1.28E-05	2.77E-03	1.44E-01
	Std	2.14E-52	4.32E-09	3.01E-52	8.96E+00	9.41E-33	6.14E-17	4.25E-12	2.44E-06	1.87E-03	4.25E-02
	Rank	1	6	2	10	3	4	5	7	8	9
F_3	Min	7.83E-126	2.43E-08	1.37E-01	3.69E+03	1.71E-33	5.15E-20	7.32E+00	5.23E+03	9.91E-02	7.56E-01
	Max	2.58E-86	4.85E-02	4.94E+02	2.13E+04	6.29E-23	1.79E-13	1.02E+02	9.20E+03	9.82E+00	4.50E+00
	Mean	8.63E-88	5.02E-03	1.38E+02	1.16E+04	2.20E-24	3.08E-14	2.89E+01	7.77E+03	3.65E+00	2.40E+00
	Std	4.70E-87	1.27E-02	1.59E+02	5.00E+03	1.15E-23	5.33E-14	1.94E+01	1.11E+03	2.47E+00	1.03E+00
	Rank	1	4	8	10	2	3	7	9	6	5
F_4	Min	3.84E-64	4.12E-06	1.48E-03	3.61E+01	4.77E-20	6.64E-14	1.57E-03	3.59E+01	3.83E-02	1.25E+01
	Max	2.90E-42	1.11E-02	2.70E+01	7.24E+01	1.51E-17	2.29E-12	6.58E-03	6.01E+01	2.96E-01	3.39E+01
	Mean	9.66E-44	8.54E-04	3.37E+00	5.29E+01	2.94E-18	1.02E-12	3.30E-03	5.11E+01	1.55E-01	2.42E+01
	Std	5.29E-43	2.29E-03	6.40E+00	9.29E+00	3.76E-18	6.56E-13	1.43E-03	5.23E+00	6.24E-02	5.67E+00
	Rank	1	4	7	10	2	3	5	9	6	8
F_5	Min	8.51E+00	6.96E+00	6.12E+00	1.85E+06	5.72E+00	8.01E-01	2.76E+00	2.74E+06	1.46E+00	7.73E+00
	Max	8.95E+00	8.10E+00	8.04E+00	4.30E+07	8.06E+00	3.16E+00	1.95E+01	2.01E+07	7.50E+01	2.89E+01
	Mean	8.73E+00	7.45E+00	6.91E+00	1.44E+07	6.71E+00	1.65E+00	9.24E+00	9.82E+06	1.46E+01	1.63E+01
	Std	1.15E-01	3.34E-01	3.67E-01	1.03E+07	6.64E-01	5.52E-01	4.45E+00	4.75E+06	1.87E+01	5.67E+00
	Rank	5	4	3	10	2	1	6	9	7	8
F_6	Min	3.57E-01	2.23E-01	2.10E-04	2.36E+03	1.32E-06	2.57E-12	7.56E-21	4.43E+03	3.21E-05	6.35E-02
	Max	1.40E+00	7.16E-01	4.27E-03	1.47E+04	2.51E-01	3.92E-11	1.52E-18	1.18E+04	1.18E-03	1.11E+00
	Mean	9.45E-01	4.88E-01	1.41E-03	8.70E+03	2.49E-02	1.28E-11	2.72E-19	8.54E+03	3.36E-04	3.16E-01
	Std	2.55E-01	1.28E-01	1.00E-03	3.41E+03	7.61E-02	8.51E-12	3.21E-19	1.84E+03	2.84E-04	1.99E-01
	Rank	8	7	4	10	5	2	1	9	3	6
F_7	Min	8.50E-05	3.09E-04	7.67E-05	4.61E-01	1.26E-04	8.53E-05	2.25E-03	1.91E-02	2.56E-03	6.90E-04
	Max	2.12E-03	1.27E-02	7.15E-03	8.93E+00	1.70E-03	2.82E-03	1.24E-02	1.15E-01	1.93E-02	1.51E-02
	Mean	6.89E-04	3.88E-03	2.50E-03	3.94E+00	6.72E-04	7.58E-04	6.36E-03	6.24E-02	1.11E-02	7.26E-03
	Std	5.27E-04	3.81E-03	2.09E-03	2.20E+00	3.99E-04	6.38E-04	2.36E-03	2.61E-02	4.06E-03	3.32E-03
	Rank	2	5	4	10	1	3	6	9	8	7
F_8	Min	−5.84E+11	−2.47E+03	−4.19E+03	−5.30E+03	−3.27E+03	−3.85E+03	−4.19E+03	−2.50E+03	−4.07E+03	−3.73E+03
	Max	−5.97E+03	−1.85E+03	−2.36E+03	−1.07E+03	−2.03E+03	−3.36E+03	−4.07E+03	−1.92E+03	−3.48E+03	−3.18E+03
	Mean	−1.97E+10	−2.13E+03	−3.22E+03	−2.64E+03	−2.63E+03	−3.58E+03	−4.16E+03	−2.26E+03	−3.71E+03	−3.53E+03
	Std	1.07E+11	1.56E+02	6.09E+02	1.24E+03	3.45E+02	1.51E+02	5.33E+01	1.63E+02	1.38E+02	1.46E+02
	Rank	1	10	6	7	8	4	2	9	3	5
F_9	Min	0.00E+00	0.00E+00	0.00E+00	6.28E+01	0.00E+00	0.00E+00	5.68E-14	4.97E+00	3.40E-05	3.44E+00
	Max	1.89E+01	1.81E+01	0.00E+00	1.34E+02	7.11E+00	4.03E-11	9.95E-01	4.48E+01	9.99E-01	1.31E+01
	Mean	3.66E+00	1.58E+00	0.00E+00	1.03E+02	1.23E+00	1.82E-12	3.32E-02	2.10E+01	7.07E-02	7.26E+00
	Std	6.74E+00	4.29E+00	0.00E+00	1.84E+01	2.17E+00	7.52E-12	1.82E-01	9.55E+00	2.52E-01	2.26E+00
	Rank	7	6	1	10	5	2	3	9	4	8

6 Discussion and Future Works

The Archimedes Optimization Algorithm (AOA) is a physics-based metaheuristic optimization algorithm that simulates the principles of buoyancy and density from Archimedes' law to solve complex real-world optimization problems. By emulating the concept of object density and volume in a fluid, the AOA algorithm provides a dynamic balance between global diversification and local intensification. As a result, the AOA algorithm has shown competitive performance compared to many classical meta-heuristics such as TS, PSO, BA, GWO, FA, and WOA, particularly

Table 12 Continued

Function	Metric	AOA	SCA	WOA	BA	GWO	MPA	DE	FA	GA	TS
F_{10}	Min	4.44E-16	1.21E-09	4.44E-16	1.63E+01	4.00E-15	4.00E-15	6.82E-11	1.68E+01	2.96E-03	2.18E-01
	Max	4.00E-15	1.15E-04	7.55E-15	2.00E+01	1.11E-14	1.47E-14	7.42E-10	1.93E+01	1.60E-02	8.42E-01
	Mean	1.39E-15	4.00E-06	3.29E-15	1.91E+01	7.31E-15	4.83E-15	2.65E-10	1.86E+01	6.67E-03	4.68E-01
	Std	1.60E-15	2.10E-05	2.70E-15	1.08E+00	1.30E-15	2.22E-15	1.55E-10	5.89E-01	2.84E-03	1.61E-01
	Rank	1	6	2	10	4	3	5	9	7	8
F_{11}	Min	0.00E+00	0.00E+00	0.00E+00	3.01E+01	0.00E+00	0.00E+00	5.00E-10	4.25E+01	1.00E-02	3.08E-01
	Max	6.49E-01	5.95E-01	7.08E-01	1.47E+02	7.22E-02	7.41E-03	2.77E-02	1.25E+02	2.03E-01	5.60E-01
	Mean	7.62E-02	7.99E-02	7.24E-02	8.78E+01	1.70E-02	2.47E-04	2.81E-03	8.23E+01	8.48E-02	4.30E-01
	Std	1.74E-01	1.72E-01	1.63E-01	2.92E+01	2.13E-02	1.35E-03	6.54E-03	1.62E+01	3.95E-02	8.73E-02
	Rank	5	6	4	10	3	1	2	9	7	8
F_{12}	Min	5.81E-02	2.76E-02	3.40E-04	1.48E+04	3.94E-07	1.32E-12	1.70E-21	2.00E+06	5.63E-07	1.27E-03
	Max	5.42E-01	1.94E-01	5.08E-02	6.99E+07	1.99E-02	4.11E-11	5.20E-20	3.22E+07	1.32E-04	5.14E-02
	Mean	3.14E-01	1.10E-01	9.52E-03	1.54E+07	2.98E-03	8.52E-12	1.41E-20	1.40E+07	1.02E-05	1.74E-02
	Std	1.20E-01	3.41E-02	1.27E-02	1.66E+07	6.89E-03	8.50E-12	1.35E-20	7.50E+06	2.41E-05	1.19E-02
	Rank	8	7	5	10	4	2	1	9	3	6
F_{13}	Min	3.12E-01	2.08E-01	5.74E-04	5.01E+05	2.57E-06	6.80E-12	4.77E-21	1.33E+07	1.19E-06	8.90E-03
	Max	8.93E-01	5.37E-01	1.52E-01	1.71E+08	1.03E-01	2.76E-10	2.30E-19	7.15E+07	1.10E-02	6.78E-02
	Mean	5.86E-01	3.20E-01	2.53E-02	6.14E+07	2.47E-02	4.94E-11	6.21E-20	3.63E+07	2.07E-03	3.03E-02
	Std	1.42E-01	8.37E-02	4.24E-02	4.51E+07	4.30E-02	5.27E-11	6.27E-20	1.58E+07	4.17E-03	1.53E-02
	Rank	8	7	5	10	4	2	1	9	3	6
F_{14}	Min	9.98E-01	9.98E-01	9.98E-01	1.99E+00	9.98E-01	9.98E-01	9.98E-01	9.98E-01	9.98E-01	9.98E-01
	Max	5.93E+00	1.08E+01	1.08E+01	5.28E+01	1.27E+01	9.98E-01	1.99E+00	6.90E+00	9.98E-01	9.98E-01
	Mean	1.30E+00	2.25E+00	2.96E+00	1.58E+01	5.49E+00	9.98E-01	1.06E+00	1.92E+00	9.98E-01	9.98E-01
	Std	9.77E-01	1.89E+00	3.39E+00	1.24E+01	4.85E+00	1.40E-16	2.52E-01	1.37E+00	4.46E-13	4.75E-13
	Rank	5	7	8	10	9	1	4	6	2	3
F_{15}	Min	3.76E-04	5.74E-04	3.10E-04	3.41E-03	3.08E-04	3.07E-04	5.46E-04	3.68E-04	3.23E-04	3.23E-04
	Max	1.70E-03	1.64E-03	1.61E-03	3.38E-01	5.65E-02	3.07E-04	9.78E-04	2.04E-02	2.04E-02	7.87E-04
	Mean	7.30E-04	1.05E-03	6.74E-04	6.58E-02	5.66E-03	3.07E-04	7.30E-04	3.34E-03	3.37E-03	5.53E-04
	Std	3.19E-04	3.59E-04	3.81E-04	6.80E-02	1.22E-02	1.78E-14	7.47E-05	6.80E-03	6.79E-03	1.13E-04
	Rank	4	6	3	10	9	1	5	7	8	2
F_{16}	Min	−9.90E+00	−6.01E+00	−1.02E+01	−2.21E+00	−1.02E+01	−1.02E+01	−1.02E+01	−1.02E+01	−1.02E+01	−1.02E+01
	Max	−3.61E+00	−3.51E-01	−2.62E+00	−2.60E-01	−2.63E+00	−1.02E+01	−8.89E+00	−2.68E+00	−2.63E+00	−1.02E+01
	Mean	−6.34E+00	−2.15E+00	−7.93E+00	−8.56E-01	−8.81E+00	−1.02E+01	−1.01E+01	−7.47E+00	−6.07E+00	−1.02E+01
	Std	2.07E+00	1.87E+00	2.80E+00	4.50E-01	2.54E+00	3.01E-11	2.69E-01	3.02E+00	3.50E+00	9.43E-05
	Rank	7	9	5	10	4	1	3	6	8	2
F_{17}	Min	−1.03E+01	−6.32E+00	−1.04E+01	−3.37E+00	−1.04E+01	−1.04E+01	−1.04E+01	−1.04E+01	−1.04E+01	−1.04E+01
	Max	−3.08E+00	−5.21E-01	−9.12E-01	−4.60E-01	−5.09E+00	−1.04E+01	−1.04E+01	−2.75E+00	−1.84E+00	−1.04E+01
	Mean	−6.36E+00	−2.71E+00	−7.38E+00	−1.24E+00	−1.02E+01	−1.04E+01	−1.04E+01	−9.75E+00	−6.18E+00	−1.04E+01
	Std	2.07E+00	1.92E+00	3.42E+00	6.72E-01	9.70E-01	3.42E-11	8.35E-03	2.02E+00	3.58E+00	3.72E-05
	Rank	7	9	6	10	4	1	3	5	8	2
F_{18}	Min	−1.04E+01	−8.34E+00	−1.05E+01	−3.48E+00	−1.05E+01	−1.05E+01	−1.05E+01	−1.05E+01	−1.05E+01	−1.05E+01
	Max	−3.11E+00	−9.44E-01	−1.86E+00	−6.30E-01	−2.42E+00	−1.05E+01	−1.05E+01	−2.42E+00	−2.42E+00	−1.05E+01
	Mean	−7.01E+00	−4.16E+00	−7.12E+00	−1.35E+00	−9.81E+00	−1.05E+01	−1.05E+01	−9.05E+00	−4.76E+00	−1.05E+01
	Std	2.40E+00	1.58E+00	3.34E+00	6.31E-01	2.24E+00	2.55E-11	1.45E-05	3.06E+00	3.56E+00	2.55E-05
	Rank	7	9	6	10	4	1	2	5	8	3

on benchmark functions and continuous optimization problems.

One of the notable advantages of the AOA algorithm is its simplicity, characterized by ease of implementation and minimal dependence on control parameters, making it suitable for both theoretical research and practical applications. Its flexible design facilitates hybridization and extensions, while its robust global search capability has proven effective for continuous, discrete, and constrained optimization problems. However, some limitations are also observed. Firstly, like many metaheuristics, it may still suffer from premature convergence, especially on high-dimensional or highly multi-modal problems. Secondly, the use of fixed parameters restricts the adaptability of the AOA algorithm

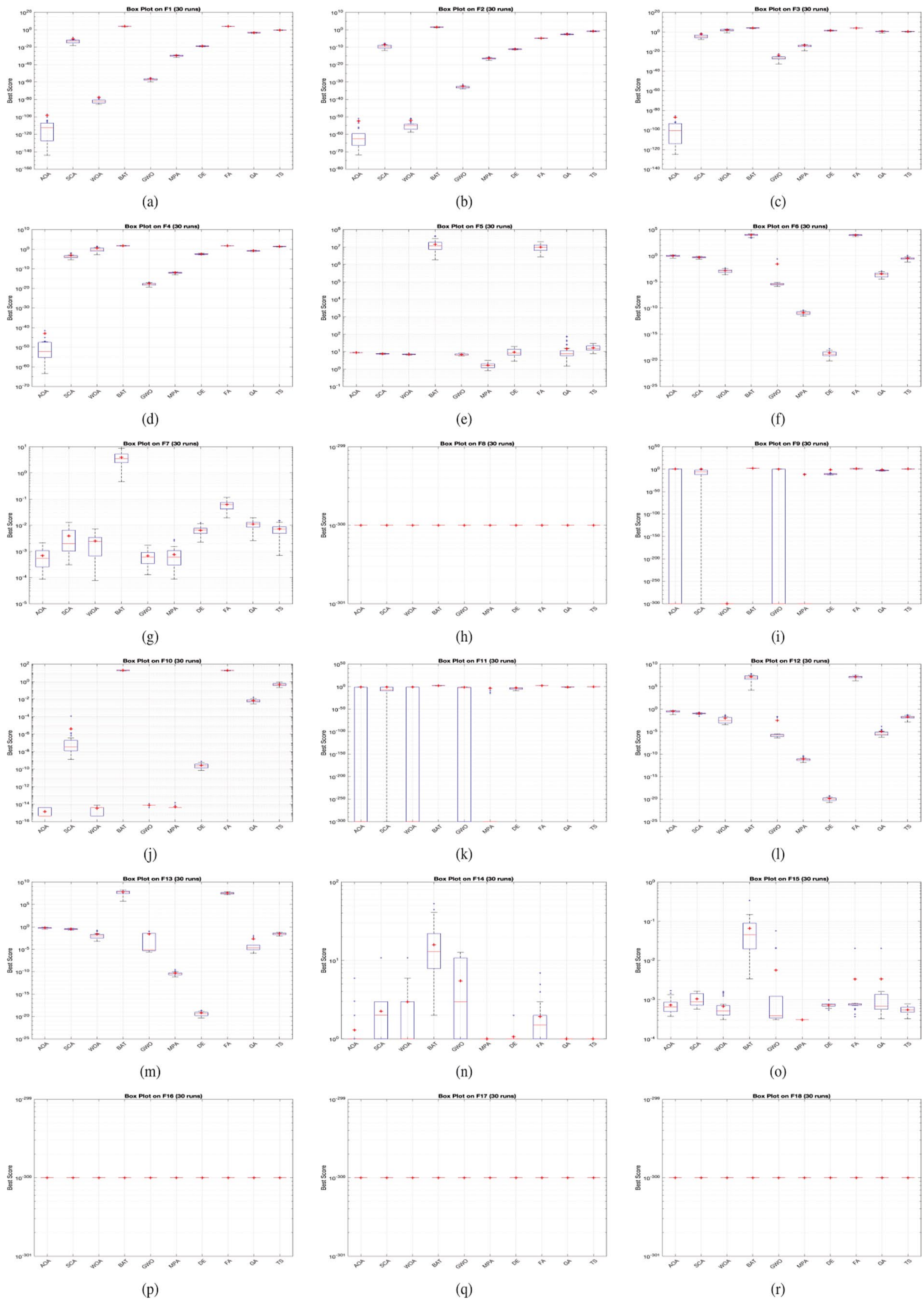


Fig. 7 Boxplot of all algorithms across 18 benchmark functions

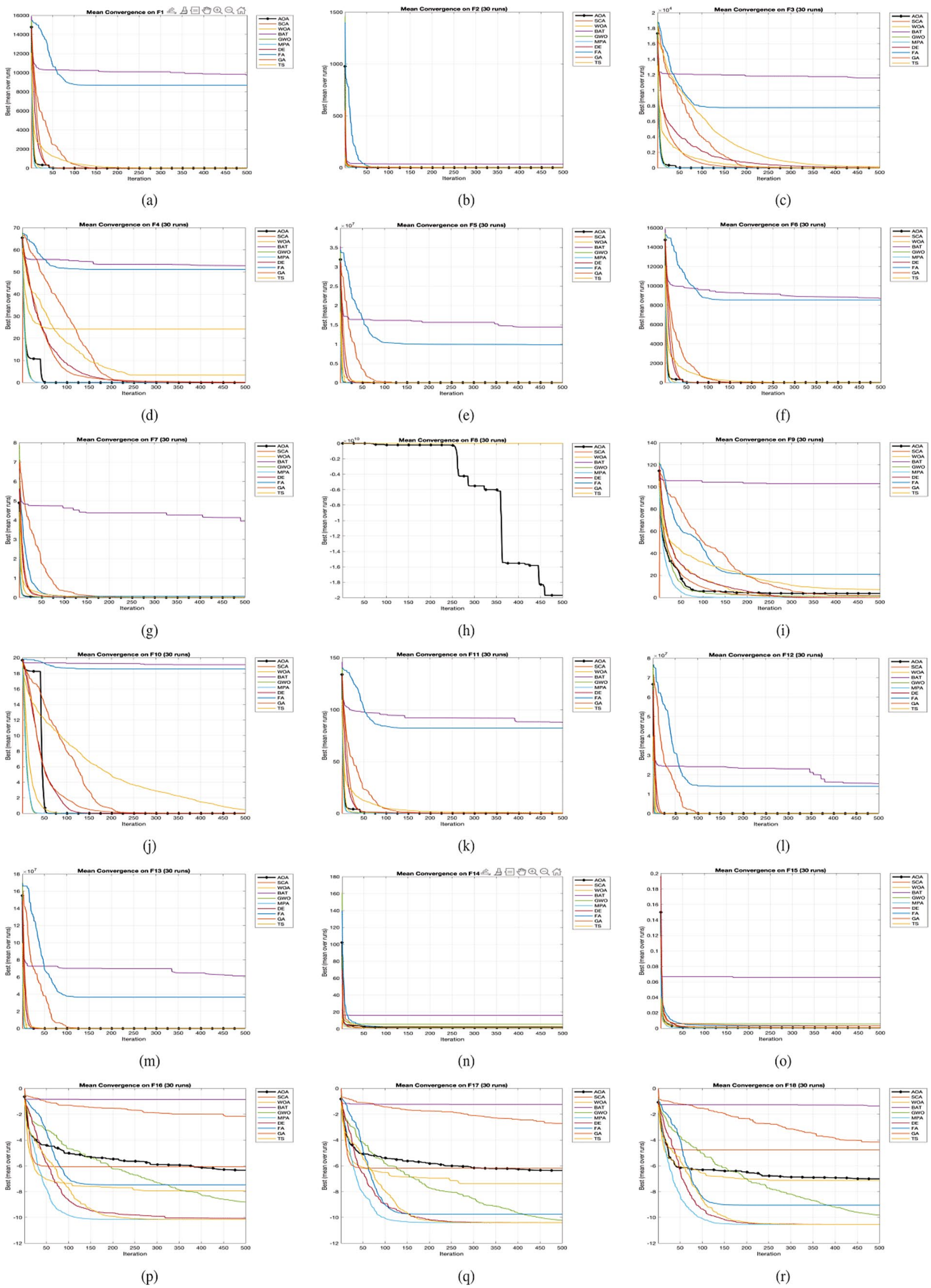


Fig. 8 Convergence of all algorithms across 18 benchmark functions

Table 13 Friedman test of the fitness values under various benchmark functions

	Results	AOA	SCA	WOA	BA	GWO	MPA	DE	FA	GA	TS
Descriptive statistics	*N*	18	18	18	18	18	18	18	18	18	18
	Mean	−1.09E+09	−1.18E+02	−1.72E+02	5.07E+06	−1.47E+02	−2.00E+02	−2.31E+02	3.34E+06	−2.06E+02	−1.95E+02
	SD	4.64E+09	5.02E+02	7.61E+02	1.49E+07	6.20E+02	8.43E+02	9.81E+02	9.10E+06	8.75E+02	8.32E+02
	Minimum	−1.97E+10	−2.13E+03	−3.22E+03	−2.64E+03	−2.63E+03	−3.58E+03	−4.16E+03	−2.26E+03	−3.71E+03	−3.53E+03
	Maximum	8.73E+00	7.45E+00	1.38E+02	6.14E+07	6.71E+00	1.65E+00	2.89E+01	3.63E+07	1.46E+01	2.42E+01
Mean rank		4.78	6.56	4.61	9.83	4.08	2.14	3.47	8.00	5.89	5.64
Test Statistics	*N*	18									
	Chi-square	90.24									
	df	9									
	Asymp. Sig.	<0.001									

Table 14 Advantages and limitations of the AOA algorithm

Advantages	Limitations
Simple structure with few control parameters	Its performance can be sensitive to the choice of its control parameters (e.g., density factor and transfer rate).
Good convergence behavior due to the gradual transition from exploration to exploitation.	Sensitive to initial population distribution
Flexible design for hybridization and extension	Exhibits susceptibility to premature convergence in challenging problem spaces
Effective in handling continuous, constrained, and multi-objective problems	Poor local search mechanism restricts the algorithm's capacity to refine solutions

to dynamic or time-varying environments. Finally, the AOAs performance is highly sensitive to initial population distribution, which may hinder effective exploration if not properly managed. The advantages and limitations of the AOA algorithm are presented in Table 14.

To address the shortcomings of the original AOA algorithm, various improved variants have been developed (i.e.: chaotic, Lévy flight, OBL, quantum, adaptive, hybridized, etc.), each focusing on enhancing specific elements of the search process.

Figure 9 depicts the classification of algorithmic modifications according to the type of improvement applied. Binary adaptations of AOA (11.4%) apply transfer functions to map the AOA algorithm to discrete domains, enabling applications like feature selection and task scheduling. Chaotic AOA variants (15.9%) employ chaotic maps during initialization or update phases to enhance randomness and avoid premature stagnation. By introducing opposite candidates at each iteration, opposition-based learning (4.5%) improves both the convergence rate and the AOAs exploration capability. Lévy flight enhancements (13.6%) introduce long exploratory steps that enable the AOA algorithm to escape local optima in multimodal problems. Quantum-inspired (4.5%) strategy improves the AOAs search behavior and resilience, especially when dealing with uncertainty or constraint problems. Similarly, mutation-based variants (2.3%) introduce stochastic perturbations to preserve population diversity, particularly in complex search landscapes. Improved versions (31.8%) often incorporate elitism, selective learning, and local search strategies to maintain high-quality solutions and improve convergence precision.

Hybrid AOA variants have demonstrated significant progress, achieving improved performance by combining complementary optimization or learning techniques. As shown in Fig. 10, the most prevalent hybridization (56.0%) involves artificial neural networks (ANNs), where the AOA algorithm is applied to optimize network parameters such as weights and biases. This approach eliminates the reliance on

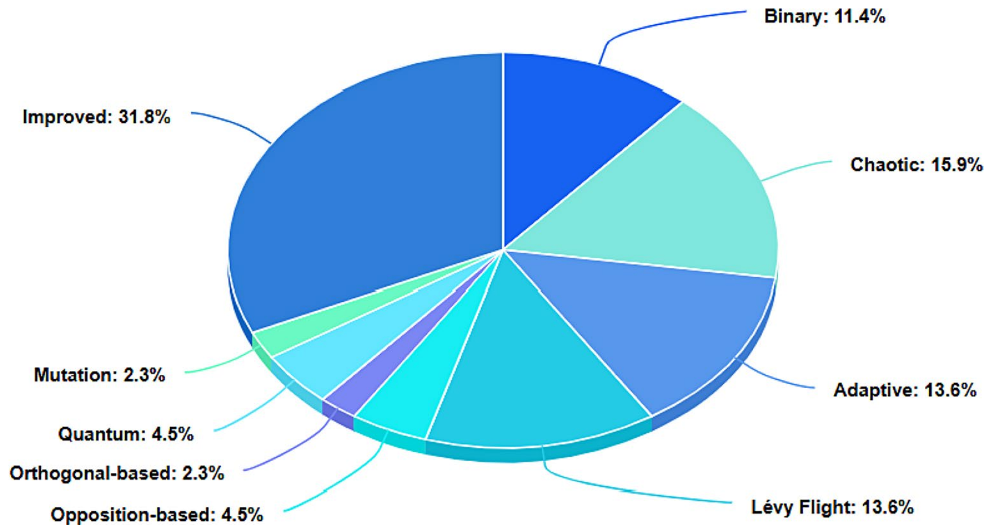


Fig. 9 The modified versions of AOA algorithm

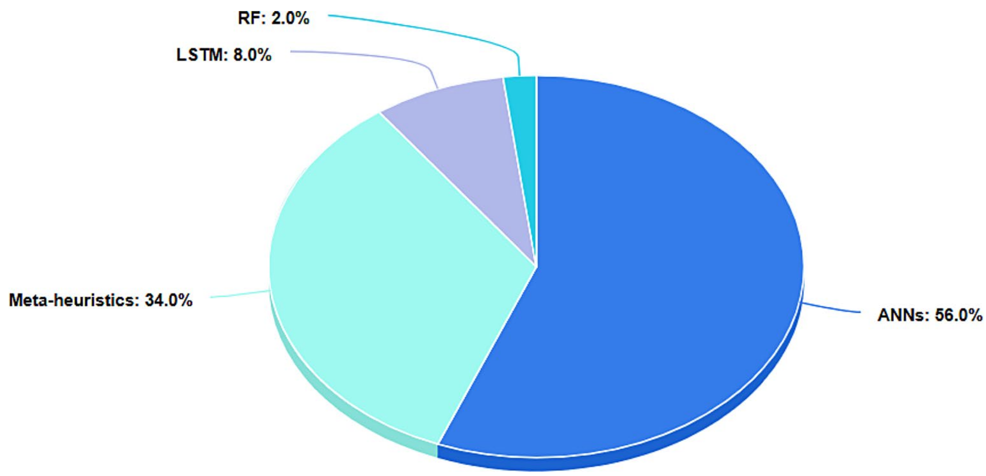


Fig. 10 The hybridized versions of AOA algorithm

gradient-based training and enhances generalization, especially in nonlinear, high-dimensional tasks such as classification, adaptive control, and regression. The second-largest category, representing 34.0%, consists of the hybridization of the AOA algorithm with other metaheuristics such as GA, ACO, WOA, and GWO. These algorithms leverage their ability to explore large search spaces and identify near-optimal solutions for complex, non-convex problems. More specialized hybridizations involve LSTM (8.O%) and RF (2.0%), which are employed for hyperparameter tuning and feature selection to improve classification performance indicating their use in more specialized or niche applications.

Figure 11 presents the distribution of related works by application domain. The largest category, Engineering, accounts for 48.2% of applications, underscoring the strong emphasis on applying optimization algorithms to real-world engineering problems. Power and Energy follows at 26.8%, reflecting the importance of optimization in enhancing efficiency and sustainability in the energy sector. Image Processing comprises 16.1%, highlighting the contribution of optimization techniques to the advancement of image analysis and processing. Finally, classification represents 8.9%, showcasing its relevance to tasks like feature selection and data categorization.

Looking ahead, the following promising research directions are recommended:

– **Parameter Adaptation:** Developing adaptive or self-tuning strategies for controlling the parameters of the AOA algorithm dynamically during the search process to improve its efficiency and reduce the need for manual tuning.
– **Hybridization:** Combining the AOA algorithms with other metaheuristics or local search mechanisms to exploit complementary strengths and overcome weaknesses such as stagnation or slow convergence in certain problem types.
– **Multi-objective Optimization:** Extending the AOA algorithm to effectively handle multi-objective optimization problems by integrating Pareto-dominance concepts, crowding distance, or decomposition techniques.

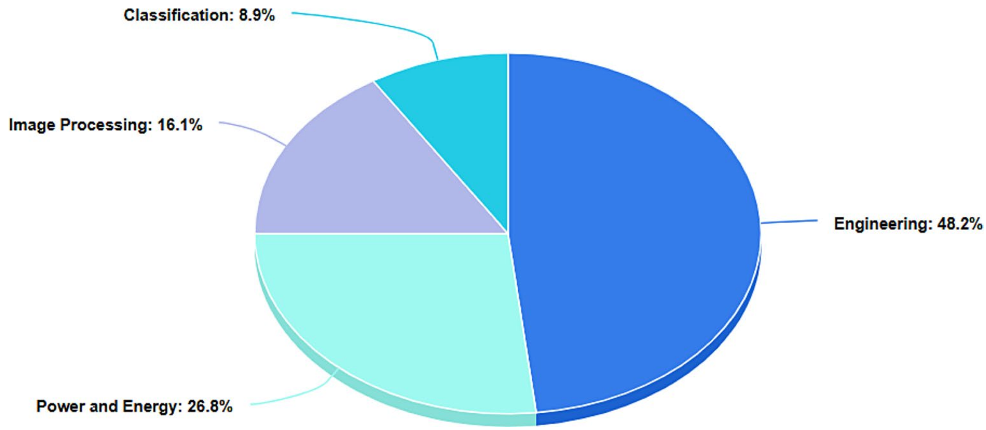


Fig. 11 The applications of AOA algorithm

- **Discrete and Combinatorial Problems:** Adapting the AOA algorithm to discrete or combinatorial optimization tasks such as scheduling, routing, or feature selection, which require specialized operators or representations.
- **Constraint Handling:** Enhancing the AOAs ability to deal with constraints efficiently through penalty methods, repair functions, or feasibility-preserving mechanisms.
- **Parallelization and Scalability:** Designing parallel or distributed versions of the AOA algorithm to handle very high-dimensional or computationally expensive problems in a reasonable time.
- **Theoretical Analysis:** Further investigation of the theoretical properties of the AOA algorithm, such as convergence guarantees, complexity analysis, and exploration-exploitation trade-offs.
- **Real-world Applications:** Applying the AOA algorithm to more diverse and complex real-world problems in engineering, data science, energy systems, and bioinformatics to validate its practical utility.

7 Conclusion

This research paper presents a comprehensive and detailed survey of the AOA algorithm and its enhanced variants, including multi-objective, hybridized, and modified versions. Since its introduction by Hashim et al. in 2021, more than 150 publications on AOA have been published, highlighting its growing prominence as a promising metaheuristic for solving diverse optimization problems. This popularity stems from its distinctive structure, ease of implementation, simplicity, fast convergence, and, notably, its flexibility to hybridize with other optimization techniques. Despite its notable successes, there are still numerous suggestions for future research to for further improving AOAs performance and applicability. For example, refining the original AOA through the development of new operators and strategies warrants additional investigation. Moreover, combining AOA with other metaheuristics is encouraged to strengthen its exploration and exploitation capabilities. Finally, extending AOAs applications to more dynamic, high-dimensional, and complex optimization challenges represents another valuable direction for future research.

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Declarations

Conflict of Interest The authors declare no competing interests.

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