Archives of Computational Methods in Engineering (2025) 32:4643–4689
https://doi.org/10.1007/s11831-025-10281-0

REVIEW

A Comprehensive Survey of Aquila Optimizer: Theory, Variants, Hybridization, and Applications

Sylia Mekhmoukh Taleb[1] · Elham Tahsin Yasin[2] · Amylia Ait Saadi[3,4] · Musa Dogan[2] · Selma Yahia[1] · Yassine Meraihi[1] · Murat Koklu[5] · Seyedali Mirjalili[6,7] · Amar Ramdane-Cherif[3]

Received: 19 January 2025 / Accepted: 26 March 2025 / Published online: 7 May 2025

Abstract

The Aquila Optimizer (AO) algorithm is a well-known Swarm-based nature-inspired optimization algorithm inspired by Aquila's behavior in hunting and catching prey. Since its development by Abualigah et al. (Comput Methods Appl Mech Eng 376:113609, 2021), AO has gained significant interest among researchers. It has been widely applied across various fields to solve optimization problems, owing to its simplicity, ease of implementation, and reasonable execution time. The main purpose of this paper is to provide a comprehensive survey of the AO algorithm and its improved variants (multi-objective, modified, and hybridized). It also illustrates the various applications of the AO algorithm in several domains of problems such as image processing, feature selection, economic load dispatch, wireless sensor networks, photovoltaic power systems, Unmanned Aerial Vehicles (UAVs) path planning, optimal parameter control, and vehicle routing problems. Furthermore, the results of the AO algorithm are compared with some well-known optimization meta-heuristics published in the literature, such as Differential Evolution (DF), Firefly Algorithm (FA), Bat Algorithm (BA), Grey Wolf Optimization (GWO), Moth Flame Optimization (MFO), and Multi-Verse Optimizer (MVO). Finally, the paper concludes with some future research directions for the AO algorithm.

✉ Sylia Mekhmoukh Taleb
s.mekhmoukh@univ-boumerdes.dz

Elham Tahsin Yasin
ilham.tahsen@gmail.com

Amylia Ait Saadi
a.aitsaadi@univ-boumerdes.dz

Musa Dogan
musa.dogan@selcuk.edu.tr

Selma Yahia
s.yahia@univ-boumerdes.dz

Yassine Meraihi
y.meraihi@univ-boumerdes.dz

Murat Koklu
mkoklu@selcuk.edu.tr

Seyedali Mirjalili
ali.mirjalili@gmail.com

Amar Ramdane-Cherif
rca@lisv.uvsq.fr

1 LIST Laboratory, University of M'Hamed Bougara Boumerdes, Avenue of Independence, 35000 Boumerdes, Algeria

2 Graduate School of Natural and Applied Sciences, Selcuk University, Konya, Türkiye

3 LISV Laboratory, University of Paris-Saclay, 10-12 Avenue of Europe, Velizy, France

4 ESME Engineering School, Ivry-sur-Seine, France

5 Technology Faculty, Department of Computer Engineering, Selcuk University, Konya, Turkey

6 Centre for Artificial Intelligence Research and Optimisation, Torrens University Australia, Fortitude Valley, Brisbane, QLD 4006, Australia

7 Yonsei Frontier Lab, Yonsei University, Seoul, Korea

1 Introduction

Meta-heuristics represent a new generation of powerful approached optimization methods, adaptable and applicable to a large class of problems. They are iterative stochastic methods that escape local minima and progress towards a global optimum of a function. These methods provide high-quality, feasible solutions within a reasonable time-frame. We distinguish two classes of meta-heuristics: those based on a single solution and those based on a population of solutions.

Single-based meta-heuristics (or trajectory methods) start with a single initial solution and gradually move away from it, building a trajectory in the search space. Essentially, they include Descent Method (DM), Simulated Annealing (SA) [1], Tabu Search (TS) [2], Variable Neighborhood Search (VNS) [3], Iterated Local Search (ILS) [4], Guided Local Search (GLS) [5], Stochastic Local Search (SLS) [6], and Greedy Randomized Adaptive Search Procedure (GRASP) [7].

Unlike single-based meta-heuristics, population-based meta-heuristics are iterative methods that improve a population of solutions over iterations. More precisely, they start from an initial population of solutions, then a new one is generated. This new population is integrated into the current population using a few selection procedures. The iterative process stops when a stopping criterion is achieved. Meta-heuristics with a population of solutions can be classified into six categories: Evolutionary-based, Physical-based, Chemical-based, Math-based, Human-based, and Swarm-based as illustrated in Fig. 1.

Evolutionary Algorithms (EAs) category includes population-based meta-heuristics which are inspired by natural evolutionary processes that make use of three main operators i.e.: mutation, selection, and recombination. Some well-known EAs are: Genetic Algorithm (GA) [8], Evolutionary Strategies (ES) [9], Genetic Programming (GP) [10], Evolutionary Programming (EP) [11], Memetic Algorithm (MA) [12], Probability-Based Incremental Learning (PBIL) [13], Differential Evolution (DE) [14], Clonal Selection Algorithm (CSA) [15], and Biogeography-Based Optimizer (BBO) [16].

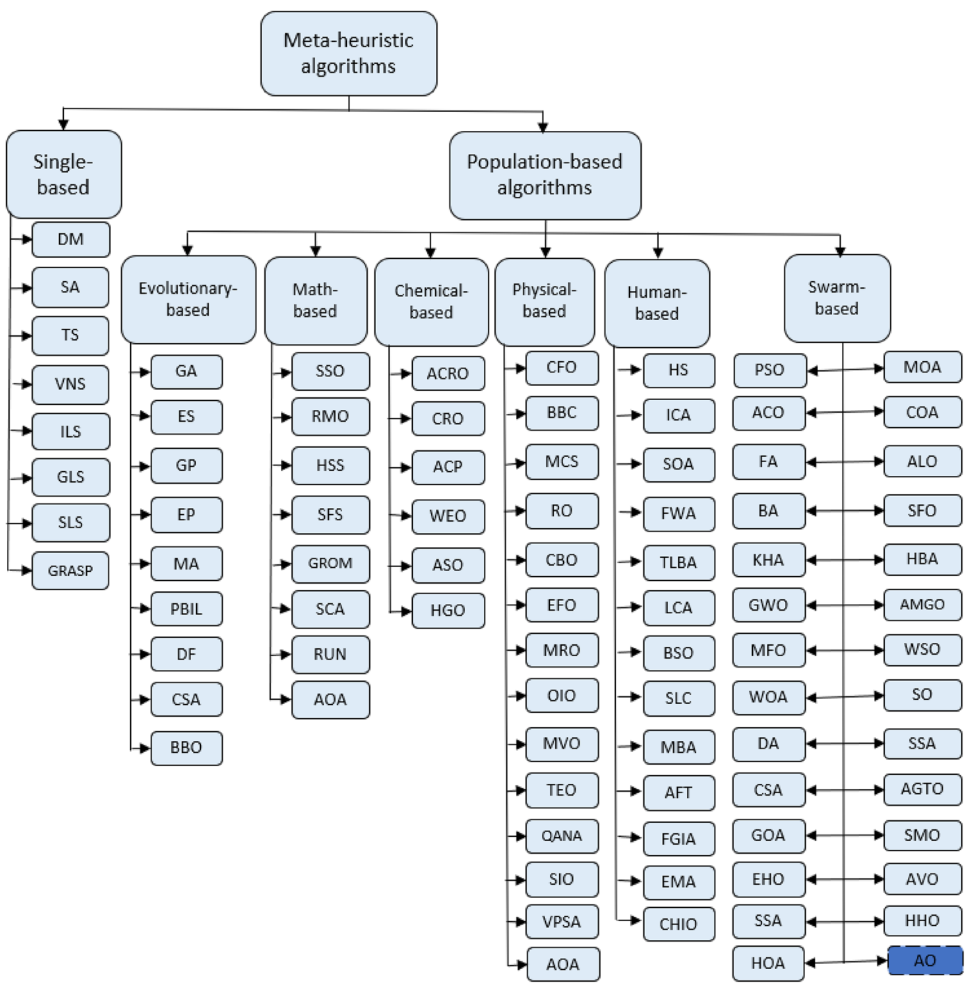

Fig. 1 Classification of meta-heuristic algorithms

Physics-based Algorithms (PAs) mimic the physical rules in the universe. Some of the most popular algorithms are: Central Force Optimization (CFO) [17], Gravitational Search Algorithm (GSA) [18], and Big-Bang Big-Crunch (BBBC) [19]. Other recently developed physics-based algorithms are: Magnetic Charged System Search (MCSS) [20], Ray Optimization (RO) algorithm [21], Colliding Bodies Optimization(CBO) [22], Electromagnetic Field Optimization (EFO) [23], Nuclear Reaction Optimization (NRO) [24], Optics Inspired Optimization (OIO) [25], Multi-Verse Optimizer (MVO) [26], Thermal Exchange Optimization (TEO) [27], Quantum-based Avian Navigation Optimizer Algorithm (QANA) [28], Sonar Inspired Optimization (SIO) [29], Vibrating Particles System Algorithm (VPSA) [30], Equilibrium Optimizer (EO) [31], Tornado Optimizer with Coriolis Force (TOCO) [32], and Archimedes Optimization Algorithm (AOA) [33].

Chemical-based Algorithms (CAs) mimic the chemical interactions and rules that appeared in the universe, respectively. Some of the popular algorithms are: Artificial Chemical Reaction Optimization (ACRO) [34], Chemical Reaction Optimization (CRO) [35], Artificial Chemical Process (ACP) [36], Water Evaporation Optimization (WEO) [37], Atom Search Optimization (ASO) [38], and Henry Gas Solubility Optimization (HGSO) [39].

Math-based Algorithms (MAs) imitate mathematical rules. Some of the most well-known math-based algorithms are: Spherical Search Optimizer (SSO) [40], Radial Movement Optimization (RMO) [41], Hyper-Spherical Search (HSS) Algorithm [42], Stochastic Fractal Search (SFS) [43], Golden Ratio Optimization Method (GROM) [44], Sine Cosine Algorithm (SCA) [45, 46], RUNge Kutta Optimizer (RUN) [47], and Arithmetic Optimization Algorithm (AOA) [48].

Human-based algorithms (HMs) are inspired by human-made events. Some of the most well-regarded human-based algorithms are: Harmony Search (HS) [49], Imperialist Competitive Algorithm (ICA) [50], Seeker Optimization Algorithm (SOA) [51], Fire Work Algorithm (FWA) [52], Teaching Learning-Based Algorithm (TLBA) [53], League Championship Algorithm (LCA) [54], Brain Storm Optimization (BSO) [55], Soccer League Competition (SLC) algorithm [56], Mine Blast Algorithm (MBA) [57], Ali Baba and the Forty Thieves (AFT) [58], Political Optimizer (PO) [59], Football Game Inspired Algorithm (FGIA) [60], Poor and Rich Optimization (PRO) Algorithm [61], Exchange Market Algorithm (EMA) [62], and Coronavirus Herd Immunity Optimizer (CHIO) [63].

The category of swarm-based algorithms mimics the behavior of swarms of animals that exist in nature such as swarms of fish, insects, or birds. Ant Colony Optimization (ACO) [64] and Particle Swarm Optimization (PSO) [65] 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 Firefly Algorithm (FA) [66], Cuckoo Search (CS) [67], Ant Bee Colony (ABC) [68], Bat Algorithm (BA) [69], Krill Herd Algorithm (KHA) [70], Grey Wolf Optimization (GWO) [71], Moth Flame Optimization (MFO) [72], Whale Optimization Algorithm (WOA) [73], Dragonfly Algorithm (DA) [74, 75], Crow Search Algorithm (CSA) [76, 77], Grasshopper Optimization Algorithm (GOA) [78, 79], Elephant Herding Optimization (EHO) [80], Social Spider Algorithm (SSA) [81], Horse herd Optimization Algorithm (HOA) [82], Mayfly Optimization Algorithm (MOA) [83], Coyote Optimization Algorithm (COA) [84, 85], Ant Lion Optimizer (ALO) [86], Sailfish Optimizer (SFO) [87], Honey Badger Algorithm (HBA) [88], Mountain Gazelle Optimizer (MGO) [89], White Shark Optimization (WSO) [90], Snake Optimizer (SO) [91], African Vultures Optimization (AVO) [92], Salp Swarm Algorithm (SSA) [93], Marine Predator Algorithm (MPA) [94], Slime Mould Algorithm (SMA) [95], Artificial Gorilla Troops Optimizer (AGTO) [96], Starling Murmuration Optimizer (SMO) [97], Harris Hawks Optimization (HHO) [98], Draco Lizard Optimizer (DLO) [99], Artificial Meerkat Algorithm (AMA) [100], Eurasian Lynx Optimizer (ELO) [101], Shrimp and Goby Association Search algorithm (SGA) [102], Dynamic Hunting Leadership (DHL) algorithm [103], Termite Life Cycle Optimizer (TLCO) algorithm [104], Rhinopithecus Swarm Optimization (RSO) algorithm [105], and Aquila Optimizer (AO) [106].

Aquila Optimizer (AO) algorithm is a novel Swarm-based meta-heuristic, proposed by Abualigah et al. [106]. The AO algorithm mimics Aquila's behavior in hunting and catching prey. In comparison with other well-known optimization algorithms, the AO algorithm demonstrates its efficiency in solving challenging optimization problems. As a result, the AO algorithm is used for solving a variety of problems including feature selection, image processing, optimal parameters control, economic load dispatch, and many others.

This paper provides an overview of the AO algorithm, exploring its variations (including modified, multi-objective, and hybridized versions) and examining its diverse applications across various domains. In order to collect published AO articles, we consider various well-regarded publishers (i.e. Elsevier, MDPI, Springer, IEEE, and others). Additionally, we use Google Scholar and employ specific search queries to build a comprehensive database of articles related to the AO algorithm, with the relevant keywords illustrated in Fig. 2:

- Aquila optimizer.
- Improved aquila optimizer.
- Modified aquila optimizer.

Fig. 2 AO-related keywords

- Enhanced aquila optimizer.
- Binary aquila optimizer.
- Multi-objective aquila optimizer.
- Hybridized aquila optimizer.
- Applications of aquila optimizer.
- Aquila optimizer survey.
- Aquila optimizer review.
- Aquila optimizer overview.

The articles included in this review exclude those that meet at least one of the following criteria:

❖ Published by unreliable or predatory publishers;

❖ Fewer than four pages in length;

❖ Written in a language other than English;

❖ Incomplete, where only the most comprehensive version is selected if multiple versions of the article exist.

As shown in Fig. 3, the paper collection process is illustrated in a detailed, diagrammatic format. This figure provides a step-by-step visual representation of the workflow, highlighting the key stages involved.

The findings from our study are depicted in the following figures. Figure 4 illustrates the number of publications related to AO categorized by publisher and publication type. Notably, Elsevier, MDPI, and Springer emerge as the primary publishers for AO-related works. Figure 5 showcases the distribution of AO publications per year. The data reveals a notable surge in interest over the past four years, reaching a peak in 2022. Since the introduction of the AO algorithm in 2021, over 200 works have been published on this algorithm.

The Top 10 Journals ranked by the number of AO publications are given in Table 1. The 10 AO co-cited articles are presented in Table 2. Lastly, Fig. 6 offers insights into the geographical distribution, presenting the top 10 countries

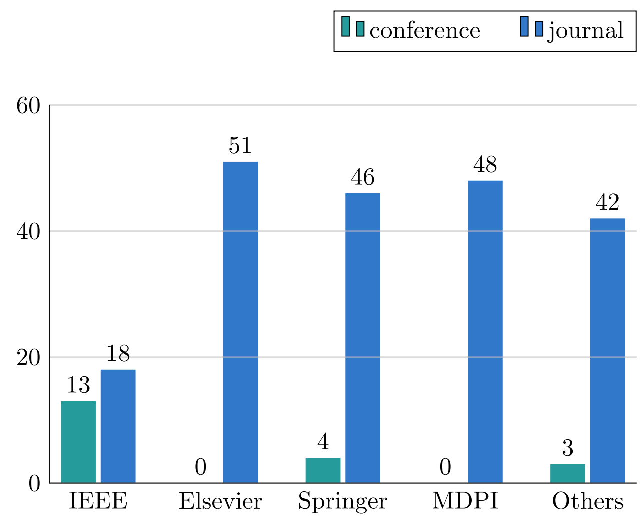

Fig. 4 Number of AO related publications per Database

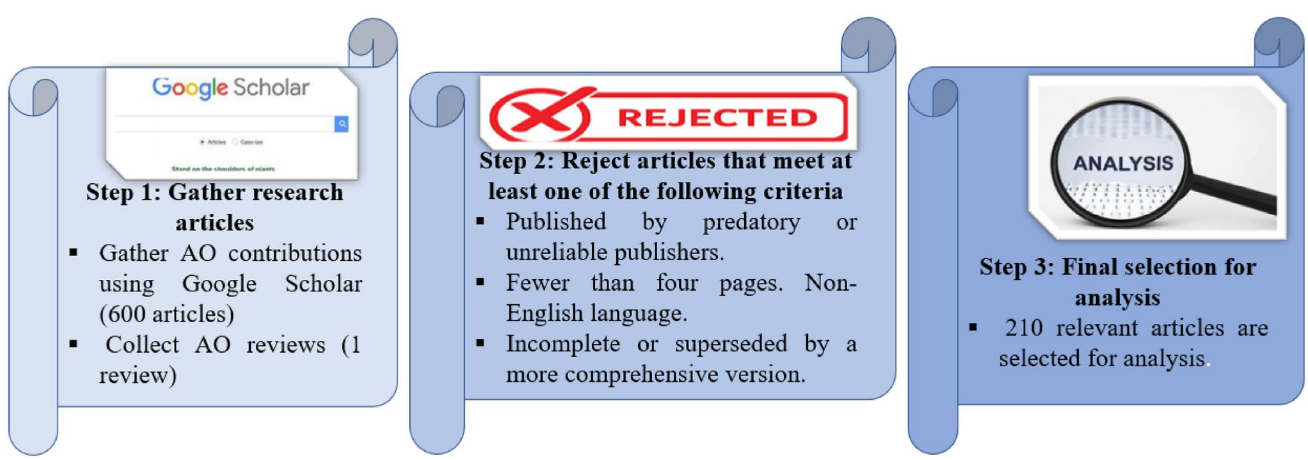

Fig. 3 Diagram illustrating the paper collection process

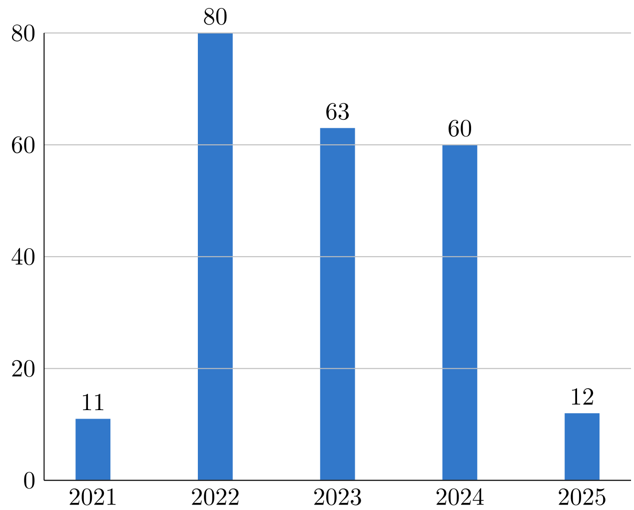

Fig. 5 Number of AO algorithm related publications per year

Table 1 Top 10 Journals ranked by the number of AO publications

Journals	Rank	Number of AO publications
Mathematics	1	9
IEEE ACCESS	2	6
Neural Computing and Applications	2	6
Sensors	2	6
Processes	2	6
Expert Systems With Applications	3	5
Applied Sciences	3	5
Soft Computing	4	3
Biomedical Signal Processing and Control	4	3
Energy	4	3

based on the number of AO publications. China and India stand out as the most active contributors, followed by Egypt, Turkey, Saudi Arabia, Algeria, Iran, Jordan, Pakistan, and Iraq.

As far as we know, there's only one survey by Sasmal et al. [116] that analyzed 112 research articles on Aquila Optimizer. Our recent AO survey, on the other hand, goes further, reviewing and discussing over 200 articles published from 2021 to December 2024. This makes our survey different from the aforementioned survey, offering a broader and more up-to-date look into AO research.

This paper is outlined as follows. Section 2 details the foundational structure of the AO algorithm. Following this, Sect. 3 offers a comprehensive exploration of the modified, multi-objective, and hybridized variants of the AO algorithm, shedding light on the specific adaptations and enhancements introduced. The practical applications of the AO algorithm across diverse domains are deliberated in Sect. 4. Comparisons and results of the AO algorithm with some well-known optimization meta-heuristics are given in Sect. 5. Section 6 engages in a detailed discussion, offering insights and recommendations for further research directions. Finally, Sect. 7 concludes the paper.

Table 2 Top 10 AO co-cited articles

Studies	Rank	Number of citations
Abualigah et al. [106]	1	1828
Fatani et al. [107]	2	149
Wang et al. [108]	3	121
Mahajan et al. [109]	4	115
Abd Elaziz et al. [110]	5	107
AlRassas et al. [111]	6	106
Zhang et al. [112]	7	77
Ma et al. [113]	7	77
Ekinci et al. [114]	8	69
Nadimi et al. [115]	9	56

2 Aquila Optimizer Algorithm

The Aquila Optimizer (AO) algorithm, as proposed by Abualigah et al. [106], is a nature-inspired meta-heuristic optimization method widely applied for solving a variety of optimization problems. The AO algorithm stimulates the behavior of the Aquila, which is a well-known bird characterized by its agility and intelligence, in hunting and catching prey. The hunting behavior of the Aquila is represented by a mathematical optimization paradigm, which includes four main methods, as follows:

2.1 Expanded Exploration

The expanded exploration represents the first method used for updating the Aquila position, where the Aquila makes a high soar with a vertical stoop as shown in Fig. 7. This behavior is mathematically presented as follows:

$$X_i^{(t+1)} = X_{best}^t \times \left(1 - \frac{t}{T}\right) + \left(X_m^t - X_{best}^t \times rand\right) \tag{1}$$

where $X_i^{(t+1)}$ represents the position of individual i at the $(t+1)$ iteration, while X_{Best} indicates the best position found at the t iteration. The term $rand$ refers to a random value within the range [0, 1], and T denotes the maximum number of iterations. Additionally, X_m^t represents the mean position value of the current positions at the t iteration, which is given by:

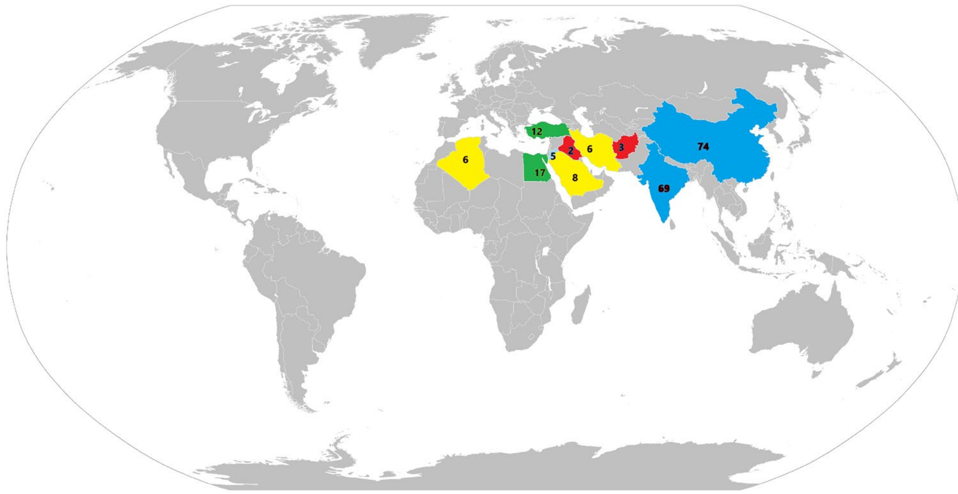

Fig. 6 Top 10 countries ranked by number of publications on the AO algorithm

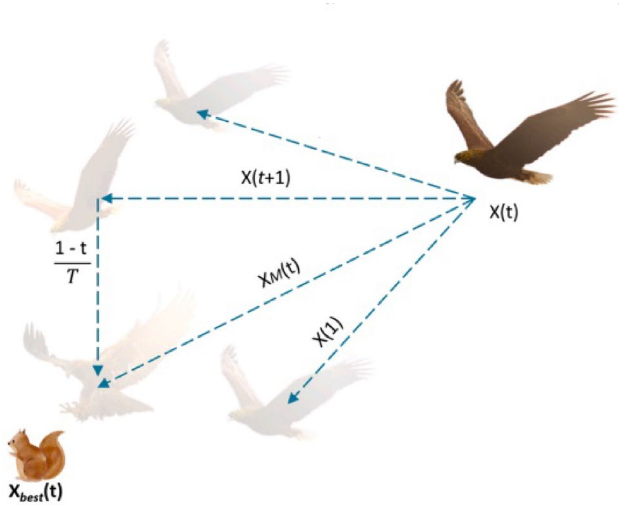

Fig. 7 The Aquila high soar behavior with the vertical stoop [106]

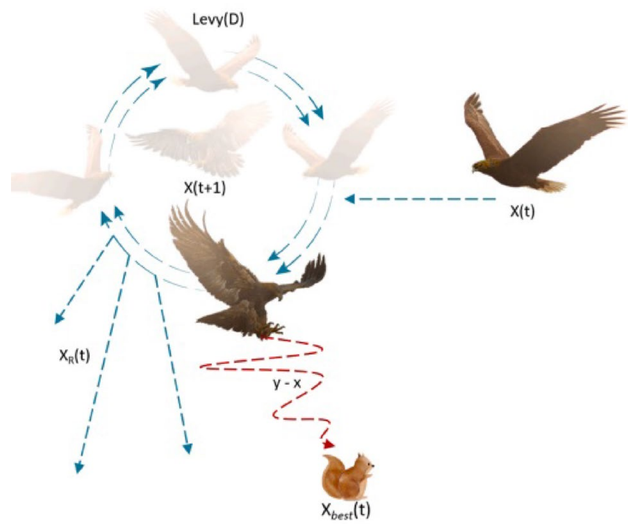

Fig. 8 The Aquila contour flight behavior with short glide attack [106]

$$X_m^t = \frac{1}{N} \sum_{i=1}^{N} X_i^t \tag{2}$$

where N is the number of population size.

2.2 Narrowed Exploration

The narrowed exploration expresses the most common hunting method applied by the Aquila, which is called contour flight with a short glide attack. In this approach, the Aquila catches the prey by contouring the flight with a short glide attack, as illustrated in Fig. 8. This method is expressed in Eq. (3).

$$X_i^{(t+1)} = X_{best}^t \times \text{Lévy}(Dim) + X_r^t + (y - x) \times \text{rand} \tag{3}$$

where Lévy(Dim) refers to the Lévy flight distribution for a space of dimension Dim. X_r^t represents a random solution. The variables y and x characterize the spiral pattern of the Aquila's movement in the search space, which is mathematically expressed as follows:

$$\begin{aligned} x &= r \times \cos\theta \\ y &= r \times \sin\theta \end{aligned} \tag{4}$$

where

$$\begin{aligned} r &= r_1 + U \times D_1 \\ \theta &= -\omega \times D_1 + \frac{3 \times \pi}{2} \end{aligned} \tag{5}$$

r_1 is a constant value within the range of [1, 20]. The values of U and ω are set to small fixed values of 0.00565 and 0.005, respectively. D_1 is an integer that ranges from 1 to the space dimension Dim.

2.3 Expanded Exploitation

This approach simulates the Aquila's hunting behavior when capturing slow-moving prey like hedgehogs, foxes, and tortoises, where the Aquila executes a low flight followed by a gradual descending attack, as depicted in Fig. 9. The process is mathematically described in Eq. (6).

$$X_i^{(t+1)} = \left(X_{best}^t - X_m^t\right) \times \alpha - rand + ((UB - LB) \times rand + LB) \times \delta \tag{6}$$

where α and δ represent the exploitation parameters adjustment. UB and LB are the upper and lower bounds, respectively.

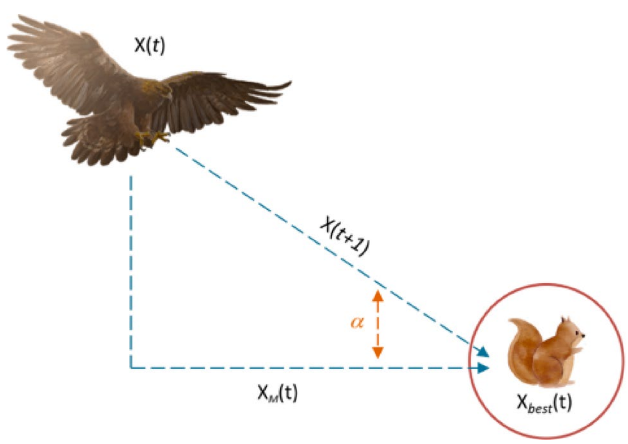

Fig. 9 The Aquila a low flight behavior with slow descent attack [106]

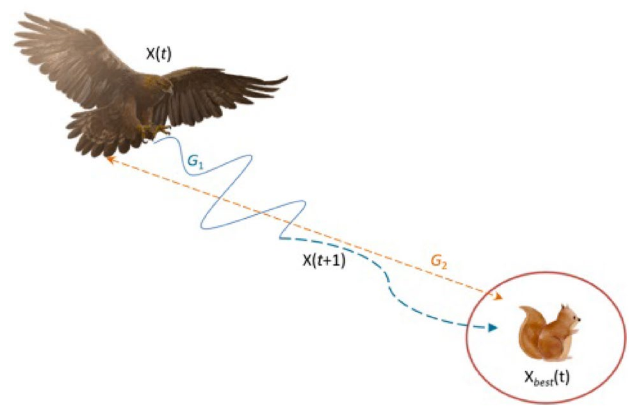

Fig. 10 The Aquila walk and grab prey behavior [106]

2.4 Narrowed Exploitation

The last method is called narrowed exploitation, which represents walking and grabbing prey performed by the Aquila, as shown in Fig. 10. This approach is used for hunting large prey such as deer and sheep and is mathematically expressed as follows:

$$X_i^{(t+1)} = QF \times X_{best}^t - \left(G_1 \times X_i^{(t)} \times rand\right) - G_2 \times \text{Lévy}(Dim) + rand \times G_1 \tag{7}$$

where QF denotes the quality function, as shown in Equation (8). G_1 and G_2 represent the Aquila's movements and the flight slope, respectively, and are given by Eqs. (9) and (10).

$$QF = \frac{2 \times rand - 1}{\sqrt{1 - T}} \tag{8}$$

$$G_1 = 2 \times rand - 1 \tag{9}$$

$$G_2 = 2 \times (1 - \frac{t}{T}) \tag{10}$$

The pseudo-code of the AO algorithm is presented in Algorithm 1 and its flowchart is presented in Fig. 11.

Algorithm 1 The pseudo-code of Aquila Optimization algorithm

Initialize Aquila Optimizer parameters: Population' size N, Maximum number of iterations T, α, δ, Dimension D, etc.
Initialize the population of Aquila Individuals: $X_i (i = 1, 2, ..., N)$
while $(t < T)$ **do**
    Calculate the fitness value $Cost(X(t))$ of each Aquila
    Determine the best solution X_{best}
    for $i = 1, 2, \dots, N$ **do**
        Update the mean value of the current solution $X_m(t)$
        Update x, y, QF, G_1, G_2, Lévy(D), etc.
        if $t \leq (\frac{2}{3} * T)$ **then**
            if $rand \leq 0.5$ **then**
                Update the current solution $X(t)$ using Equation (1)
                Evaluate the fitness value $Cost(X(t))$
                Update the solutions $X(t)$ and X_{best} according to the fitness value
            else
                Update the current solution $X(t)$ using Equation (3)
                Evaluate the fitness value $Cost(X(t))$
                Update the solutions $X(t)$ and X_{best} according to the fitness value
            end if
        else
            if $rand \leq 0.5$ **then**
                Update the current solution $X(t)$ using Equation (6)
                Evaluate the fitness value $Cost(X(t))$
                Update the solutions $X(t)$ and X_{best} according to the fitness value
            else
                Update the current solution $X(t)$ using Equation (7)
                Evaluate the fitness value $Cost(X(t))$
                Update the solutions $X(t)$ and X_{best} according to the fitness value
            end if
        end if
    end for
    $t = t + 1$
end while
Return the best solution X_{best}

2.5 Time and Space Complexity of AO

2.5.1 Time Complexity Analysis

The time complexity of the AO algorithm is influenced by several factors, including the population size (N), initialization process, fitness evaluation, individual updates, number of iterations (T), and problem dimension (Dim). The complexity of initializing the population is $O(N)$, while updating individuals requires $O(T \times N) + O(T \times N \times Dim)$.

The time complexity of the AO algorithm can be broken down into several components:

1. *Population size* (N): the population size directly affects the number of candidate solutions being processed.
2. *Initialization process*: initializing the population involves generating N random candidate solutions, which has a complexity of $\mathcal{O}(n)$.
3. *Fitness evaluation and individual updates*: updating individuals involves both fitness evaluation and applying the optimization strategies. This process requires $\mathcal{O}(T \times N)$ for the update operations themselves and $\mathcal{O}(T \times N \times Dim)$ for the calculations involving the problem dimension Dim, where T is the number of iterations.
4. *Number of iterations* (T): the algorithm iterates T times, with each iteration updating all N individuals.
5. *Problem dimension* (Dim): the dimensionality of the problem affects the complexity of updating each individual.

Therefore, the overall time complexity of the AO algorithm is expressed as:

$$O(N \times T \times (Dim + 1)) \tag{11}$$

This formula encapsulates the linear dependencies on population size N, number of iterations T, and problem dimension Dim.

2.5.2 Space Complexity Analysis

we can infer the space complexity based on typical requirements for optimization algorithms:

1. *Candidate solutions*: storing n candidate solutions, each with D dimensions, requires $\mathcal{O}(n \times Dim)$ space.
2. *Auxiliary variables*: additional variables for fitness values, intermediate calculations, and algorithm parameters contribute a smaller constant factor, typically $\mathcal{O}(N)$ or less.

Thus, the overall space complexity is approximately:

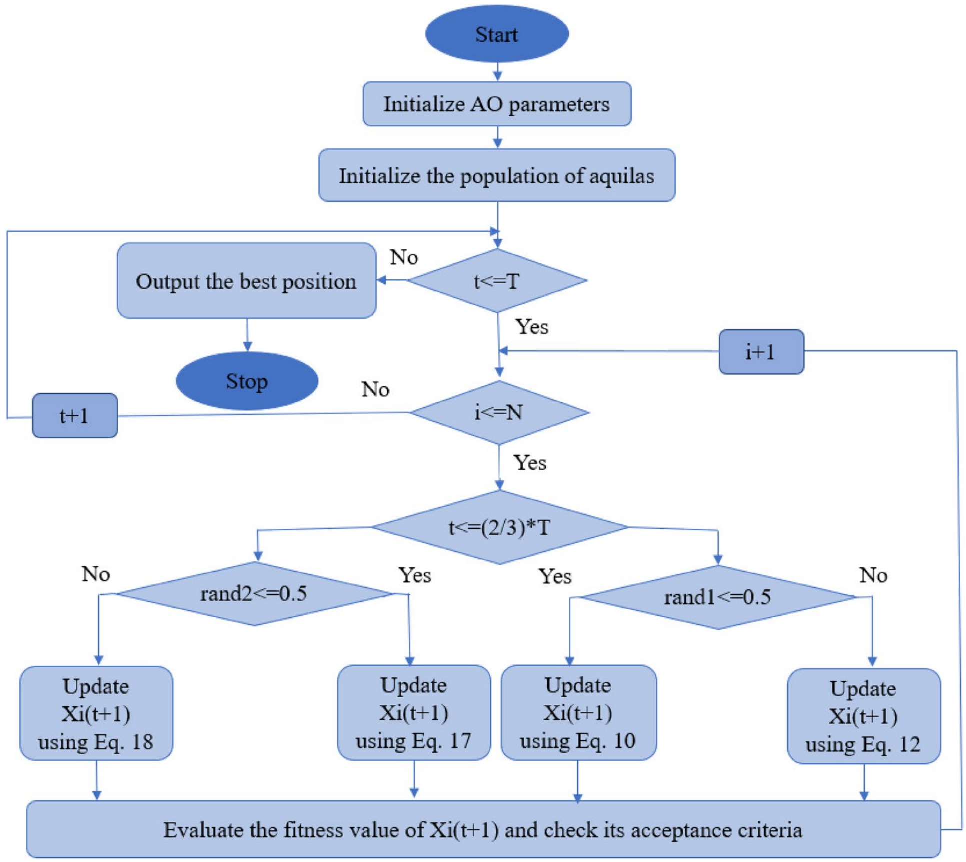

Fig. 11 Flowchart of AO algorithm

$$\mathcal{O}(N \times Dim). \tag{12}$$

2.6 Parameter Sensitivity

The performance of the AO algorithm relies on several key parameters. Among these, α, δ, population size are crucial as they influence the exploitation capability of the AO algorithm [116].

2.6.1 Role of α and δ

Both α and δ are mining adjustment parameters that affect how the AO algorithm exploits the search space. Smaller values of these parameters, typically set to 0.1, have been found to yield better results in many cases.

1. *Exploitation capability*: these parameters play a crucial role in balancing exploration and exploitation during the optimization process. While AO has significant exploration ability, its exploitation capability can be limited by fixed values of α and δ [116, 117].
2. *Exploration vs. exploitation balance*: this highlights the need for adaptive strategies to balance exploration and exploitation dynamically [118].

2.6.2 Population Size and its Influence

The population size and its initial individuals significantly influence the AO's performance.

1. *Impact on performance*: however, the literature suggests that AO is relatively robust to changes in population size, with minimal impact on its ability to find optimal solutions [118].
2. *Adaptation mechanisms*: to achieve a well-balanced exploration and exploitation, adapting the population size can be beneficial. This involves dynamically adjusting the population size based on the problem's complexity and the optimization progress [118].

2.6.3 Parameter Tuning Suggestions

To enhance the AO's performance, consider the following strategies:

1. *Adaptive α and δ*: implement mechanisms to adaptively adjust α and δ based on the optimization progress. This could involve increasing α and δ as the algorithm converges to enhance exploitation.

2. *Dynamic population size adjustment*: develop strategies to dynamically adjust the population size during optimization. This could involve increasing the population size in early stages for better exploration and reducing it later for focused exploitation.
3. *Hybrid approaches*: combine the AO algorithm with other optimization techniques or machine learning models to leverage their strengths and mitigate weaknesses. For example, integrating AO with reinforcement learning could enhance its adaptive capabilities.
4. *Experimental benchmarking*: conduct thorough benchmarking across various mathematical functions and real-world problems to identify optimal parameter settings for different scenarios.

3 Recent Variants of the Aquila Optimizer Algorithm

In this section, a variant of the AO algorithm proposed in the literature categorized into modified, multi-objective, and hybridized versions are presented as illustrated in Fig. 12.

3.1 Modified Versions of Aquila Optimizer Algorithm

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

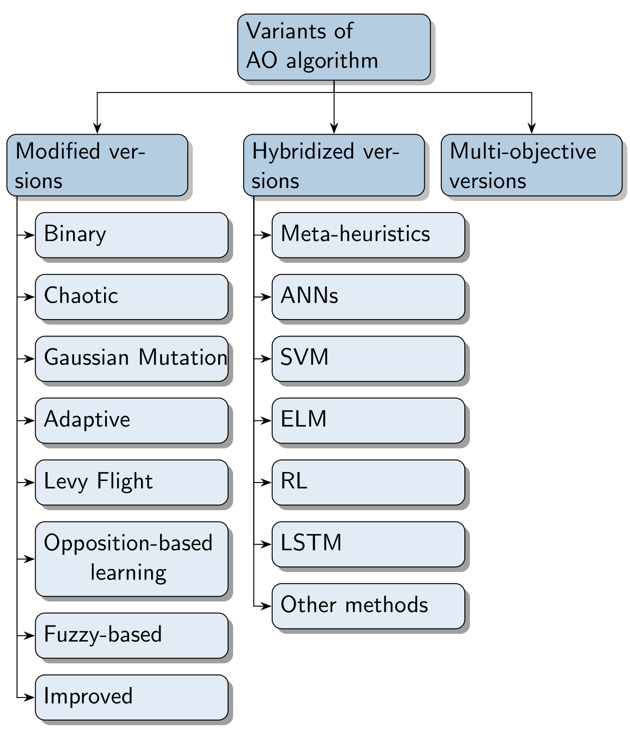

Fig. 12 Variants of AO algorithm

3.1.1 Binary Aquila Optimizer Algorithm

Fatani et al. [107] used the binary version of the AO algorithm for feature selection in the IoT Intrusion Detection System. To validate the efficiency of the proposed approach, four datasets were used, including KDDCup-99, NSL-KDD, BoT-IoT, and CICIDS-2017. According to simulation results, the Binary AO algorithm outperforms state-of-the-art methods such as PSO, WAO, GWO, MFO, MVO, and FA regarding accuracy, recall, precision, and performance improvement rate metrics.

Authors in [115] applied two variants of the binary AO algorithm, called S-shaped Binary AO (SBOA) and V-shaped Binary AO (VBOA), to enhance the feature selection in medical case studies. The efficacy of the proposed approaches was validated using seven benchmark medical datasets and real-dataset COVID-19. Results showed that the proposed approaches offer best results compared to Binary BA, Binary GSA, Binary GWO, Binary DA, S-shaped Binary SCA, and V-shaped Binary SCA.

Li et al. [119] introduced a binary version of the AO algorithm, referred to as NBAO, tailored for feature selection in CT image datasets used in COVID-19 detection. The proposed method employs S-shaped transfer functions to transform continuous values into binary form, aiming to speed up and increase the detection accuracy. Experimental results demonstrate that NBAO algorithm not only significantly improves the AO algorithm's effectiveness in feature selection but also yields superior outcomes when compared to other methods like SMA, SSA, and GWO algorithms.

Abd El-Mageed et al. [120] introduced an enhanced binary AO variant (IBAO) designed to handle feature selection strategies for supervised classification. The introduced IBAO integrates random position amendment approach and Local Search strategy into the AO algorithm to improve its efficiency. The performance of the IBAO algorithm is benchmarked against the original Binary AO algorithm and twelve other recent algorithms, including ABC, BA, PSO, WOA, GWO, SFO, HGSO, and HHO. Experiments showed that the proposed IBAO demonstrates its superiority in both small and large dimensional benchmarks, achieving impressive classification accuracies up to 100% in some instances and reducing feature size by up to 92%.

Alawad et al. [122] introduced an enhanced binary AO (EBAO) framework to design an Intrusion Detection Systems (IDS) in WSNs. The EBAO algorithm integrated two binarization techniques (S-shaped and V-shaped) into the original AO algorithm for solution space modeling. The EBAO algorithm was evaluated on ten WSN datasets using eight transfer functions and compared with eight metaheuristic-based IDSs and six machine learning models. Statistical analysis using Wilcoxon and Friedman tests confirmed its superiority in classification accuracy and fitness value. The

Table 3 Modified versions of AO algorithm

Variant	Name	Application	Author	Year
Binary AO	BAO	Feature selection problem	Fatani et al. [107]	2021
	VBAO/SBAO	Feature selection in medical case studies	Nadimi et al. [115]	2022
	NBAO	Feature selection problem	Li et al. [119]	2022
	IBAO	Feature selection problem	Abd El-Mageed et al. [120]	2023
	BinCAO	Binary optimization problems	Yildizdan and Baş [121]	2024
	EBAO	Intrusion detection systems	Alawad et al. [122]	2025
Chaotic AO	FOCOBAO	Global optimization problems	Cavlak et al. [123]	2023
	CAO	Residential Microgrid System	Kujur et al. [124]	2023
	IAO	Global optimization problems	Guo et al. [125]	2023
	CAO	Two-phase equilibrium test problems	Turgut et al. [126]	2024
	TEAO	Constrained engineering problems	Fu et al. [117]	2024
	CAO	Phase equilibrium problems	Turgut et al. [126]	2024
	FGMAO	Wireless sensor networks	Wu et al. [127]	2024
	PGAO	Engineering design problems	Cui et al. [128]	2024
	IAO	Multi-threshold image segmentation	Guo et al. [129]	2024
	CAO	Global optimization problems	Gopi and Mohapatra [130]	2024
Gaussian AO	IAO	Global optimzation problems	Gao et al. [131]	2022
	mRMR-MBAO	Classification	Pashaei [132]	2022
	SGAO	Global Optimization and engineering problems	Zeng et al. [133]	2023
	SMAO	Reconfiguration scheduling problem	Pang et al. [134]	2023
	CAO	Solar radiation prediction	Duan et al. [135]	2023
	GAO	Classification	Subha et al. [136]	2024
	SMAO	High-dimensional computationally expensive problems	Rouhi and Pira. [137]	2024
	MAO	FOPID controller	Ni et al. [138]	2024
Adaptive AO	IAO	Power systems	Li and Mobayen [139]	2022
	DAAO	Large-scale radial distribution systems	Mahdad [140]	2023
	AAOXAI-CD	Cancer diagnosis on medical imaging	Alkhalaf et al. [141]	2023
	NCAAO	Benchmark functions and three engineering optimization problems	Zhang et al. [142]	2023
	EAO	Power allocation	Guda et al. [143]	2023
	AAO	Smart grid stability prediction	Al-Selwi et al. [144]	2024
	CME-VAO	Multi-robot space exploration	Gul et al. [145]	2024
	AAO	Traffic congestion in an IoT-enabled smart city	Chahal et al. [146]	2024
	MAOA	Wireless communications	Tarek et al. [147]	2024
Levy Flight AO	DAO	Power systems	Wang et al. [148]	2022
	MAOA-RPS	Optimal routes in UAV networks	Chaudhari et al. [149]	2022
	IAO	Optimal cluster routing protocol for wireless sensor networks	Ramamoorthy et al. [150]	2022
	mAO	Intrusion detection	Abualigah et al. [151]	2024
Opposition-based AO	IAO	Rural community population forecasting	Ma et al. [152]	2021
	QOAO	Task scheduling problem in IoT cloud environments	Kandan et al. [153]	2022
	MAO	Distributed generation allocation problem	Ali et al. [154]	2022
	AOOBL	Forecasting oil production	Al-qaness et al. [155]	2022
	mOA	Global optimization and constrained engineering problems	Yu et al. [156]	2022
	HAO	Antennas optimal design	Hou et al. [157]	2022
	enOA	Automatic voltage regulator problem	Ekinci et al. [114]	2023
	OAOFS-MLIDS	Secure access control in Internet of drones environment	Perumalla et al. [158]	2023
	CFDQRAO	Superpixel-based white blood cell segmentation	Dhal et al. [159]	2023
	VAIAO	Global optimization problem	Wang et al. [160]	2023
	IAO	Efficient text-based information retrieval	Kumar et al. [161]	2023
	CmOBL-AO	Vehicle cruise control system	Ekinci et al. [162]	2023

Table 3 (continued)

Variant	Name	Application	Author	Year
	FROBLAO	Real-life engineering optimzation problems	Gopi et al. [163]	2024
	EAO	Complex optimzation problems	Guo et al. [164]	2024
	DGSAO	Global optimzation problems	Deng et al. [165]	2024
	LEOAO	UAV path planning problem	Zhang et al. [166]	2025
Fuzzy-Based AO	AO-ANFIS	Forecasting oil production time series	Alrassas et al. [111]	2021
	AOSSA-ANFIS	residual and solubility carbon tracking	Al-qaness et al. [167]	2022
	ANFIS-HA2O	Distributed energy systems	Zahariah et al. [168]	2024
Improved AO	IAO	Global optimization problems	Zhao et al. [118]	2022
	HAO	Real-world problems	Zhao and Gao. [169]	2022
	ACMAO	Benchmark functions	Li et al. [170]	2022
	WMAO-EAR	Routing protocol for energy-aware wireless communication	Alangari et al. [171]	2022
	CME-AO	Multi-Robot space exploration	Gul et al. [172]	2023
	HMAO	Global optimization problems	Zhang et al. [173]	2023
	MAO	Energy Consumption	Utama et al. [174]	2023
	bAO	Air-fuel ratio system control	Ekinci et al. [175]	2023
	HAO	clustering optimization	Huang et al. [176]	2023
	AAO	Magnetic force prediction of hybrid magnet	Hu et al. [177]	2023
	DAQUILA	Complex optimization problems	Turgut and Turgut [178]	2023
	FGMAO	Nodes localization and positioning in WSNs	Wu et al. [127]	2025
	I-AO	Global optimization problems	Guo and Yi [179]	2025
	IEP-AO	Trajectory planning in stereoscopic agricultural multi-UAV systems	Liu et al. [180]	2025

results highlight the EBAO's robustness and effectiveness in optimizing IDS performance.

3.1.2 Chaotic Aquila Optimizer Algorithm

Cavlak et al. [123] introduced an enhanced version of the AO algorithm (FOCOBAO) by incorporating the fractional chaotic mechanism for solving global optimization problems. The proposed approach specifically identified and replaced random variables in AO with coefficients derived from chaotic functions. The effectiveness of FOCOBAO was validated through twenty-three benchmark functions, demonstrating its performance compared to other optimization algorithms such as GA, EO, GWO, MPA, WOA, SMA, and the basic AO.

Kujur et al. [124] introduced a novel Chaotic AO technique (CAO) for addressing the challenge of the demand response program in Grid-Connected Residential Micro-Grid (GCRMG) systems. Their primary goal was to enhance the scheduling of appliances within a building in a way that reduces the total cost for users taking into account the fluctuating electricity prices. Simulation results demonstrated the CAO's efficiency compared to the standard AO, PSO, and hybrid CONOPT-PSO approaches.

Guo et al. [125] proposed an improved AO algorithm (IAO) for tackling global optimization problems. The IAO algorithm employed chaotic mechanism for population initialization and probabilistic jump strategy to achieve a good balance between local and global search. The proposed IAO approach outperforms the original AO algorithm and other meta-heuristic techniques on the CEC2005 test set. To demonstrate its capability to solve practical optimization problems, IAO is applied to the multi-threshold segmentation problem using symmetric cross-entropy. The findings show that IAO exhibits superior performance and achieves good segmentation results.

Turgut et al. [126] developed a new version of the AO algorithm (CAO), by incorporating the chaotic sequence into the AO algorithm, for solving two-phase equilibrium test problems as well as parameter estimation of semi-empirical models. In the CAO algorithm, 25 different chaotic maps were used to replace uniformly generated Gaussian random numbers, to improve its problem-solving capabilities, revealing that the Ikeda chaotic map performed well in optimizing both unimodal and multimodal test functions. The experimental results demonstrated the superiority of the CAO algorithm in comparison with other optimization approaches such as AO, CSA, WOA, and Spotted Hyena Optimizer (SHO) with minimum prediction error values not exceeding 0.05.

A Chaotic AO (CAO) algorithm was introduced by Gopi and Mohapatra [130] to address global optimization and engineering problems. Its performance was validated through CEC 2005 and CEC 2022 test functions, as well as six real-world engineering problems. Simulation results demonstrated the superior performance of CAO compared to nine popular algorithms, including the original AO, Farmland Fertility Algorithm (FFA), AVOA, MGO, AGTO, SSA, GWO, MVO, SCA, and TSA.

3.1.3 Gaussian Mutation Aquila Optimizer Algorithm

Gao et al. [131] introduced an Improved AO (IAO) based on the integration of Gaussian Mutation, search control factor, and Opposition-Based Learning (OBL) into the traditional AO to enhance its efficiency. The performance of the IAO algorithm was evaluated using 23 uni-modal and multi-modal benchmark functions and four real-world engineering problems. According to simulation results, the IAO outperforms some well-regarded meta-heuristics such as PSO, SCA, WOA, HBA, FA, SMA, MFO, GA, and AOA.

An improved mutated AO algorithm, named mRMR-MBAO, was suggested in the work of Pashaei [132] for gene selection in cancer classification. Mutation mechanism and Minimum Redundancy Maximum Relevance (mRMR) selection method are integrated into the binary AO algorithm to improve its efficacy and efficiency. The performance of the mRMR-MBAO approach was tested on eleven benchmark micro-array datasets and results confirmed its superiority compared to current state-of-the-art methods.

Zeng et al. [133] developed a Spiral Aquila optimizer based on the dynamic Gaussian mutation (SGAO) approach for solving global Optimization and engineering problems. The efficiency of this approach was assessed using constraints and unconstrained test sets. According to simulation results, the SGOA algorithm provides better results in terms of fitness function values compared to the traditional AO and other well-advanced meta-heuristic algorithms.

A modified version of the AO algorithm (MAO) was proposed by Ni et al. [138] for regulating the parameters of Fractional-Order Proportional-Integral-Derivative (FOPID) controllers. The MAO algorithm is based on the integration of five strategies into the original AO including greedy-based Gaussian mutation, Tent map-based initialization, probability-based dynamic update, a fully random search strategy with uniform distribution, and wraparound dynamic weight update for local exploitation. The MAO's effectiveness was evaluated using 23 benchmark functions and in five cases of FOPID controller tuning. Simulation results demonstrated the superiority of MAO in regulating FOPID controller parameters compared to AO, WOA, and GWO algorithms.

Pang et al. [134] introduced a novel Mutation-based Aquila Optimizer (SMAO) algorithm to tackle the reconfiguration scheduling problem considering multi-machine cooperation in flexible job-shops. In the proposed SMAO algorithm, a Gaussian mutation mechanism has been introduced into the AO algorithm to enhance its optimization accuracy. Experimental results on standard test functions and a practical case showcase the SMAO's capability to enhance production efficiency with minimal reconfiguration costs.

3.1.4 Adaptive Aquila Optimizer Algorithm

Li and Mobayen [139] introduced an Improved AO algorithm (IAO) for optimizing the design of proton-exchange membrane fuel cells. The IOA algorithm incorporates a self-adaptive weight strategy to enhance the convergence rate of the original AO. Simulation results substantiated the superior efficiency of IOA when compared to the original AO and Nondominated Sorting Genetic Algorithm II (NSGA II).

Mahdad [140] introduced a novel AO algorithm, named Dynamic Adaptive AO algorithm (DAAOA), to enhance the performance of large-scale radial distribution systems (RDS). The proposed DAAOA was validated under two different scenarios. Firstly, using thirteen benchmark functions with various characteristics. Secondly, using two electric test systems (33-Bus and extensive 85-Bus RDS). The experiments highlighted the success of DAAOA in enhancing RDS optimization by maximizing loading margins and minimizing power loss when compared to the original AO algorithm and recent optimization methods.

An enhanced version of the AO algorithm, named NCAAO, based on the integration of Adaptive Niche Thought (ANT) and Dispersed Chaotic Swarm (DCS) strategies was suggested in the work of Zhang et al. [142]. The performance of NCAAO was tested across 15 standard benchmark functions and three engineering optimization problems, Experimental results demonstrated that NCAA gives superior search performance and good convergence when compared with other well-known meta-heuristics.

Guda et al. [143] introduced an adaptive AO algorithm, called EAO, based on the integration of the representative-based hunting strategy to the original AO algorithm for optimizing the relay selection and power allocation in the CR-NOMA model. According to experimental results, the EAO algorithm outperforms the ES, PSO, GA, SSA, and AO algorithms in terms of throughput and secrecy rate metrics.

3.1.5 Lévy Flight-Based Aquila Optimizer Algorithm

An enhanced Aquila Optimization (DAO) was proposed in [148], based on the integration of Lévy flight and chaotic search strategies into traditional AO algorithm for enhancing the hybrid biomass-based Solid Oxide Fuel Cell/Gas turbine power system. According to the results, the DAO algorithm offers efficient results regarding energy/exergy effectiveness, and energy/economic efficiency compared to state-of-the art methods.

Chaudhari et al. [149] introduced a modified AO-based route planning technique (MAOA-RPS) by incorporating the Lévy flight strategy into the AO algorithm for detecting optimal routes in UAVs networks. The performance of the proposed MAOA-RPS algorithm was validated under three scenarios by varying the number of clients from 10 to 30 with an increment of 10. Simulation results depicted that the MAOA-RPS technique has gained better performance compared to SA, GA, ACO, and GA-PSO.

3.1.6 Opposition-Based Learning Aquila Optimizer Algorithm

An Improved AO (IOA) algorithm was suggested in the work of [152] to optimize the parameters of the Consistent Fractional Accumulation Nonhomogeneous Grey Bernoulli Model (CFANGBM). The IOA algorithm is based on the incorporation of the Quasi Opposition-based learning (QOBL) and wavelet mutation strategies into conventional AO to enhance its efficiency. Empirical findings consistently affirm the effectiveness of IOA compared to AO, AOA, PSO, HHO, SCA, WOA, ACO, and GA in optimizing the CFANGBM model parameters.

Kandan et al. [153] suggested a novel approach, called the Quasi-Oppositional Aquila optimizer (QOAO) algorithm, for solving the task scheduling problem in an Internet of Things (IoT) cloud environment. The QOBL strategy was introduced into the traditional AO algorithm to enhance its efficiency and outcome. Results revealed that the QOAO algorithm provides competitive results in terms of makespan, throughput, flowtime, lateness, and utilization ratio metrics when compared with current state-of-the-art approaches.

Ali et al. [154] proposed a Modified AO (MOA) based on the integration of the QOBL strategy into the conventional AO to tackle the Optimal Distributed Generation Allocation (ODGA) problem. MOA was tested on the IEEE 33-bus in different cases with several multiple distributed generator types. In comparison to the original OA, MOA stands out for its ability to provide superior solutions to the ODGA problem with faster convergence.

Yu et al. [156] proposed an enhanced version of the AO algorithm (mAO) for solving global optimization and constrained engineering problems. Three mechanisms are integrated into the traditional AO algorithm such as OBL, Chaotic Map, and Restart Search to improve its efficacy. Simulation results showed the efficiency of the mAO algorithm in finding optimal results compared to the original AO, CSA, EHO, GOA, LSHADE, Lshade-EpSin, MFO, MVO, and PSO algorithms.

An enhanced version of the AO algorithm (enAO) was proposed by Ekinci et al. [114] for solving the automatic voltage regulator problem. The proposed enAO approach integrates two main strategies: modified OBL strategy and Nelder-Mead (NM) simplex search to improve the performance efficacy of the AO algorithm. The resultant outcomes demonstrated the superiority of the enAO algorithm compared to the standard AO and other existing algorithms in the literature such as CS, SCA, WOA, and MRFO-SA.

Dhal et al. [159] introduced an enhanced AO algorithm, termed CFDQRAO, for Superpixel-based white blood cell segmentation. The chaotic fitness-dependent quasi-reflection-based OBL strategy was incorporated into the classical AO algorithm to enhance its optimization capability and performance. Comparative results show that the proposed CFDQRAO outperforms other existing nature optimization approaches such as PSO, SCA, EO, and the original AO demonstrating superior optimization ability and consistency.

Wang et al. [160] introduced an advanced AO algorithm, named Velocity-Aided Adaptive Opposition-Based AO (VAIAO), for solving global optimization problems. In the proposed VAIAO, the adaptive OBL approach is introduced to enhance the efficacy of the AO algorithm. Moreover, velocity and acceleration components are incorporated into the update formula to enhance local optima. The effectiveness of VAIAO was validated using 27 classical benchmark functions and five engineering optimization problems. Experimental results indicated that the proposed VAIAO outperforms AO, IAO, and several other comparative algorithms, including AOA, HHO, SSA, Chimp Optimization Algorithm (ChOA), Sea Lion Optimization Algorithm (SOA), PSO, and DE.

3.1.7 Fuzzy-Based Aquila Optimizer Algorithm

Alrassas et al. [111] presented a novel hybrid intelligence approach (AO-ANFIS) based on the combination of AO and optimized Adaptive Neuro-Fuzzy Inference System (AO-ANFIS) for forecasting oil production time series. The performance of the developed AO-ANFIS was evaluated using real-world datasets from China and Yemen against other modified ANFIS models including PSO-ANFIS, SCA-ANFIS, SSA-ANFIS, GWO-ANFIS, and SMA-ANFIS. Experimental results indicated that the AO-ANFIS model achieved significant improvements compared to the other models in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R2.

A hybrid model, named AOSSA-ANFIS, was proposed by Al-qaness et al. [167], combining the AO with SSA and ANFIS model, to predict residual trapping and solubility carbon trapping in underground storage formations. ANFIS is a hybrid system that combines the principles of fuzzy logic and neural networks to model complex systems. The performance of AOSSA-ANFIS was assessed using four performance indicators including MAE, RMSE, Mean Relative Absolute Error (MRAE), and Root Mean Square

Relative Error (RMSRE). Simulation results demonstrated the effectiveness of AOSSA-ANFIS compared to other models such as MVO-ANFIS, MFO-ANFIS, SCA-ANFIS, GA-ANFIS, and AO-ANFIS.

To address the problem of harmonic mitigation in grid-connected solar-fed distributed energy systems, Zahariah et al. [168] proposed a novel Adaptive Neuro-Fuzzy Inference System-based Hybrid Aquila Arithmetic Optimization (ANFIS-HA2O) technique. Simulation results demonstrated that the proposed approach achieved an impressive PV module efficiency of 93%, outperforming other existing methods.

3.1.8 Other Improved Aquila Optimizer Algorithm

A simplified AO algorithm (IOA) was proposed in the work of Zhao et al. [118], based on the exclusion of the two exploitation strategies of the AO algorithm for solving global optimization problems. IAO's performance was evaluated across uni-modal and multi-modal benchmark functions, as well as applied to tackle three well-known real-world engineering problems. The obtained results confirmed the superiority of the IOA algorithm in comparison with the original AO, GOA, EO, PSO, DA, ALO, GWO, MPA, SSA, SCA, WOA, and SMA algorithms.

In [169], authors introduced the Heterogeneous AO (HAO), utilizing a multiple updating principle to address real-world problems. The HAO's performance was evaluated by comparing it with various algorithms, including the original AO, ALO, AVO, EO, GOA, GWO, HHO, MFO, MOA, PSO, SCA, and WOA. Simulation results confirmed the superior performance of HAO in comparison to the mentioned algorithms.

Li et al. [170] proposed an enhanced version of AO, termed ACMAO, which incorporates three strategies into the original AO algorithm such as inertia weight factor, vertical and horizontal cross strategy, and Cauchy lite variation. The effectiveness of ACMAO was evaluated across 23 benchmark functions and simulation outcomes demonstrated the superior efficiency of ACMAO when compared to SCA, SOA, PSO, ALO, and GA algorithms.

Gul et al. [172] suggested a novel approach, called Coordinated Multi-robot Exploration Aquila Optimizer (CME-AO), which incorporates Coordinated Multi-robot Exploration strategy with AO algorithm. This approach was applied to enhance the multi-robot space exploration process and evaluated in three maps. Experiments showed the robustness of CME-AO in comparison with CME-AOA, CME-WOA, and Frequency Modified Hybrid-WOA (FMH-WOA) algorithms.

Zhang et al. [173] developed a Hybrid Multi-Strategy Aquila Optimizer (HMAO) for global optimization problems. The introduced HMAO algorithm incorporates four improvement strategies such as an energy mechanism, soft and hard encirclement, and elite evolutionary to provide a more suitable balance between the exploitation/exploration and improve the convergence speed and global search capabilities of the AO algorithm. The efficiency of the HMAO algorithm, assessed on 23 benchmark functions, demonstrated its superiority compared to recent intelligent algorithms such as AO, SSA, SMA, SFO, and HHO.

A modified version of the AO algorithm (MAO) is proposed in the work of Utama et al. [174] for optimizing energy consumption in the context of the No-Idle Permutation Flow Shop Scheduling Problem (NIPFSP). The Largest Ranked Value (LRV) procedure is integrated into the original AO to convert its positions into schedule sequences. The performance of the modified AO was evaluated across small, medium, large, and huge case scenarios. Simulation results demonstrated the efficiency of the modified AO in terms of energy consumption when compared to GWO.

A novel method, called balanced AO (bAO), was proposed in the work of Ekinci et al. [175] for the air-fuel ratio system control. bAO algorithm is constructed via the integration of the random learning mechanism and the Nelder-Mead simplex search method for better exploration and exploitation tasks. GA, SCA, Lévy fight distribution (LFD) algorithm, and the original AO were employed for comparative assessments of the proposed bAO algorithm. Results confirmed the superiority of bAO in terms of robustness analyses, control ability, transient, and input signal tracking for the air-fuel ratio system.

An enhanced version of AO, named IEP-AO, was proposed by Liu et al. [180] for collaborative trajectory planning in stereoscopic agricultural multi-UAV systems. The IEP-AO algorithm integrates an interference combination model into the AO algorithm to enhance its exploration and exploitation capabilities in large-scale and complex environments. Simulated flights in real 3D scenarios demonstrate that the IEP-AO algorithm effectively handles diverse tasks, significantly improving UAV mission efficiency and agricultural productivity.

3.2 Multi-Objective Aquila Optimizer Algorithm

This section investigates the multi-objective variants of the AO algorithm as summarized in Table 4.

Long et al. [181] proposed a multi-objective AO algorithm (MOIAO) for tackling the optimal reactive power dispatch problem. The proposed MOIAO integrates three strategies including probabilistic perturbation, Cauchy operator, and elite group navigation to obtain a good balance between global exploitation and local exploration. The efficacy of the suggested MOIAO was evaluated using three test systems with different sizes (i.e. IEEE-30, IEEE-57, IEEE-118 bus systems). Evaluation experiments

Table 4 Multi-objective versions of AO algorithm

	Name	Application	Author	Year
Multi-objective AO	MOIAO	Optimal reactive power dispatch problem	Long et al. [181]	2022
	MOMAO	Optimal distributed generation allocation problem	Ali et al. [182]	2022
	IMOAO	Task offloading in Internet of Things	Nematollahi et al. [183]	2024
	MOAO	Time–cost-quality-CO2 emissions	Eirgash et al. [184]	2024
	MOAO	Optimal aggregation function weights	Xia et al. [185]	2024

demonstrated that the proposed MOIAO achieves better results when compared with state-of-the-art multi-objective methods such as MOPSO, MOIPSO, and MOAO.

Ali et al. [182] suggested a Multi-Objective Modified AO (MOMAO) for solving the optimal distributed generation allocation problem. The proposed multi-objective AO was assessed on the IEEE 33-bus test system with several multiple DG types considering two objectives (i.e.: decreasing power loss and total voltage deviation). Obtained results showed that the proposed algorithm provides superior and competitive solutions compared to some well-known meta-heuristics with faster convergence in distribution systems.

Nematollahi et al. [183] introduced an Improved Multi-Objective AO (IMOAO) algorithm equipped with a Pareto front and OBL mechanism for task offloading in IoT. The introduced IMOAO algorithm was assessed focused on the number of fog nodes and tasks in order to decrease the response time. Experiments showed that IMOAO outperforms PSO, FA, ACO, and Bacterial Foraging Optimization (BFO) in terms of response time and failure rate.

3.3 Hybridized Versions of Aquila Optimizer Algorithm

In this section, the hybridization of the AO algorithm with other algorithms are presented as shown in Table 5.

3.3.1 Hybridization with Genetic Algorithm

Verma et al. [186] introduced an enhanced hybrid method (CMAOE) based on the hybridization of AO and GA algorithms for solving real-world design engineering problems. CMAOE was evaluated using various unimodal and multimodal benchmark functions, and its practical applicability is demonstrated by addressing an industrial real-world problem. Simulation results proved the effectiveness of the CMAOE approach in comparison with the standard AO algorithm.

3.3.2 Hybridization with Tabu Search

Utama and Primayesti [188] introduced a hybrid algorithm, called HAO, based on the combination of AO and TS algorithms for solving the Flow Shop Scheduling Problem. The performance of the HAO algorithm was evaluated in comparison with GA, PSO, ACO, Tiki-taka, FA, and ABC algorithms using 24 scenarios. The experimental results proved the efficiency of HAO in terms of total energy consumption.

3.3.3 Hybridization with Simulated Annealing

In the research conducted by Ait-Saadi et al. [189], a novel hybrid algorithm named CAOSA was introduced to address the UAVs path planning problem. CAOSA integrates the SA algorithm and the chaotic map concept into the original AO algorithm. The performance of the proposed CAOSA algorithm was assessed using three benchmark maps with various numbers of threats. Simulation results showcased the commendable performance of the CAOSA algorithm in comparison with other algorithms including SA, PSO, BA, FA, GWO, SCA, WOA, DA, and AO algorithms.

Elmeshah et al. [190] proposed a hybrid model, AOS-PNN, which integrates the AO with SA and the Probabilistic Neural Network (PNN) for addressing classification and pattern recognition challenges in data mining. The performance of AOS-PNN was validated against several alternative methods, including SA-PNN, CHIO-PNN, African Buffalo Algorithm-based PNN (ABO-PNN), and Hill Climbing. Simulation results demonstrated the superior effectiveness of AOS-PNN, particularly in terms of classification accuracy, data distribution handling, convergence speed, and statistical significance.

A hybrid model called SA-AO-KELM is proposed in the work of Peng et al. [191] for illumination correction of dyed fabrics. The model integrates AO with the Kernel Extreme Learning Machine (KELM) model and SA. Experimental results demonstrate that the proposed hybrid method reduces color difference by approximately 24.43%, achieving an average color difference of 2.9991 using the CIEDE2000 metric, compared to traditional KELM.

Table 5 Hybrid versions of AO

Variant	Name	Application	Author	Year
AO + GA	CMAOE	Real-world design engineering problems	Verma et al. [186]	2022
	HAGCNN	Image classification	Wang et al. [187]	2022
AO + TS	HAO	Flow shop scheduling problem	Utama and Primayesti [188]	2022
AO + SA	SGOA	UAVs path planning problem	Ait-Saadi et al. [189]	2022
	AOS-PNN	Classification and pattern recognition challenges in data mining	Elmeshah et al. [190]	2024
	SA-AO-KELM	Illumination correction of dyed fabrics	Peng et al. [191]	2024
AO + PSO	IAO	IoT task scheduling problem	Abualigah et al. [192]	2022
	CS-PSO-AO	Epithelial layer segmentation	Sasmal et al. [193]	2023
	PSAO	Topological structure optimization	Song et al. [194]	2023
	IAO	Cloud computing	Liu [195]	2023
	PSAO	Global optimization and four engineering problems	Wu et al. [196]	2024
AO + FA	HAOFA	Clustering and routing issues in IoT ecosystems	Hosseinzadeh et al. [197]	2022
	MA-FHS	Multipath routing for mobile ad hoc networks	Satyanarayana et al. [198]	2024
	FA-AO	Routing and data transmission in Wireless Sensor Networks	Soni et al. [199]	2024
AO + GWO	AGWO	Global optimization problem	Ma et al. [113]	2022
	GAOA	Global Optimization and five engineering problems	Varshney et al. [200]	2024
AO + WOA	IAO	Feature selection problem	Ewees et al. [201]	2022
	AWO	Skin cancer detection problem	Kumar and Vanmathi [202]	2022
	AOWOA	Global optimization and feature selection problems	Bousmaha [203]	2022
	WTSA-AO	Routing problem in Wireless Sensor Networks	Singh and Gupta [204]	2022
AO + AOA	AO-AOA	Global optimization task problems	Mahajan et al. [109]	2022
	AOAOA	Clustering	Abualigah and Almotairi [205]	2022
	AOAAO	Real-world optimization problems	Zhang et al. [112]	2022
	IAOA	Hybrid renewable-storage design problem	Kharrich et al. [206]	2022
	RAOA	Global optimization problems	Liu et al. [207]	2023
	AIAO	Sentiment analysis problem	Sangeetha et al. [208]	2023
	AO-AOA	Optimal power flow problem	Ahmadipour et al. [209]	2024
	AOAOA	Parameter identification in Proton Exchange Membrane Fuel Cells	Singla et al. [210]	2025
AO + HHO	IHAOHHO	Industrial engineering problems	Wang et al. [108]	2021
	CHHOAO	Engineering optimization problems	Zhang et al. [211]	2022
AO + SSA	IHSSAO	Benchmark functions and UAV path planning problem	Yao et al. [212]	2022
AO + AVOA	IHAOAVAO	Global optimization problem	Xiao et al. [213]	2022
	AOAVAO	Scheduling requests in IoT-fog-cloud networks	Liu et al. [214]	2023
	AOAVAO	Scheduling Tasks and Balancing Loads in Cloud Computing	Raghavender Reddy et al. [215]	2023
	HAOAVAO	Piezoelectric energy harvesters	Thulasi et al. [216]	2024
	IBAVO-AO	Fake news detection	Abd El-Mageed et al. [217]	2024
AO + SMA	AOSMA	Optimization of LSTM parameters	Al-qaness et al. [218]	2023
AO + SOA	SOAAO	Optimization of DNR parameters	Al-qaness et al. [219]	2022
AO + MPA	EHAOMPA	Combinatorial optimization problems	Wang et al. [220]	2024
	AOMPA	Droop control in DC microgrid	Aribowo et al. [221]	2024
AO + SO	CASO-DCNN	Detection and classification of sugarcane billet damage	Nagapavithra and Umamaheswari [222]	2023
AO + MFA	MFA-AOA	Wireless Sensor Networks	Natesan et al. [223]	2022
AO + AHA	AHA-AO	Feature selection	Abd Elaziz et al. [224]	2022
	AOAHA	Global optimization problems	Hamoodi and Mitras [225]	2023
AO + PDO	APDO	Feature selection	Zitouni et al. [226]	2023
AO + ROA	RODAO	Global optimization problems	Varshney et al. [227]	2024

Table 5 (continued)

Variant	Name	Application	Author	Year
AO + HGS	CHGSAO	Benchmark functions	Zhang et al. [228]	2021
AO + SMO	ASMO	Brain tumor classification	Nirmalapriya et al. [229]	2023
AO + EHO	AOEHO	Dynamic data replication problems in the fog computing environment	Mohamed et al. [230]	2023
AO + COA	AqCO	Classification of bare skinned images in websites	Gupta et al. [231]	2022
AO + TSA	AO-TSA	Global optimization problems	Akyol et al. [232]	2023
AO + ARO	CHAOARO	Real World optimization problems	Wang et al. [233]	2022
AO + EOA	AO-EOA	Speech Recognition	Rathod et al. [234]	2022
AO + GOA	AGO	benchmark function and real world optimization problems	Verma et al. [235]	2021
AO + GOA	SHyAq	Bare skin images classification in websites	Gupta et al. [236]	2022
AO + CHIO	MCHIAO	Real-world engineering problems	Selim et al. [237]	2024
AO + LA	AOLA	Prediction of dogecoin price	Shahvaroughi et al. [238]	2024
AO + SCA	ASCA	Digital image forgery detection	Nirmalapriya et al. [239]	2023
	HSCAO	PID-Automatic Generation Controller parameters	Al-Majidi et al. [240]	2025
AO + HBA	HBAO	diabetic macular edema classification	Reddy and Soma [241]	2025
AO + CO	MCOA	Prediction of Average Daily Electricity Consumption	Hu et al. [242]	2024
AO + NN	CSDCNN-AO	Hyperspectral image classification	Subba et al. [243]	2022
	AOBNN-BDNN	Breast Ccncer detection	Obayya et al. [244]	2022
	DWT-PSR-AOA-BPNN	Wind speed forecasting	Jnr et al. [245]	2022
	ANN-AOA	Energy Management for PV Powered Hybrid Storage System	Narasimhulu et al. [246]	2022
	AO-CNN	Parkinson disease diagnosis	Yousif et al. [247]	2023
	AGQIC-AAODL	Groundwater quality index prediction and classification	Amudha et al. [248]	2023
	CGAN-AO-VGG19	Detection of cyber-attacks on smart grids	Mhmood et al. [249]	2023
	AAO-DCNN	Prediction of Student Performance	Lu et al. [250]	2023
	CNN-AO	Classification and segmentation of breast cancer images	Balaha et al. [251]	2023
	HMAODL-CTC	Hyperspectral Imaging classification	Alahmari and al. [252]	2023
	RF-IAO-TCN	Multi-step runoff prediction	Qiao et al. [253]	2023
	AO-CNN	Early heart disease prediction	Barfungpa et al. [254]	2023
	CNN-LSTM-AO	Classification of ECG signals	Honnashamaiah and Rathnakara [255]	2023
	AO-SSNN	Early detection of pulmonary nodules	Ayshwarya et al. [256]	2024
	FLANN-QAOA	Digital channel equalization	Panda [257]	2024
	SabGAN	Energy-Aware Routing in WSNs	Soundararajan et al. [258]	2024
	AO-BP	City-level CO_2 emissions estimation	Luo et al. [259]	2024
AO + SVM	AO-LSSVM	Prediction thermal error of electric spindle	Li et al. [260]	2022
	AO-SVM	Feature selection problem	Ajay et al. [261]	2022
AO + ELM	AO-ELM	Intermetallic compound thickness prediction	Dele-Afolabi [262]	2024
AO + RL	AOTL-CDA3S	Classification	Al Duhayyim et al. [263]	2022
	MAO-XGB	Identification of probable seizure status in Neonates	Mumenin et al. [264]	2023
	AOPTML-AD	Anomaly detection in cyber-physical system environment	Ramachandran et al. [265]	2023
AO + LSTM	AO-LSTM	Rolling Bearing Fault Diagnosis	Ma et al. [266]	2021
	AO-LSTM-SVM	Malware prediction and detection	Grace and Sughasiny [267]	2022
	MAOSDL-TC	Sentiment analysis of COVID-19	Almasoud et al. [268]	2023
	IAO-LSTM	Photovoltaic power generation	Liu and Yang [269]	2023
	LSTM-RUNAO	Streamflow prediction	Adnan et al. [270]	2024
	EAQ-FEE-enBi-LSTM	Tweet sentiment analysis and classification	Sherin et al. [271]	2024
AO + Other	QL-AO	Blocking Flow-shop Scheduling	Ge and Wang [272]	2023

Table 5 (continued)

Variant	Name	Application	Author	Year
methods	MAO-Kmeans	Brain tumor segmentation	Jamazi et al. [273]	2024
	AO-SGM	Wind power generation prediction	Ren et al. [274]	2024

3.3.4 Hybridization with Particle Swarm Optimization Algorithm

In [192], authors suggested a hybrid algorithm (IAO) based on the combination of AO and PSO algorithms for solving the IoT Task Scheduling problem. For evaluation, the IAO algorithm was compared with the original AO, GA, PSO, and DE using different tasks. Based on simulation results, the IAO gives competitive results in terms of fitness function values.

A novel Cooperative Search (CS) method that combines AO and PSO algorithms is suggested in the work of Sasmal et al. [193]. The proposed method is specifically designed to work in conjunction with superpixel techniques for the effective segmentation of the epithelial layer extracted from histopathology images. Experimental results revealed superior performance of the proposed CS method compared to classical AO, PSO, and other algorithms in terms of computational time and accuracy.

Similarly, Liu [195] proposed a hybrid algorithm, called IAO, based on the hybridization of AO and PSO algorithms to enhance the Quality of Service in Cloud Computing applications. The performance of the IAO algorithm was assessed in two different cases using different numbers of tasks and compared with PSO, GA, ACO, and Max-Min Ant System (MMAS) algorithms. Results demonstrated the efficiency of the IAO algorithm in terms of fitness value and execution time metrics.

A hybrid model (PSAO) based on the combination of AO with PSO algorithms is developed in the work of Wu et al. [196] for solving global Optimization and four engineering problems. The PSAO's efficiency was assessed considering benchmark functions, CEC2017 complex functions, and four multi-constraint engineering design problems. Results proved the superiority and capability of PSAO compared with some well-known intelligent algorithms.

3.3.5 Hybridization with Firefly Algorithm

The Hybrid Aquila Optimizer and Firefly Algorithm (HAOFA) was introduced in [197] to address the clustering and routing issues in the IoT ecosystem. The performance of HAOFA was validated through comparisons with GA, WOA, and GWO algorithms, considering various metrics such as energy consumption, Packet Delivery Ratio (PDR), End-to-End (E2E) delay, and throughput. Simulation results indicate that HAOFA enhances the system energy usage by a minimum of 18% and increases the PDR by at least 25%.

A hybrid Firefly Algorithm-Aquila Optimization (FA-AO) was proposed by Soni et al. [199] to efficiently manage routing and data transmission in Wireless Sensor Networks (WSNs) within the IoT. Simulation results demonstrated that the FA-AO method significantly outperforms existing techniques, including Black Widow Optimization (BWO), Fixed Parameter Tractability (FPT), and Multipath Link Routing Protocol (MLRP), achieving superior performance with a Network Lifetime of 1900 rounds, PDR of 0.98, and End-to-End Delay (ETED) of 0.80 ms.

3.3.6 Hybridization with Grey Wolf Optimization Algorithm

Ma et al. [113] suggested a hybrid approach (AGWO) based on the hybridization of AO with GWO to address the global optimization problems. To validate the efficiency of the proposed AGWO algorithm, various tests were conducted using the popular benchmark functions and engineering problems. Results proved the reliability of the AGWO algorithm in terms of fitness function values and cost.

Varshney et al. [200] proposed a hybrid optimization technique, called GAOA, that integrates the Grey Wolf alpha position mechanism and QOBL strategy into the original AO to increase its exploration ability. The efficiency of the GAOA algorithm was validated using 23 well-known benchmark functions and five practical engineering issues and compared to various optimization algorithms such as SCA, RSA, WOA, etc. Results showed that the GAOA algorithm provides better performance compared with state-of-the-art approaches in terms of fitness function values.

3.3.7 Hybridization with Whale Optimization Algorithm

Authors in [201], suggested a novel approach (IAO) based on the combination of the AO and WOA algorithms for enhancing the Cox Proportional-Hazards Model. To validate the efficiency of the IAO algorithm, four medical datasets were used, such as Diffuse large B-cell lymphoma, Lung cancer, Dutch Breast Cancer, and cytogenetically normal acute myeloid leukemia. Simulation results confirmed the efficiency of the IAO algorithm compared to state-of-the-art meta-heuristics such as original AO, GA, FA, SSA, DE, PSO, WOA, and MFO in terms of fitness function values, selected features ratio, and accuracy metrics.

Kumar and Vanmathi [202] presented a hybrid optimization-driven model (AWO-based SqueezeNet) based on the hybridization of AO and WOA algorithms for solving the skin cancer detection problem. The efficiency of the proposed AWO-based SqueezeNet model was validated using the Malignant vs. Benign dataset and results proved the superior performance of the AWO-based SqueezeNet approach in comparison with the original AO-based SqueezeNet, GA-based SqueezeNet, PSO-based SqueezeNet, and WOA-based SqueezeNet in terms of accuracy, sensitivity, and specificity metrics.

Bousmaha [203] introduced a novel hybrid algorithm (AOWOA) based on the hybridization of AO and WOA Algorithms for global optimization, feature selection, and optimizing SVM parameters. To validate the effectiveness of AOWOA, two sets of experiments were conducted based on 13 standard benchmark functions and ten labeled datasets in comparison to AO, WOA, MVO, MFO, PSO, SSA. BA, and GWO. The results of these experiments demonstrated that AOWOA not only effectively reduces the number of features and finds optimal parameters for SVM, but also avoids local optima, achieving high classification accuracy on most datasets compared to the other algorithms.

A hybrid approach (WTSA-AO) was introduced in the work of Singh and Gupta [204] for solving the routing problem in WSNs. The proposed hybrid approach is based on the combination of the Whale-based Tunicate Swarm Algorithm (WTSA) presented in [275] with the original AO. WTSA-AO is validated in terms of delay, number of alive nodes, throughput, and average energy consumption. Simulation results have proven the good performance of WTSA-AO in comparison with five state-of-the-art techniques under three different network scenarios.

3.3.8 Hybridization with Arithmetic Optimization Algorithm

Mahajan et al. [109] proposed a hybrid approach (AO-AOA) by combining AO and AOA Algorithms for solving global optimization task problems. The performance of the AO-AOA algorithm was validated using 23 uni-modal and multi-modal benchmark test functions taking into account the impact of varying dimensions. Results revealed that the AO-AOA outperforms AO, PSO, AOA, GOA, GWO, HGSO, and WOA in terms of fitness function values.

In the work of Abualigah and Almotairi [205], a novel method, called AOAOA, based on the combination of AO, AOA, and DE algorithms was suggested for optimizing the data and text clustering. Authors used in their experiments eight standard data clustering and ten text documents benchmark datasets for performance evaluation. Simulation results revealed that the AOAOA algorithm outperforms existing meta-heuristics in the literature such as original AO, DA, SSA, WOA, SCA, GWO, PSO, MPA, AOA, ALO, and EO, regarding fitness function values, accuracy, F-measure, precision, recall, entropy, and purity metrics.

Kharrich et al. [206] developed a hybrid approach (IAOA) by hybridizing AOA and AO algorithms for solving the hybrid renewable-storage design problem. The efficacy of the proposed IAOA model was validated using two different system layouts (PV diesel/battery and PV/wind/diesel/battery) situated in El Kharga Oasis in Egypt. Experiments demonstrated that the proposed IAOA gives better results when compared with other well-known algorithms such as GWO, HHO, AEF, EO, and AOA.

Liu et al. [207] proposed a combined approach, called RAOA algorithm, based on combining AO, AOA, and Reinforcement Learning for solving global optimization problems. The efficiency of the introduced RAOA algorithm was validated using unimodal and multimodal benchmark functions and two engineering optimization problems. Results demonstrated the efficiency of the RAOA approach compared to other optimization algorithms by obtaining higher convergence speed and accuracy.

In [208], a hybrid approach (AIAO) based on the combination of AO and AOA algorithms was proposed for solving the sentiment analysis problem. The robustness of the proposed AIAO algorithm was evaluated using four different datasets such as Twitter and Stanford, Movie Review, Amazon, and Social Media. Results demonstrated the efficiency of the AIAO algorithm compared to existing models in the literature.

A hybrid method (AO-AOA) based on the combination of AO and AOA algorithms was proposed in the work of Ahmadipour et al. [209] for addressing the optimal power flow problem. The AO-AOA's efficiency was assessed using two well-known power systems (i.e. IEEE 30-bus and IEEE 118-bus test systems) considering the voltage deviation, power loss, generation fuel cost, emission, and L index parameters. Simulation results validated the good performance of AO-AOA in comparison with TLBO and some recently published works.

Singla et al. [210] developed a hybrid model, named AOAOA, based on the combination of AO and AOA for parameter identification in Proton Exchange Membrane Fuel Cells (PEMFCs). The AOAOA algorithm was validated using six commercial PEMFCs, including BCS 500W-PEM, 500 W SR12PEM, Nedstack PS6 PEM, H-12 PEM, HORIZON 500 W PEM, and a 250 W stack, across twelve case studies, where its I/V and P/V characteristics closely matched experimental data. The AOAAO algorithm also exhibited a 98% efficiency improvement in runtime, making it a powerful tool for real-time PEMFC modeling.

3.3.9 Hybridization with Harris Hawks Optimization Algorithm

In [108], a novel approach, called IHAOHHO, was proposed by Wang et al. for solving industrial engineering problems. The IHAOHHO approach is based on the hybridization of AO, HHO, and Random OBL (ROBL). To validate the robustness of the IHAOHHO, several experiments were conducted using 23 different benchmark functions and four different engineering design problems. The IHAOHHO method offers remarkable results compared to original AO and HHO and state-of-the-art algorithms

3.3.10 Hybridization with Salp Swarm Algorithm

Yao et al. [212] proposed an enhanced hybrid algorithm (IHSSAO) that integrates the leader mechanism of SSA, the chaotic map, and the OBL into the original AO algorithm. IHSSAO's performance was evaluated on 23 classical benchmark functions, 17 IEEE CEC2017 test functions, and is further applied to address the UAVs path planning problem. The experimental results underscore the superiority of the IHSSAO method over the original SSA and AO algorithms.

3.3.11 Hybridization with African Vultures Optimization Algorithm

Xiao et al. [213] introduced a novel approach, called IHAOAVOA, based on the hybridization of AO algorithm with African Vultures Optimization Algorithm (AVOA) to solve global optimization problems. The performance of the proposed IHAOAVOA was evaluated using classical unimodal and multimodal benchmark functions, as well as five engineering design problems. Based on the simulation results, the IHAOAVOA provides, in most cases the best results in terms of average fitness value, standard deviation, average computational time, Statistical test, and weight of tension in comparison with other algorithms such as SCA, WOA, MFO, GWO, and AOA.

Liu et al. [214] developed a hybrid meta-heuristic algorithm (AOAVOA) combining AO and AVOA algorithms for scheduling requests in IoT-fog-cloud networks. The proposed AOAVOA approach enhances the exploration phase of AVOA using AO operators to find the optimal scheduling solution. In comparative studies with AVOA, AO, FA, PSO, and HHO, AOAVOA demonstrated superior performance in terms of makespan and throughput, proving its effectiveness in solving scheduling issues in IoT-fog-cloud networks.

Raghavender Reddy et al. [215] proposed an optimization model (AVAO) combining AO with AV for Scheduling Tasks and Balancing Loads in Cloud Computing. An augmented version of the cloud simulator (Cloudsim) was employed to test the proposed model. Based on experimental findings, the proposed AVAO model outperforms other conventional methods in terms of makespan time and throughput.

3.3.12 Hybridization with Slime Mould Algorithm

A hybrid swarm intelligence approach (AOSMA) combining AO with SMA was proposed in the work of Al-qaness et al. [218]. The proposed AOSMA approach was used to optimize the Long Short-Term Memory (LSTM) parameters and boost its prediction capability. Ealuation experiments revealed that the proposed AOSMA gives significant and competitive results compared to the original AO, SMA, and other swarm intelligence algorithms in terms of Solubility Trapping Index (STI) and Residual Trapping Index (RTI) metrics.

3.3.13 Hybridization with Seagull Optimization Algorithm

In [219], a hybrid model (SOAAO) based on the hybridization of the Seagull Optimization Algorithm (SOA) with the AO algorithm was developed for optimizing Dendritic Neural Regression (DNR) parameters for the Wind Power Forecasting application. The performance of the proposed SOAAO model was assessed using four wind speed datasets with different performance indicators. The effectiveness of the proposed SOAAO was validated in terms of fitness function values, RMSE, and MAE metrics compared to the original versions of AO and SOA, as well as some well-known meta-heuristics.

3.3.14 Hybridization with Marine Predators Algorithm

Wang et al. [220] developed a hybrid model, known as EHAOMPA, based on the hybridization of AO with MPA algorithms for tackling combinatorial optimization problems. The EHAOMPA's performance was tested on three standard mathematical benchmark functions, 29 CEC2017 complex test functions, and six constrained industrial engineering design problems. Experimental results showed that the EHAOMPA algorithm achieves the best performance when compared with other well-known methods.

3.3.15 Hybridization with Sailfish Optimizer

Nagapavithra and Umamaheswari [222] suggested a novel technique (CASO-DCNN) hybridizing AO, SFO, and Deep Convolution Neural Network (DCNN) for detection and classification of sugarcane billet damage. The proposed CASO-based DQNN was validated using a sugarcane billets dataset considering different input images in comparison with PSO-DQNN and AO-DQNN approaches. Experiments showed that the CASO-DCNN model has demonstrated significant improvements in precision (91%), recall (93.3%), F-measure (92.1%), and accuracy (91.5%).

3.3.16 Hybridization with Mayfly Optimization Algorithm

Natesan et al. [223] introduced an energy-efficient clustering routing model using a hybrid Mayfly-Aquila optimization (MFA-AOA) algorithm for enhancing lifespan and ensuring energy stability in WSNs. In the proposed model, the Mayfly algorithm selects the optimal Cluster Head (CH) from a group of nodes, while the AO algorithm identifies and chooses the best route between the CH and the Base Station (BS). Simulation results indicated that the proposed MFA-AOA approach reduced energy consumption by 10.22%, 11.26%, and 14.28%, and normalized energy by 9.56%, 11.78%, and 13.76% compared to the Hybrid Red Deer-Simulated Annealing (RDSA), Genetic Algorithm-Particle Swarm Optimization (GAPSO), Clan Separator Elephant Herding Optimization operator (CSEHO), and Moth Flame-Genetic Algorithm (MFGA) methods.

3.3.17 Hybridization with Artificial Hummingbird Algorithm

Abd Elaziz et al. [224] introduced a new hybrid optimization algorithm (AHA-AO) based on AO and Artificial Hummingbird Algorithm (AHA) for feature selection in medical image classification. The proposed AHA-AO algorithm was evaluated using four datasets including ISIC-2016, PH2, Chest-XRay, and Blood-Cell, and compared with five well-known optimization algorithms: PSO, WOA, MFO, AO, and AHA. The results showed that AHA-AO not only performs better but also is faster in identifying relevant features.

3.3.18 Hybridization with Prairie Dog Optimization

In the work of Zitouni et al. [226], a novel hybrid method (APDO) based on the combination of AO and Prairie Dog Optimization (PDO) algorithms was proposed for solving the global optimization problem. The efficiency of the APDO algorithm was evaluated using unimodal, multimodal, hybrid, and composition benchmark functions and compared with traditional meta-heuristics such as GWO, WOA, Golden Jackal Optimization (GJO), AO, and PDO. According to test results, the APDO achieves the best fitness results.

3.3.19 Hybridization with Remora Optimization Algorithm

A hybrid optimization algorithm, called RODAO, integrating the Remora Optimization Algorithm (ROA) and dynamic oppositional-based learning (DOL) technique with AO, is proposed in the work of Varshney et al. [227] to solve global optimization problems. RODAO's performance was evaluated using IEEE CEC 2017 benchmark functions, traditional benchmark functions, and three engineering optimization problems. Results, supported by statistical tests and convergence graphs, demonstrate RODAO's robustness, efficiency, and ability to solve real-world optimization challenges effectively.

3.3.20 Hybridization with Hunger Games Search

A hybrid approach (CHGSAO), which combines an enhanced version of Hunger Games Search (CHGS) with the original AO algorithm, was proposed in the work of Zhang et al. [228]. The efficiency of CHGSAO was evaluated using three classical unimodal functions and three classical multimodal functions. Simulation results demonstrated the effectiveness of CHGSAO compared to both AO and HGS algorithms.

3.3.21 Hybridization with Sine Cosine Algorithm

The authors in [240] proposed a Hybrid Aquila Optimizer-Sine Cosine Algorithm (HSCAO) to optimize PID-Automatic Generation Controller (PID-AGC) parameters for multi-area power systems. The HSCAO's performance was validated using CEC-2019 benchmarks and statistical analysis, including Wilcoxon and Friedman tests. A two-area power system simulation in MATLAB demonstrated its superiority in handling load fluctuations and fault conditions. The HSCAO-based PID-AGC model achieved the lowest ITAE index of 5.2s, outperforming conventional fuzzy logic AGC (10.9s) and traditional PID-AGC (17.4s), highlighting its robustness and efficiency in frequency regulation.

3.3.22 Hybridization with Artificial Neural Networks

A hybrid model (CSDCNN-AO) based on the combination of AO algorithm with Compressed Synergic DCNN (CSDCNN) is introduced in [243] for hyperspectral image classification. For evaluation, four datasets are utilized, namely Houston U (HU), Indiana Pines (IP), Kennedy Space Center (KSC), and Salinas Scene (SS). Simulation results confirm the superiority of CSDCNN-AO over existing deep learning models and other techniques, including CSDCNN-ALO, CSDCNN-PSO, CSDCNN-WOA, and CSDCNN-GWO.

Obayya et al. [244] introduced a novel approach, called AOBNN-BDNN based on the combination of AO with Bayesian Neural Network (BNN) for enhancing breast cancer detection on ultrasounds images. For efficiency validation, the SEODTL-BDC, ESD, LSVM, ESKNN, FKNN, and LD models were employed and compared with the AOBNN-BDNN model. The simulation results demonstrated the effectiveness of the proposed model in terms of accuracy, precision, recall, f-score, and classification time.

In the work of Amudha et al. [248], a hybrid technique (AGQIC-AAODL), which combines the adaptive AO algorithm with Deep Learning model, was designed for automated groundwater quality index prediction and classification. The introduced technique contains three phases including data normalization, multihead bidirectional gated recurrent unit (MHBGRU) classification, and AO-based hyper-parameter tuning. The proposed AGQIC-AAODL was validated using pre-monsoon and post-monsoon groundwater datasets (containing 1250 samples with 5 classes) in Tiruvallur district, India. Experimental results proved the efficiency of the proposed model in terms of accuracy, precision, recall, and f-score metrics.

A hybrid model, called CGAN-AO-VGG19, was introduced in the work of Mhmood et al. [249] for detecting cyber-attacks on smart grids. The introduced CGAN-AO-VGG19 combines AO algorithm, Conditional Generative Adversarial Networks (CGAN), and VGG19 neural network. The performance of CGAN-AO-VGG19 was evaluated using the NSL-KDD dataset, consisting of 42 features (41 input features and 1 output feature), with 23 types of traffic (22 attacks and 1 normal traffic). Simulation results demonstrated the superiority of the CGAN-AO-VGG19 model compared to other optimization techniques.

Lu et al. [250] introduced a hybrid Adaptive AO-based DCNN (AAO-BDCNN) for student performance prediction. The efficiency of the proposed model was evaluated using two distinct datasets corresponding to students' performance in Portuguese language and mathematics. According to the results, the proposed model achieves minimal values of MARE, MSRE, MAE, RMSRE, MSE, MAPE, and RMSE when compared with other optimization techniques.

Balaha et al. [251] proposed a hybrid framework (CNN-AO) based on the hybridization of AO algorithm with Convolutional Neural Networks (CNN) for classification and segmentation of breast cancer images. The effectiveness of the proposed framework is evidenced using four different datasets including Histopathology, MRI, Ultrasound, and Mammographic images taking into account different metrics. Reported results demonstrated the efficiency of the hybrid framework in comparison with current state-of-the-art studies in the field.

Alahmari et al. [252] developed a Hybrid Multi-Strategy model (HMAODL-CTC) based on the hybridization of AO with Deep Learning-Driven Crop Type Classification model. The proposed HMAODL-CTC model primarily focuses on accurately classifying various crop types in HyperSpectral Imaging (HSI). To demonstrate its effectiveness, a series of detailed simulations were conducted. These simulations showed that the HMAODL-CTC algorithm significantly outperformed other methods in similar tasks, highlighting its advanced capabilities in crop type classification.

Qiao et al. [253] developed a hybrid optimization model (RF-IAO-TCN) using improved AO algorithm, Temporal Convolutional Network (TCN), and Random Forest (RF) for rainfall-runoff simulation and multi-step runoff prediction. They used RF to select highly correlated input variables, reducing dimensionality and computation time. These inputs were then fed into a TCN model optimized by IAO. The hybrid model's effectiveness was tested on a dataset taken from five stations in the Jinsha River, China, with a focus on the Panzhihua station. Comparative analysis of the predictive results from multiple approaches confirmed the effectiveness of the proposed RF-IAO-TCN model.

Barfungpa et al. [254] proposed an intelligent system (CNN-AO) based on hybrid AO algorithm with CNN for early heart disease prediction. The efficiency of the proposed system was assessed using five heart disease datasets (ie: long beach VA, Switzerland, Statlog, Cleveland, Hungary) against some recent existing models. Simulated results proved the efficacy of the proposed intelligent system by reaching the highest accuracy of 99.57%.

Honnashamaiah and Rathnakara [255] have introduced a novel hybrid approach, known as CNN-LSTM-AO, for the classification of electrocardiogram (ECG) signals. The proposed CNN-LSTM is based on the hybridization of three distinct techniques including AO, CNNs, and LSTM networks. The efficacy of CNN-LSTM-AO was assessed using a diverse and extensive ECG dataset. The results validate the superiority of CNN-LSTM-AO over existing classification methodologies, showcasing remarkable performance in achieving both high classification accuracy and robustness across various cardiac arrhythmia classes.

A hybrid model named Chebyshev FLANN-QAOA, combining Chebyshev-based Functional Link Artificial Neural Networks (FLANN) with the Quantum Aquila Optimization Algorithm (QAOA), was developed by Panda [257] for digital channel equalization. The model's performance was evaluated on two nonlinear finite impulse response (FIR) channels under noisy conditions. Results demonstrated that Chebyshev FLANN-QAOA outperformed when compared with other FLANN architectures, FIR filter-based equalizers trained using the AO, GWO, PSO, and Least Mean Squares (LMS) algorithm. It achieved superior results in terms of Mean Squared Error (MSE), normalized MSE, training runtime, and Bit Error Rate (BER) values.

In [258], a Self-attention-based Generative Adversarial Network (SabGAN) combined with the Aquila Optimization Algorithm (AqOA) has been proposed for Multi-Objective Cluster Head Selection and Energy-Aware Routing (SabGAN-AqOA-EgAwR-WSN) in WSNs. The proposed approach, tested using the NS2 simulator, achieves significant improvements over existing methods, including a 12.5-–59.5% increase in alive nodes, 71.96-–85.71% reduction in delay, and a 20.63-–61.65% increase in normalized network energy.

A hybrid model, AO-BP, which integrates the Aquila Optimizer (AO) with the Back-Propagation (BP) neural network, is proposed in the work of Luo et al. [259] for estimating CO_2 emission levels. The AO-BP model is applied to estimate city-level CO_2 emissions in the Yangtze River Delta (YRD) region from 2000 to 2022, covering 41 cities across Shanghai, Jiangsu, Zhejiang, and Anhui provinces. The results confirm the superior performance of the AO-BP model compared to other models, including Multiple Linear Regression (MLR), Ridge Regression (RR), BP, PSO-BP, and SSA-BP.

3.3.23 Hybridization with Support Vector Machine

In the study of Li et al. [260], a hybrid model (AO-LSSVM) combining AO with the Least Squares Support Vector Machine (LSSVM) was introduced for predicting thermal errors of high-speed motorized spindles. The performance of the proposed AO-LSSVM was assessed using ten groups of datasets (eight groups of temperature data and two groups of thermal error data). Experimental results validated the superior performance of AO-LSSVM in comparison to PSO-LSSVM and LSSVM models in terms of average prediction accuracy, average absolute error, and root mean square error.

In [261], authors proposed a hybrid classifier, called AO-SVM, combining AO with Suport Vector Machine for feature selection in diabetes prediction applications. The AO-SVM model was validated using PIMA Indian diabetes dataset where most individuals have similar lifestyles. Simulation results demonstrated the efficiency of the proposed AO-SVM compared to Decision Tree, Naive Bayes, Random Forest, Logistic regression, SVM, and Kernel SVM approaches in terms of accuracy (96%), precision (92.5%), recall (92.1%), and F1 measure (91%).

3.3.24 Hybridization with Extreme Learning Machine

A novel hybrid model, termed AO-ELM, which combines the AO with Extreme Learning Machine (ELM) model, was developed by Dele-Afolabi [262] to predict the intermetallic compound (IMC) thickness at the interface of Sn-5Sb/Cu solder joints. The performance of the AO-ELM model was rigorously validated in terms of statistical accuracy measures. The results demonstrated that AO-ELM significantly outperforms traditional ANN and ELM models in terms of predictive accuracy, confirming the superiority of the proposed hybrid approach.

3.3.25 Hybridization with Regression Learning algorithm

Al Duhayyim et al. [263] introduced a hybrid model named AOTL-CDA3S, combining AO with the XGBoost model, to classify crowd densities for sustainable smart cities. The performance evaluation of the AOTL-CDA3S model was conducted using a crowd dataset containing 1000 samples, categorized into four classes: dense crowd, medium dense crowd, sparse crowd, and no crowd. Simulation results demonstrated the effectiveness of the AOTL-CDA3S model compared to recent models across various evaluation metrics.

Mumenin et al. [264] introduced a hybrid classifier model based on the hybridization of modified AO and XGBoost algorithms for detecting and identifying probable seizure status in Neonates. The efficiency of the proposed MAO-XGB model was tested on the EEG signals dataset obtained from Helsinki University Hospital in comparison with Decision Tree (DT), Gradient Boosting Classifier (GBC), and Random Forest (RF). Through experiments, the proposed MAO-XGB model has achieved better results compared to other traditional machine learning algorithms, showing 93.38% accuracy score, 93.38% sensitivity, 93.9% Area Under the Curve (AUC), 77.52% specificity, and 92.72% F1 score.

Ramachandran et al. [265] proposed a new model, called Aquila Optimizer with Parameter Tuned Machine Learning Based Anomaly Detection (AOPTML-AD), for anomaly detection in a cyber-physical system (CPS) environment. First, pre-processing was applied to convert the data to a suitable format. The pre-processed data was selected with improved AO algorithm-based feature selection (IAOFS) to select appropriate subsets. Then, the selected features were classified with adaptive neuro-fuzzy inference system (ANFIS). The proposed AOPTML-AD demonstrated superior performance, achieving 99.37% accuracy when compared to other methods.

3.3.26 Hybridization with Long Short-Term Memory Networks

A hybrid model named MAOSDL-TC was introduced in the work of Almasoud et al. [268] for sentiment analysis of COVID-19. The MAOSDL-TC model combines a modified version of the AO algorithm introduced in [264] with the Attention-based Stacked Bidirectional Long Short-Term Memory (ASBiLSTM) model. The performance of the MAOSDL-TC technique was validated using the eKaggle dataset, which contains 2750 samples categorized into 11 classes (optimistic, thankful, empathetic, pessimistic, anxious, sad, annoyed, denial, surprise, official report, and joking). Simulation results demonstrated the superior performance of the MAOSDL-TC model in terms of accuracy, precision, recall, and F-score when compared to recent models.

A hybrid model, IAO-LSTM, was developed by Liu and Yang [269] for predicting photovoltaic power generation, integrating an enhanced version of the Aquila Optimization Algorithm (IOA) with the LSTM neural network. The IOA improves the original Aquila Optimization by incorporating a Cauchy variational strategy, which enhances its optimization capabilities. Experimental results show that the IAO-LSTM model outperforms the previous AO-CNN model, achieving significantly higher accuracy and overall performance in forecasting photovoltaic power generation.

A hybrid model called LSTM-RUNAO, which combines LSTM with AO and Runge-Kutta, was developed by Adnan et al. [270] to improve streamflow prediction accuracy. Simulation results demonstrated that the LSTM-RUNAO model outperformed traditional ANN methods, achieving a 28.7% reduction in RMSE and a 20.3% reduction in MAE compared to standard ANN models.

A new hybrid approach, named EAQ-FEE-enBi-LSTM, was proposed in the work of Sherin et al. [271], combining a novel radial basis Aquila Optimizer, a fuzzy sentiment-based emotion extractor, and an ensemble Bi-LSTM with Gated Recurrent Units (GRUs) for tweet sentiment analysis and classification. The EAQ-FEE-enBi-LSTM model was validated using the Sentiment 140, T4SA, and Airline Twitter datasets. Simulation results confirmed the superiority of the proposed model when compared to other state-of-the-art algorithms.

An efficient malware detection approach, named AO-LSTM-SVM, was proposed in the work of Grace and Sughasiny [267], combining AO and a Hybrid LSTM-SVM classifier. AO is utilized to select the most relevant features based on prediction accuracy, while the Hybrid LSTM-SVM classifier is employed to predict the type of malware. The proposed model achieves an impressive 97% accuracy, significantly outperforming existing techniques such as LSTM, SVM, RF, and NB.

3.3.27 Hybridization with Other Algorithms

A hybrid approach, named QL-AO, was proposed by Ge and Wang [272] to address the integrated optimization problem of blocking flow-shop scheduling and preventive maintenance. The introduced QL-AO approach is based on the integration of Q-Learning (QL) strategy and five additional local search methods into the original AO algorithm. The performance of QL-AO was evaluated across small, medium, and large-scale instances. Simulation results demonstrated the efficiency of QL-AO compared to GA, QL-GA, ABC, QL-ABC, PSO, CS, JAYA, and AO algorithms.

In the recent work of Jamazi et al. [273], a sophisticated hybrid algorithm, named MAO-Kmeans, based on the combination of improved AO (MAO) with K-means algorithms is proposed for assisting brain tumor segmentation. Firstly, the MAO algorithm integrated Cauchy mutation and selection scheme mechanisms into the original AO. Then, MAO was hybridized with K-means model. Experimental results underscore the effectiveness of the proposed MOA-Kmeans approach when compared against twelve optimization techniques using the Brain Tumor Segmentation dataset (BraTS 2020).

A hybrid model named AO-SGM, combining AO with the Seasonal Grey Model (SGM), is proposed in the work of Ren et al. [274] for wind power generation prediction. The model is applied to predict wind power generation in Sichuan Province, and the results demonstrated the superior performance of AO-SGM compared to other forecasting models.

4 Applications of the Aquila Optimizer Algorithm

4.1 Continuous Optimization

4.1.1 Network Clustering

In the work of Taha et al. [276], the AO algorithm was employed to address the clustering problem in Wireless Sensor Networks. The efficiency of the AO algorithm was evaluated in various scenarios using different base station positions. Results showed the superiority of the AO algorithm compared to GA, HHO, and COA algorithms regarding the lifetime and power consumption metrics.

4.1.2 Nodes Localization in Wireless Sensor Networks

Agarwal et al. [278] concentrated on developing an intelligent AO algorithm-Based Node Localization Scheme (IAOAB-NLS) for WSNs. Their proposed IAOAB-NLS model employs anchor nodes to accurately determine the positions of other nodes within WSNs. The results from this approach highlighted the effectiveness of the IAOAB-NLS model, showing its capability to deliver reliable outcomes regardless of variations in network parameters.

4.1.3 QoS in Wireless Sensor Networks

Hemavathi and Latha [279] applied the AO algorithm for enhancing the Quality of Service (QoS) in Wireless Sensor Network applications. The efficiency of the AO algorithm was evaluated based on different metrics such as Cost, energy level, and distance. Results proved that the AO algorithm enhance the QoS in WSNs against some state-of-the-art models.

4.1.4 Photovoltaic Power System

Karmouni et al. [290] implemented the AO algorithm for Global Maximum Power Point (GMPP) tracking control, specifically for a string of battery energy storage in photovoltaic power systems. The AO algorithm is primarily employed to predict the GMPP with high accuracy, incorporating an integral action to ensure continuous MPP and global asymptotic stability in partial shade conditions (PSCs). The performance of the AO algorithm was benchmarked against other algorithms like Perturb and Observe (P&O), PSO, SSA, and SCA in PSCs scenarios. Simulation results demonstrated the efficiency and superiority of the proposed AO algorithm over the compared algorithms.

Tadj et al. [291] applied the AO algorithm to optimize the FOPID controller for tracking the MPP in photovoltaic power systems. The performance of this AO-based FOPID controller was compared with a system using MFO algorithm. Simulation results demonstrated the superiority and high efficiency of the proposed AO-optimized control system in accurately tracking the MPP of PV power systems.

4.1.5 Water-Energy-Food Nexus (WEFN) Security

AO algorithm was applied in the work of Ru et al. [292] for the Water-Energy-Food Nexus (WEFN) security assessment. The AO algorithm was applied to the Hongxinglong branch of China's Beidahuang Farming Group, where spatiotemporal variations in WEFN security were analyzed across 12 subsidiary farms. Simulation results demonstrated that the AO model outperformed other models, such as the BP neural network, RF, and PSO-RF, in terms of fitting performance, reliability, stability, and reasonableness.

4.1.6 Partial Discharge Signal Denoising

Zhong et al. [293] introduced an innovative method based on the AO algorithm for partial discharge (PD) signal denoising. The proposed approach was evaluated against other methods using both simulated and real engineering signals. Results confirmed its superior noise reduction performance, effectively preserving signal characteristics while minimizing noise.

4.1.7 Text Categorization of Arabic News Articles

Alzaidi et al. [294] used the AO algorithm for the automated text categorization of Arabic news articles. The performance of the AO algorithm was validated using the Sanad dataset, which contains 45,500 samples across 7 classes (finance, sports, culture, technology, politics, medical, and religion). Comprehensive simulations demonstrate the superior performance of the AO algorithm compared to existing methods, highlighting its effectiveness in improving the accuracy of Arabic text classification.

4.1.8 Optimal Parameters Control

Wang et al. [295] introduced a new checkerboard usage calibration method utilizing the AO algorithm. They approach the calibration process as a nonlinear optimization problem, focusing on minimizing the distance between feature points intersected by the checkerboard and the laser. By employing AO, they efficiently obtain all parameters of the calibration model in one step, simplifying the traditionally complex calibration and solution processes of nonlinear underwater structured light vision models. Experimental results show that this method accurately calibrates system parameters and the refractive index of water, significantly enhancing the accuracy of underwater measurements.

Aribowo et al. [323] applied the AO algorithm to determine the PID controller parameters for managing the DC motor's speed. The efficiency of the AO algorithm was validated using two metrics such as integral total time-weighted square of error (ITSE) and integral total weighted absolute value error (ITAE) in comparison with MPA, SOA, ChOA, GPC algorithms. Experimental results indicated the superior performance of the AO algorithm by reducing the PID's overshoot by an 0.023% and enhancing the PID's undershoot by 0.5%.

Mehmood et al. [297] used the AO algorithm to estimate the control autoregressive (CAR) model parameters. The AO algorithm was evaluated in nine cases under different population sizes, maximum number of iterations, and noise variance. Compared to RSA, AOA, and SCA algorithms, AO achieves the best results in most cases regarding the fitness function values and the estimated weights.

In the study conducted by Abou El-Ela et al. [298], the AO algorithm was employed for the optimal estimation of Weibull parameters. The effectiveness of the AO algorithm was verified using real data collected over a year from the Zafarana and Shark El-Ouinate sites in Egypt. Comparative analysis with alternative methods revealed that the AO approach exhibited remarkable performance, demonstrating superior accuracy and stability in obtaining outcomes for Weibull parameters and wind energy calculations.

AO was adopted in the work of Guo et al. [324] to regulate the PID parameters of Phase-locked loop (PLL). The validation process encompassed three distinct regulation strategies including PLL regulation strategy, global regulation strategy, and step regulation strategy. Notably, simulation results underscored the efficacy of the AO based on PLL regulation strategy, demonstrating its capacity to significantly reduce power fluctuation and overshoot while maintaining a short response time, low complexity, and minimal time cost.

Aribowo et al. [296] applied the AO algorithm to optimize the parameters of droop proportional-Integral controller for Direct Current (DC) microgrids. The authors evaluated the AO's reliability and performance using two case studies by changing the load-sharing control and the irradiation value. The findings revealed that the AO algorithm effectively reduces the settling time by 0.7% and achieves better final power output of 0.798% compared to other conventional optimization methods.

Korich et al. [299] employed the AO algorithm to optimize the parameters of a controller for a DC/DC boost converter. The AO algorithm was tasked with minimizing the difference between the reference and the actual inductor current, especially during switch openings, to address the chaotic behavior of the converter. The effectiveness of the AO approach was demonstrated through MATLAB simulations, which showcased its ability to successfully optimize the controller, enhancing the performance and stability of the DC/DC boost converter.

To optimize the PID controller coefficients of a Four-Switch Buck-Boost (FSBB) converter, the AO algorithm is used in the work of Ren et al. [301]. The performance of the AO algorithm is validated under various conditions, including normal conditions, load step changes, and input voltage variations. Simulation results confirmed the superiority of the AO algorithm when compared to PSO and GA algorithms in PID tuning for FSBB converters.

The AO algorithm was employed in the work of Gupta et al. [302] for adjusting the FOPID controller to enhance load frequency control in a deregulated hybrid power system. Its performance was evaluated under Poolco and bilateral agreements, as well as varying operating conditions. Comparative analyses highlighted the superior effectiveness of the AO algorithm over PSO and WOA techniques, demonstrating significant improvements in system metrics, including frequency regulation across different areas, tie-line power variations, and generator outputs.

4.2 Constrained Optimization

4.2.1 Economic Environmental Dispatch Problem

AO algorithm was proposed in the work of Aljumah et al. [303], for solving the Economic Environmental Dispatch (EED) problem. OA algorithm was validated on CEC 2017 benchmarks, the IEEE 30-bus power system, and a large-scale 160-unit system. Results demonstrated significant performance, achieving a mean fuel cost of $16,784.45/h for a 225 MW load, and reductions of 7.68, 47.42, and 57.39% in fuel costs, emissions, and compromise costs, respectively, when compared to other existing models.

4.2.2 UAVs Path Planning

The AO algorithm was used in the work of Huang et al. [304] to address the multi-UAVs path planning problem. The AO algorithm was tested using three UAVs specified for Close Air Support (CAS) missions. Simulation results showed that the trajectory generated by the AO algorithm can meet the requirements of CAS missions.

4.2.3 Real-World Engineering Optimization Problem

AO was introduced by Abualigah et al. [106] as a novel approach to solve real-world engineering optimization problems. Its performance was thoroughly evaluated using 23 standard benchmark functions, 30 CEC2017 test functions, 10 CEC2019 test functions, and seven real-world engineering problems. Comparative analyses against prominent meta-heuristic algorithms, including GOA, EO, PSO, DA, ALO, GWO, MPA, SSA, SCA, WOA, and SMA, demonstrated the superior performance and remarkable effectiveness of the proposed AO algorithm across diverse optimization scenarios.

Sharma et al. [308] introduced the AO algorithm to tackle complex optimization problems. The algorithm's effectiveness was thoroughly assessed using 23 classical functions and five real-world engineering problems. The results demonstrate that the AO algorithm outperforms other algorithms, including MGO, PSO, GWO, ALO, SCO, and WOA, in terms of speed, efficiency, computational complexity, and adaptability.

Varshney et al. [309] applied the AO algorithm for solving constrained real engineering design problems. The AO algorithm was validated for three real engineering problems including pressure vessel design, welded beam design, and cantilever beam design problems. Simulation results confirmed the superiority of the AO algorithm compared to several metaheuristic algorithms, including WOA, GOA, RSA, and BSO.

4.2.4 Code High-Quality Software

The AO algorithm is proposed in the work of Mohamed et al. [310] for code high-quality software improvement. AO performance's was evaluated on five open-source Java projects, detecting nine types of code smells before and after refactoring. The results reveal an average detection accuracy of 95.18 and 95.68% for recall and precision, with better performance in large projects compared to medium ones.

4.2.5 Renewable Energy Systems Design

To tackle the hybrid renewable energy systems design problem, the AO algorithm was proposed in the work of

Zhou et al. [311]. Two configurations of the systems were considered to test the performance of the AO algorithm: one consisting of a wind turbine, a diesel engine, a battery, and solar energy, and the other composed of solar energy, a diesel engine, and a battery. Simulation results demonstrated that the AO algorithm significantly outperformed three optimization algorithms such as MVO, SHO, and Emperor Penguin Optimizer (EPO), in terms of cost-efficiency, highlighting its potential for optimizing complex renewable energy systems.

4.2.6 Radial Distribution Networks

Wang et al. [312] introduced a method using the AO algorithm for optimizing soft open points (SOPs) in radial distribution networks, aiming to reduce the impacts of electric vehicle load and renewable energy variability. Their study used the modified IEEE 33-bus and IEEE 69-bus ADNs for simulations, revealing significant improvements. AO demonstrated superior performance and efficiency in terms of reducing losses and enhancing voltage stability, outperforming other algorithms like multiobjective PSO (MOPSO), PSO, and CSA algorithms.

4.2.7 Allocation of Distributed Generations

Samal et al. [313] utilized the AO algorithm for the optimal allocation and sizing of distributed generations. They conducted a thorough examination of the AO algorithm's parameters, focusing on minimizing the total active power loss (TACPL) across 23 different scenarios. The results from this study clearly indicated that the AO approach successfully reduced the TACPL in all the 23 distinct scenarios.

4.2.8 Hearing Aid System

Rawandale et al. [314] employed the AO algorithm to optimize the Hearing Aid system. The AO algorithm was evaluated under various numbers of bands and multipliers. Compared to state-of-the-art approaches, the AO algorithm achieves the best results in terms of matching error, delay, and power consumption.

4.2.9 Harmonic Elimination in a Modified H-Bridge Inverter

Authors in [315] implemented AO for harmonic elimination in a Cascade H-Bridge (CHB) inverter in power systems. The AO algorithm was tested based on seven-level modified H-bridge inverter, utilizing the DSP-TMS320F28335 Launchpad within the MATLAB environment. The simulation outcomes highlighted the superior performance of the AO algorithm compared to several well-known meta-heuristic algorithms, such as GA and DE.

4.2.10 Wind Speed Combined Forecasting System

Xing et al. [316] used the AO algorithm for accurate point and interval forecasts. Validated using six datasets from two sites in China, the AO algorithm demonstrates superior prediction accuracy and dependable forecasting intervals with high coverage and minimal width error, ensuring enhanced power system security and stability compared to existing models.

4.2.11 Lot-Sizing Inventory Management

Utama et al. [317] employed AO to address the multi-item lot-sizing inventory problem. The AO algorithm was assessed considering the metrics of cost, quantity order, fuel consumption, order cycle, and safety factor, taking into account the impact of varying fuel price, standard deviation, and vehicle capacity. Comparative analysis with other algorithms revealed that AO efficiently minimized costs.

4.2.12 Diagonal Loading Beamforming

Liu and Zhen [318] applied the AO algorithm for diagonal loading beamforming. Initially, the identity matrix is linearly combined with the original covariance matrix. Following this, the Aquila Optimizer is employed to optimize the diagonal loading process of the matrix. The improved loading value obtained from this process is then integrated with the Sample Matrix Inversion (SMI) method to form the beam. Simulation results indicate that the AO algorithm effectively reduces beam distortion caused by the divergence of small eigenvalues.

4.3 Combinatorial Optimization

4.3.1 0–1 Knapsack Problem

The AO algorithm was applied by Bacs [320] for solving the 0–1 knapsack problem. The AO algorithm was rigorously tested on 63 benchmark cases of the knapsack problem, spanning low, medium, and large scales. The results demonstrated that the AO algorithm outperforms other recently meta-heuristics existing in the literature, positioning it as a highly effective and competitive approach for tackling the 0-1 knapsack problem.

4.3.2 Feature Selection

Authors in [110] applied the AO algorithm for selecting features in COVID-19 image classification. The performance of the AO algorithm was validated using two different datasets with X-ray and CT COVID-19 images and compared to several meta-heuristics such as MFO, WOA, FA, BA, Transient Search Optimization (TSO), and Hunger Games Search (HGS). Results proved that the AO algorithm outperforms other meta-heuristics in terms of accuracy, sensitivity, specificity, and F1-Score.

Maaram et al. [322] applied the AO technique for feature selection in Alzheimer's Disease classification. Simulation results on the ADNI dataset showcased the AO method's remarkable superiority in accuracy compared to traditional approaches, highlighting its effectiveness and potential in advancing diagnostic methodologies (Table 6).

Table 6 Applications of AO algorithm

Class	Problem	Research works
Continuous Optimization	Network clustering	Taha et al. [276]
	Node localization in WSNs	Yang and Ding [277], Agarwal et al. [278]
	QoS in WSNs	Hemavathi and Latha [279]
	Multi-robot space exploration	Gul et al. [172]
	Information management in WSNs	Abualkishik et al. [280]
	Image segmentation	Rajinikanth et al. [281], Sonthi et al. [282]
	Hyperspectral image classification	Subba et al. [243]
	Computer vision-based classification	Nguyen and Hoang [283]
	Fruit classification	Shankar et al. [284]
	Prostate cancer patients classification	Balaha et al. [285]
	Malware detection for Android applications	Grace and Sughasiny [267]
	Wind energy potential prediction	Khamees et al. [286]
	Exploration of China's total CO2 emissions	Li et al. [287]
	Monitoring marine environmental information	Guan et al. [288]
	Shaming emotion analysis	Aarthi and Chelliah [289]
	Photovoltaic power systems	Karmouni et al. [290], Tadj et al. [291], Narasimhulu et al. [246]
	Water-Energy-Food Nexus (WEFN) security	Ru et al. [292]
	Partial discharge (PD) signal denoising	Zhong et al. [293]
	Text categorization of Arabic news articles	Alzaidi et al. [294]
	Optimal parameters control	Wang et al. [295], Aribowo et al. [296], Mehmood et al. [297], Abou El-Ela et al. [298], Korich et al. [299], Bankole et al. [300], Ren et al. [301], Gupta et al. [302]
Constrained Optimization	Economic environmental dispatch	Aljumah et al. [303]
	UAV path planning	Huang et al. [304], Ait-Saadi et al. [189], Bao et al. [305]
	Multi-point PV & wind-based DG integrated radial distribution network	Chowdhury et al. [306]
	Optimal power flow solution of wind-integrated power system	Khamees et al. [307]
	Real world engineering optimization	Sharma et al. [308], Varshney et al. [309]
	Code high-quality software	Mohamed et al. [310]
	Renewable energy system design	Zhou et al. [311]
	Radial distribution networks	Wang et al. [312]
	Allocation of distributed generations	Samal et al. [313]
	Hearing Aid system	Rawandale et al. [314]
	Harmonic elimination in a modified H-bridge inverter	Hussan et al. [315]
	Wind Speed Combined Forecasting System	Xing et al. [316]
	Lot-sizing inventory management	Utama et al. [317]
	Diagonal loading beamforming	Liu and Zhen [318]
	Predicting energy usage in smart grids	Badhe et al. [319]
Combinatorial Optimization	0–1 Knapsack problem	Bacs [320]
	Feature Selection	Abd Elaziz et al. [110], Jamei et al. [321], Maaram and Chandre [322]
	PID controller	Aribowo et al. [296, 323], Guo et al. [324]

Table 7 Parameter setting of the evaluated optimization algorithms

Parameter (s)	Value (s)
DE	
Crossover factor *CR*	0.7
Mutation factor *F*	0.8
FA	
Minimum frequency f_{Min}	0
Maximum frequency f_{Max}	2
Initial loudness A_0	1
Initial pulse emission rate r_0	1
Loudness constant α	0.5
Emission rate constant γ	0.5
GWO	
Control parameter $a1_{max}$	2
Control parameter $a1_{min}$	0
MFO	
Control parameter *b*	1
Convergence factor a_{min}	-2
Convergence factor a_{max}	-1
MVO	
Minimum of Wormhole Existence Probability WEP_{Min}	0.2
Maximum of Wormhole Existence Probability WEP_{Max}	1
AO	
Exploitation adjustment α	0.1
Exploration adjustment β	0.1

5 Results and Comparison

This section evaluates and confirms the performance of the AO algorithm using the parameter settings summarized in Table 7, across three sets of mathematical tests (i.e. unimodal, multimodal, and fixed-dimension multimodal) illustrated in Tables 8, 9, and 10. A comparison is established between the AO algorithm and six well-known optimization algorithms, including DE, FA, BA, GWO, MFO, and MVO. In this experiment, 30 search agents are used and 500 iterations are performed. The simulation results are reported in Table 11. Based on the results, it can be noticed that the AO algorithm gives superior results with the best stability on 6 out of 7 test function (F1, F2, F3, F4, F5, F7). In this case, we can conclude that the AO algorithm provides significantly better exploitation than other existing algorithms. For multimodal functions (F8-F13), the AO algorithm outperforms on F9, F10, and F11 functions. Therefore, the AO algorithm offers relatively good exploration compared to other methods. Finally, for the fixed-dimension multimodal functions (F14-F18), the optimization results given by the AO algorithm (F16, F17, and F18) are relatively better than those provided by the other algorithms. Consequently, the AO algorithm significantly prevents the local optima stagnation and obtains reasonable exploration.

Figure 13 depicts the boxplot curves for the AO algorithm and its comparable counterparts across the benchmark functions. As noticed from this figure, in most cases, the AO algorithm boxplots are narrower than the other algorithms. Based on these results, the AO algorithm appears to achieve a better data distribution than other methods, illustrating its superior performance.

Table 12 presents the Friedman Rank Test analysis results for all the algorithms across all the functions. As evidenced, the AO algorithm achieves the best mean rank of 2.19, proving its superiority. Notably, the DE algorithm provides a significant mean rank of 2.75, closer to the AO 's rank. The BA algorithm remains in the last position with the worst mean rank of 7. Regarding the Asymptotic Significance, which is less than 0.001 in the test. Statistically, its indicates that it exists a difference between the algorithms and it is significant.

Furthermore, the ANOVA with Fisher's Least Significant Difference is performed to validate the superiority of the AO algorithm. The test results are displayed in Table 13. Based on the results, we can notice that the significant (p-value) is equal to 1 in most cases, which is greater than 0.05. In these cases, there are no significant differences between the AO and the other algorithms. However, the p-value of AO and BA methods is less than 0.05, indicating a significant difference between them.

Table 8 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	$f(x) = \max_i \left\{ \lvert x_i \rvert, 1 \leq i \leq n \right\}$	10	$[-100, 100]$	0
F5	$f(x) = \sum_{i=1}^{n-1} \left[100\left(x_i^2 - x_{i+1}\right)^2 + \left(1 - x_i\right)^2 \right]$	10	$[-30, 30]$	0
F6	$f(x) = \sum_{i=1}^{n} \left(\lvert x_i + 0.5 \rbrack \right)^2$	10	$[-100, 100]$	0
F6	$f(x) = \sum_{i=0}^{n} i x_i^4 + \text{random}\ [0, 1)$	10	$[-1.28, 1.28]$	0

Table 9 Multimodal benchmark functions

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

Table 10 Fixed-dimension multimodal benchmark functions

Function	Description	Dimension	Range	$f_{\min}$
F_{14}	$\left(\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i - a_{ij})}\right)^{-1}$	2	$[-65, 65]$	1
F_{15}	$\sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}\right]^2$	4	$[-5, 5]$	0.00030
F_{16}	$4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	2	$[-5, 5]$	−1.0316
F_{17}	$\left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos x_1 + 10$	2	$[-5, 5]$	0.398
F_{18}	$f(x) = \left[1 + \left(x_1 + x_2 + 1\right)^2\left(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2\right)\right]$ $\times\left[30 + \left(2x_1 - 3x_2\right)^2\left(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2\right)\right]$	2	$[-2, 2]$	3

The convergence of the AO algorithm is analysed in comparison with other algorithms as shown in Fig. 14. The AO algorithm demonstrates faster and more stable convergence compared to MFO, MVO, DE, FA, WOA, and GWO. While MFO and MVO struggle with premature convergence, AO maintains a smooth transition between exploration and exploitation. DE, though strong in global search, converges more slowly, whereas AO efficiently balances both phases. FA tends to stagnate in complex spaces, while AO adapts dynamically for better performance. WOA and GWO exhibit slower convergence on multimodal functions, but AO avoids stagnation and reaches optimal solutions more efficiently, making it a robust optimization algorithm.

6 Discussion and Future Works

The Aquila Optimizer (AO) algorithm is a recent and innovative nature-inspired optimization algorithm introduced in 2021, drawing inspiration from the hunting behaviors of the Aquila bird. The AO algorithm demonstrates strong capabilities in both exploration and exploitation, making it suitable for a wide range of applications.

On the other hand, like many optimization algorithms, the AO algorithm faces certain challenges. One of the main limitations is premature convergence, which occurs when the algorithm becomes stuck in local optima and fails to effectively explore the search space. This limitation can lead to suboptimal solutions and restrict the algorithm's ability to find the global optimum. Additionally,

Table 11 The optimization results for solving benchmark functions

Function	Measure	DE	FA	BA	GWO	MFO	MVO	AO
F1	Best	2.09E^{-20}	2.67E−09	1.85E+03	1.38E−61	1.90E−15	3.1E−03	1.86E−162
	Worst	1.11E−18	8.04E−09	1.78E+04	4.02E−54	1.90E−18	4.32E−02	6.09E−107
	Mean	2.42E−19	5.32E−09	8.77E+03	9.18E−56	2.80E−13	1.49E−02	1.22E−108
	STD	2.41E−19	1.17E−09	3.93E+03	5.69E−55	4.33E−13	7.6E−03	8.61E−108
F2	Best	8.42E−13	1.10E−05	1.565E1	1.29E−34	1.41E−10	1.8E−2	1.42E−81
	Worst	1.75E−11	2.34E−05	5.223E1	3.26E−31	1E1	8.28E−2	3.12E−56
	Mean	6.73E−12	1.88E−05	3.35E1	1.22E−32	6E−1	3.94E−2	6.24E−58
	STD	3.72E−12	2.67E−06	8.6433	4.69E−32	2.399	1.52E−2	4.41E−57
F3	Best	7.6681	3.06E−09	2.79E+03	8.67E−33	2.94E−04	2.76E−2	1.41E−156
	Worst	9.62E1	1.19E−08	2.63E+04	3.18E−22	5.00E+03	4.590E−1	9.95E−100
	Mean	3.25E1	7.07E−09	1.18E+04	7.67E−24	4E1	1.209E−1	1.99E−101
	STD	2.0735E1	2.04E−09	5.25E+03	4.52E−23	1.37E+03	8.53E−2	1.41E−100
F4	Best	1.2E−3	2.80E−05	2.90E+01	2.17E−20	4.69E−04	5E−2	3.91E−82
	Worst	6.8E−3	4.94E−05	6.89E+01	1.99E−17	1.92E+01	2.416E−1	2.07E−52
	Mean	3.5E−3	3.97E−05	4.88E+01	2.30E−18	1.8137	9.97E−2	4.14E−54
	STD	1.4E−3	5.04E−06	1.00E+01	3.94E−18	3.41E+00	4.31E−2	2.92E−53
F5	Best	1.375	1.11E−2	4.61E5	5.4809	4.3E−3	4.7374	5.1033E−7
	Worst	2.487E1	8.336E−1	4.773E7	8.0577	9E4	2.056E3	1.11E−2
	Mean	8.6247	4.628E−1	1.252E7	6.5557	5.68E3	1.1E2	1.3E−3
	STD	4.8161	1.517E−1	8.84E6	5.606E−1	2.15E4	3.06E3	2.1E−3
F6	Best	2.4532E−20	3.01E−9	3.9374E4	1.36E−9	1.73E−15	4.1E−3	7.36E−8
	Worst	1.0779E−18	7.62E−9	1.8271E4	2.335E−1	3.78E−12	3.42E−2	2.45E−4
	Mean	2.294E−19	5.16E−9	9.49E3	4.7E−3	4.65E−13	1.56E−2	3.44E−5
	STD	1.942E−19	1.23E−9	3667.4	0.033	9.29E−13	7E−3	5.39E−5
F7	Best	1.8E−3	7.44E−5	0.7613	1.1E−4	1.5E−3	3.21E−4	2.31E−6
	Worst	1.42E−2	5.09E−4	1.13E1	2.5E−3	3.75E−2	1.22E−2	5.4E−4
	Mean	6.8E−3	2.23E−4	4.1579	6.63E−4	9.9E−3	3.3E−3	1.28E−4
	STD	2.8E−3	9.23E−5	2.9707	5.02E−4	7.2E−3	2.4E−3	1.07E−4
F8	Best	−4.19E3	−4.07E3	−5.06E3	−3.32E3	−4.07E3	−3.76E3	−4.19E3
	Worst	−4.07E3	−2.80E3	−1.03E3	−1.81E3	−2.52E3	−2.1E3	−2.02E3
	Mean	−4.18E3	−3.49E3	−2.37E3	−2.69E3	−2.99E3	−2.99E3	−3.58E3
	STD	28.41	2.62E2	1.18E3	3.24E2	3.52E2	3.48E2	8.4E2
F9	Best	8.53E−14	2.98	5.94E1	0	7.96	2.99	0
	Worst	7.65E−10	1.59E1	1.37E2	7.31	5.67E1	4.48E1	0
	Mean	7.82E−11	8.26	9.98E1	8.46E−1	2.23E1	1.6E1	0
	STD	1.54E−10	3.21	1.81E1	1.86	1.2E1	7.47	0
F10	Best	7.19E−11	1.82E−5	1.11E1	4E−15	1.48E−8	0.0223	4.44E−16
	Worst	9.72E−10	3.58E−5	2E1	1.11E−14	2.01	1.65	4.44E−16
	Mean	2.49E−10	2.84E−5	1.87E1	6.91E−15	0.0634	0.1958	4.4409E−16
	STD	1.58E−10	3.82E−6	1.46	1.55E−15	3.25E−1	0.4319	0
F11	Best	3.64E−11	2.73E−8	1.87E1	0	1.97E−2	1.49E−1	0
	Worst	1.65E−2	1.43E−1	1.53E2	1.09E−1	4.61E−1	6.73E−1	0
	Mean	1.8E−3	5.07E−2	7.27E1	2.23E−2	1.52E−1	3.43E−1	0
	STD	3.6E−3	2.64E−2	3.05E1	2.37E−2	8.01E−2	1.26E−1	0
F12	Best	3.92E−22	2.27E−11	6.22E4	5.2E−7	4.79E−17	1.92E−4	2.38E−10
	Worst	7.11E−20	7.56E−11	9.47E7	3.41E−2	3.69	3.85E−1	8.68E−5
	Mean	1.53E−20	5.11E−11	2.14E7	4.6E−3	2.04E−1	3.99E−2	1.09E−5
	STD	1.75E−20	1.3E−11	2.25E7	9E−3	6.06E−1	1.07E−1	2.28E−5
F13	Best	4.41 E −21	1.34 E −10	1.91E5	1.74E−6	1.15E−16	2.91E−4	1.91E−8
	Worst	6.16E−19	3.92E−10	1.93E8	1.1E−1	4.39E−2	2.45E−2	3.26E−4

Table 11 (continued)

Function	Measure	DE	FA	BA	GWO	MFO	MVO	AO
	Mean	5.82E−20	2.54E−10	3.46E7	2.43E−2	5.9E−3	5.9E−3	1.9E−5
	STD	1.15E−19	6.35E−11	3.31E7	4.37E−2	1.22E−2	6.7E−3	4.79E−5
F14	Best	9.98E−1	9.98E−1	2.21	9.98E−1	9.98E−1	9.98E−1	9.98E−1
	Worst	9.98E−1	5.93	2.64E2	1.27	6.9	9.98E−1	1.27
	Mean	9.98E−1	1.18	4.28E1	4.9	2.3	9.98E−1	2.57
	STD	7.19E−1	7.9E−1	7.22E1	4.23	1.83	3.06E−11	3.01
F15	Best	3.92E−4	3.07E−4	1.9E−3	3.08E−4	5.08E−4	4.98E−4	3.27E−4
	Worst	1.2E−3	1.2E−3	1.65	2.09E−2	2.04E−2	2.04E−2	1.4E−3
	Mean	7.12E−4	3.74E−4	1.01E−1	5.4E−3	1.5E−3	5.9E−3	5E−4
	STD	1.67E−4	2.19E−4	2.46E−1	8.6E−3	2.9E−3	8.4E−3	1.68E−4
F16	Best	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316
	Worst	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316
	Mean	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316
	STD	2.24E−16	1.15E−14	5.36E−01	1.71E−8	2.24E−16	5.53E−7	4.2E−4
F17	Best	3.979E−1	3.979E−1	3.979E−1	3.979E−1	3.981E−1	3.979E−1	3.979E−1
	Worst	3.979E−1	3.979E−1	5.4478	3.98E−1	3.979E−1	3.979E−1	3.986E−1
	Mean	3.979E−1	3.979E−1	9.684E−1	3.979E−1	3.979E−1	3.979E−1	3.98E−1
	STD	0	9.3462E−15	8.86E−1	9.474E−6	0	5.7076E−7	1.6468E−4
F18	Best	3	3	3.03	3	3	3	3
	Worst	3	3	97.62	84	3	84	3.12
	Mean	3	3	23.53	4.62	3	4.62	3.03
	STD	5.78E−16	1.11E−3	24.07	11.45	2.12E−15	11.45	3.25E−2

the AO algorithm may exhibit slow convergence, particularly in high-dimensional and complex optimization problems, often requiring more time to reach optimal solutions compared to other algorithms. Furthermore, the AO's scalability is limited, making it less effective for large-scale problems with numerous variables and constraints.

Another critical limitation of the AO algorithm is its sensitivity to parameter tuning. The performance of the algorithm heavily depends on the proper selection of control parameters, such as population size and learning rates. Improper tuning can lead to inefficient search behavior, either causing excessive exploration without convergence or premature exploitation, which increases the risk of stagnation in suboptimal regions.

Moreover, the AO algorithm's performance may degrade in highly dynamic environments where the optimization landscape frequently changes. Since AO primarily relies on iterative updates based on a predefined search strategy, it may struggle to adapt to time-varying objectives or constraints, making it less suitable for real-time or adaptive optimization tasks.

Another challenge is the computational overhead associated with AO when applied to large-scale problems. The algorithm's iterative nature and reliance on function evaluations can lead to high computational costs, especially when dealing with expensive objective functions. This can make it impractical for real-time applications or scenarios where rapid decision-making is required.

Finally, the AO algorithm may suffer from a lack of diversity in later iterations. As the algorithm progresses, the search agents may become too concentrated around certain regions, reducing population diversity. This can hinder the ability to escape local optima, necessitating the integration of diversity-preserving mechanisms such as mutation operators or adaptive strategies to enhance exploration capabilities.

The advantages and disadvantages of AO are summarized in Table 14.

To address these issues, researchers have proposed various enhancements aimed at boosting its performance and adaptability across diverse optimization challenges.

Figure 15 illustrates the classification of related works on AO based on the type of modification applied to the original algorithm. Opposition-Based AO (23.85%) represents the largest portion, leveraging opposition-based learning technique to accelerate convergence and improve global search ability. Improved AO (20%) follows, encompassing integration of other methods to refine AO's performance. Chaotic AO (14.28%) is another significant category, introducing chaotic maps to enhance exploration capabilities. Both Gaussian AO (14.43%) and Adaptive AO (12.86%) contribute equally, with Gaussian AO focusing on convergence

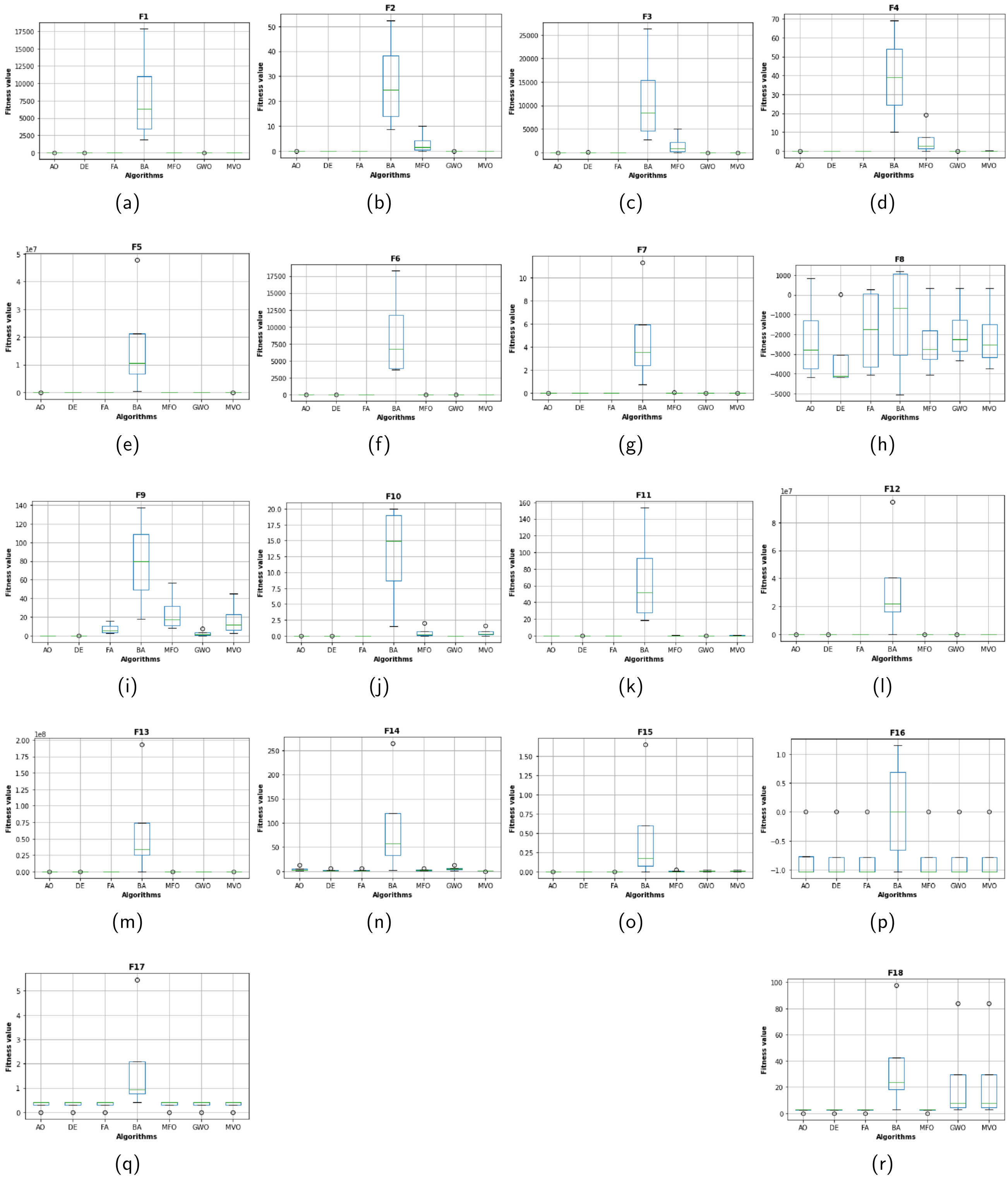

Fig. 13 Boxplot of all algorithms

improvement using Gaussian-based techniques and Adaptive AO emphasizing dynamic parameter adjustment for uncertain environments. Binary AO (8.57%) targets binary optimization problems, while both Lévy Flight AO (5.71%) and Fuzzy-Based AO (4.42%) focus on global optimization

Table 12 The Friedman tests of the fitness value

	Results	AO	DE	BA	FA	GWO	MFO	MVO
Descriptive statistics	N	18	18	18	18	18	18	18
	Minimum	−3.58E3	−4.18E3	−2.37E3	−3.49E3	−2.69E3	−2.99E3	−2.99E3
	Maximum	3.03	3.25E1	3.46E7	8.26	6.56	5.68E3	1.1E2
	Mean	−1.99E2	−2.29E2	3.8E6	−1.93E2	−1.48E2	1.74E2	−1.59E2
	STD	8.44E2	9.86E2	9.55E6	8.22E2	6.34E2	1.55E3	7.07E2
Rank	Mean rank	2.19	2.75	7	3.03	3.72	4.53	4.78
Statistic tests	N	18						
	Chi-square	64.643						
	Df	6						
	Asymp. sig	< 0.001						

Table 13 The post hoc test of the mean fitness of each algorithm

Multiple comparison						
Dependent variable: fitness						
Algorithm (I)	Algorithm (J)	Mean difference (I–J)	SE	Sig	95 % Confidence interval	
					Lower bound	Upper bound
AO	DE	3.11E1	1.20E6	1	−2.38E6	2.38E6
	FA	−5.41	1.20E6	1	−2.38E6	2.38E6
	BA	−3.81E6	1.20E6	0.002	−6.19E6	−1.42E6
	GWO	−5E1	1.20E6	1	−2.38E6	2.38E6
	MFO	−3.72E2	1.20E6	1	−2.38E6	2.38E6
	WVO	−3.98E1	1.20E6	1	−2.38E6	2.38E6

through random walks and handling uncertainty using fuzzy logic, respectively.

Figure 16 illustrates the categorization of studies related to AO based on the hybridization methods employed. The majority (65.21%) of works focus on combining AO with meta-heuristic algorithms, highlighting a strong trend toward enhancing AO's performance by leveraging meta-heuristic techniques. Additionally, 18.48% of studies integrate AO with ANN models, reflecting a growing interest in utilizing ANN for tasks like parameter tuning and adaptive strategies. Hybridization with SVM (2.17%), ELM (1.1%), RL (3.26%), and LSTM (6.52%) collectively accounts for 13.33% of the studies, demonstrating efforts to combine the AO algorithm with machine learning techniques for improved optimization. Finally, 3.26% of the works explore AO's integration with other methods, such as fuzzy logic and statistical approaches, pointing to the potential for further innovation in domain-specific applications.

Figure 17 presents the classification of related works on AO based on the type of the optimization problems. The majority of studies, accounting for 55.36%, focus on continuous optimization, where the AO algorithm is utilized to address real-valued problems, showcasing its effectiveness in handling continuous decision variables. Constrained optimization represents 32.14% of the research, emphasizing the integration of constraint-handling techniques to solve problems with strict limitations and feasibility requirements. Finally, 12.5% of the studies are dedicated to combinatorial optimization, where the AO algorithm is adapted for discrete and finite search spaces. This classification highlights the versatility of the AO algorithm, with a significant emphasis on continuous optimization applications while also addressing the challenges posed by constrained and combinatorial problems through tailored strategies.

The relevant directions for future can be determined as follows:

1. Consider implementing multi-swarm or multi-population tactics in future planning, along with advanced improvement strategies based on randomization.
2. Investigate the application of AO's variants in multi-objective and discrete scenarios as a promising area for further exploration.
3. Focus on making AO's parameters adaptive rather than fixed to improve its performance across different domains.

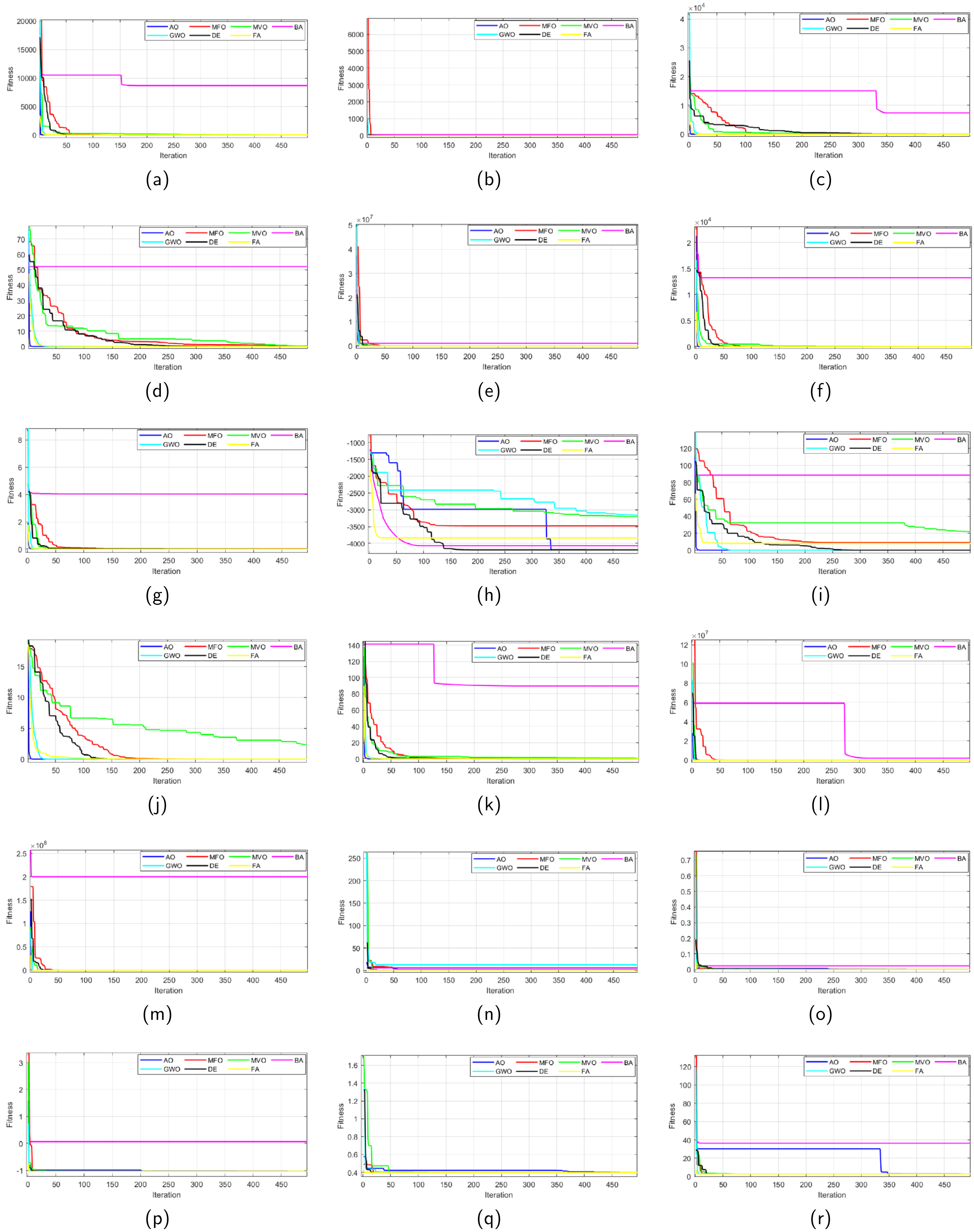

Fig. 14 Convergence of all algorithms

Table 14 Strengths and weaknesses of the AO algorithm

Strengths	Weaknesses
Good balance between exploration and exploitation	Prone to premature convergence, reducing its ability to find the global optimum
Versatile across various optimization problems	Slow convergence speed, especially in high-dimensional problems
Hybridization with other metaheuristics enhances performance	Limited scalability for large-scale problems with many variables and constraints
Simple, robust, and easy to implement	Requires careful tuning of parameters for optimal results
Efficient in finding optimal or near-optimal solutions	

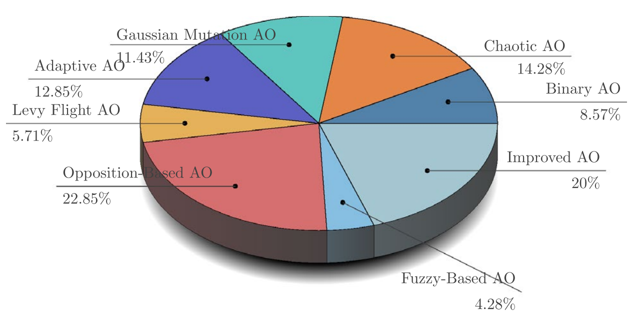

Fig. 15 Classification of related AO works based on the type of the modification

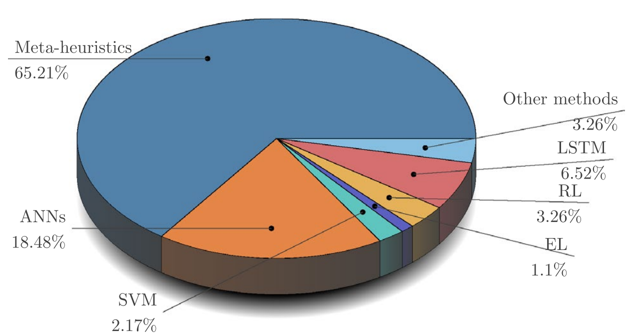

Fig. 16 Classification of related AO works based on the hybridized methods

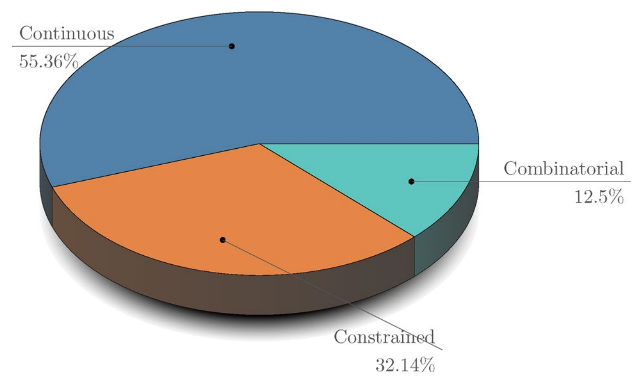

Fig. 17 Classification of related AO works based on the type of the optimization problem

4. Extending fuzzy-based modifications to tackle high-dimensional problems with uncertainty and imprecise data.
5. Integrate Fitness Distance Balance (FDB) and its enhanced versions to further improve the convergence and diversity of the AO algorithm.
6. The AO algorithm can be used to handle various optimization problems in different domains such as: telecommunication network design, antenna array optimization, and supply chain optimization.
7. Defining new operators and strategies to enhance the exploitation and exploration capabilities of AO.
8. Combine the AO algorithm with deep learning architectures to enhance feature extraction and optimization tasks. This integration can improve the AO's ability to handle complex data and optimize deep learning model hyperparameters effectively.
9. To adaptively adjust AO parameters for better exploration-exploitation balance. This can enhance the AO's dynamic behavior in complex search spaces, allowing it to adapt to different optimization scenarios more effectively.

7 Conclusion

Aquila Optimizer (AO) is a recent and well-known nature-inspired optimization algorithm inspired by the behavior of Aquila in hunting and catching the prey. This research paper provides an exhaustive survey of AO and its enhanced variants (multi-objective, modified, and hybridized). Since the introduction of AO algorithm in 2021, over 210 AO papers have been published by researchers and academics. These related papers have proved the efficiency, scalability, and robustness of AO algorithm in tackling a wide variety of optimization problems in different fields. The success of AO algorithm can be attributed to its simplicity, easiness of implementation, reasonable execution time, and and its capacity to be easily combined with other optimization methods.

Future research on the Aquila Optimizer (AO) can focus on several promising directions to further enhance its performance and applicability. Implementing multi-swarm or multi-population techniques combined with advanced randomization strategies can improve AO's optimization capabilities. Expanding its use to multi-objective and discrete optimization problems is another area with significant potential. Transitioning from fixed to adaptive parameter settings could further boost AO's performance across diverse domains. Additionally, incorporating fuzzy-based modifications could enable AO to tackle high-dimensional problems with uncertainty and imprecise data.

Author Contributions Sylia Mekhmoukh Taleb and Yassine Meraihi wrote the main manuscript text. Elham Tahsin Yasin, Amylia Ait Saadi, Musa Dogan, and Selma Yahia conducted the literature review and simulations. Murat Koklu, Seyedali Mirjalili, and Amar Ramdane-Cherif reviewed the manuscript for technical accuracy and provided critical revisions. All authors reviewed and approved the final manuscript.

Availability of Data and Materials No datasets were generated or analysed during the current study.

Declarations

Conflict of Interest The authors declare that there is no Conflict of interest with any person(s) or Organization(s).

References

1. Kirkpatrick S, Gelatt CD Jr, Vecchi MP (1983) Optimization by simulated annealing. Science 220(4598):671–680
2. Glover F (1990) Tabu search: a tutorial. Interfaces 20(4):74–94
3. Mladenović N, Hansen P (1997) Variable neighborhood search. Comput Oper Res 24(11):1097–1100
4. Stützle T (2006) Iterated local search for the quadratic assignment problem. Eur J Oper Res 174(3):1519–1539
5. Voudouris C, Tsang E (1999) Guided local search and its application to the traveling salesman problem. Eur J Oper Res 113(2):469–499
6. Hoos HH, Stützle T (2004) Stochastic local search: foundations and applications. Elsevier
7. Feo TA, Resende MGC (1995) Greedy randomized adaptive search procedures. J Glob Optim 6:109–133
8. Holland J (1975) Adaptation in natural and artificial systems. Ann Arbor
9. Beyer H-G, Schwefel H-P (2002) Evolution strategies-a comprehensive introduction. Nat Comput 1:3–52
10. Koza JR (1993) Genetic programming: on the programming of computers by means of natural selection (complex adaptive systems). Bradford Book 1:18
11. Fogel LJ, Owens AJ, Walsh MJ (2000) Introduction to artificial intelligence through simulated evolution. Artif Intell: Crit Concepts 3:259
12. Neri F, Cotta C (2012) Memetic algorithms and memetic computing optimization: a literature review. Swarm Evol Comput 2:1–14
13. Baluja S (1994) Population-based incremental learning: a method for integrating genetic search based function optimization and competitive learning. Carnegie Mellon University, Pittsburgh, School of Computer Science
14. Storn R, Price K (1997) Differential evolution-a simple and efficient heuristic for global optimization over continuous spaces. J Glob Optim 11:341–359
15. Nunes De Castro L, Von Zuben FJ (2000) The clonal selection algorithm with engineering applications. Proc GECCO 2000:36–39
16. Simon D (2008) Biogeography-based optimization. IEEE Trans Evol Comput 12(6):702–713
17. Formato RA (2007) Central force optimization. Prog Electromagn Res 77(1):425–491
18. Rashedi E, Nezamabadi-Pour H, Saryazdi S (2009) Gsa: a gravitational search algorithm. Inf Sci 179(13):2232–2248
19. Erol OK, Eksin I (2006) A new optimization method: big bang-big crunch. Adv Eng Softw 37(2):106–111
20. Kaveh A, Motie Share Mohammad A, Moslehi M (2013) Magnetic charged system search: a new meta-heuristic algorithm for optimization. Acta Mech 224(1):85–107
21. Kaveh A, Khayatazad M (2012) A new meta-heuristic method: ray optimization. Comput Struct 112:283–294
22. Kaveh A, Mahdavi VR (2014) Colliding bodies optimization: a novel meta-heuristic method. Comput Struct 139:18–27
23. Abedinpourshotorban H, Shamsuddin SM, Beheshti Z, Jawawi DNA (2016) Electromagnetic field optimization: a physics-inspired metaheuristic optimization algorithm. Swarm Evol Comput 26:8–22
24. Wei Z, Huang C, Wang X, Han T, Li Y (2019) Nuclear reaction optimization: a novel and powerful physics-based algorithm for global optimization. IEEE Access 7:66084–66109
25. Kashan AH (2015) A new metaheuristic for optimization: optics inspired optimization (OIO). Comput Oper Res 55:99–125
26. Mirjalili S, Mirjalili SM, Hatamlou A (2016) Multi-verse optimizer: a nature-inspired algorithm for global optimization. Neural Comput Appl 27(2):495–513
27. Kaveh A, Dadras A (2017) A novel meta-heuristic optimization algorithm: thermal exchange optimization. Adv Eng Softw 110:69–84
28. Zamani H, Nadimi-Shahraki MH, Gandomi AH (2021) Qana: quantum-based avian navigation optimizer algorithm. Eng Appl Artif Intell 104:104314
29. Tzanetos A, Dounias G (2017) A new metaheuristic method for optimization: sonar inspired optimization. In: International conference on engineering applications of neural networks. Springer, pp 417–428
30. Kaveh A, Ilchi Ghazaan M (2017) A new meta-heuristic algorithm: vibrating particles system. Sci Iran Trans A, Civ Eng 24(2):551
31. Faramarzi A, Heidarinejad M, Stephens B, Mirjalili S (2020) Equilibrium optimizer: a novel optimization algorithm. Knowl-Based Syst 191:105190
32. Braik M, Al-Hiary H, Alzoubi H, Hammouri A, Al-Betar MA, Awadallah MA (2025) Tornado optimizer with coriolis force: a novel bio-inspired meta-heuristic algorithm for solving engineering problems. Artif Intell Rev 58(4):1–99
33. Hashim FA, Hussain K, Houssein EH, Mabrouk MS, Al-Atabany W (2021) Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems. Appl Intell 51:1531–1551
34. Alatas B (2011) Acroa: artificial chemical reaction optimization algorithm for global optimization. Expert Syst Appl 38(10):13170–13180

35. Lam AYS, Li VOK (2012) Chemical reaction optimization: a tutorial. Memet Comput 4:3–17
36. Irizarry R (2004) Lares: an artificial chemical process approach for optimization. Evol Comput 12(4):435–459
37. Kaveh A, Bakhshpoori T (2016) Water evaporation optimization: a novel physically inspired optimization algorithm. Comput Struct 167:69–85
38. Zhao W, Wang L, Zhang Z (2019) Atom search optimization and its application to solve a hydrogeologic parameter estimation problem. Knowl-Based Syst 163:283–304
39. Hashim FA, Houssein EH, Mabrouk MS, Al-Atabany W, Mirjalili S (2019) Henry gas solubility optimization: a novel physics-based algorithm. Fut Gener Comput Syst 101:646–667
40. Zhao J, Tang D, Liu Z, Cai Y, Dong S (2020) Spherical search optimizer: a simple yet efficient meta-heuristic approach. Neural Comput Appl 32:9777–9808
41. Rahmani R, Yusof R (2014) A new simple, fast and efficient algorithm for global optimization over continuous search-space problems: radial movement optimization. Appl Math Comput 248:287–300
42. Karami H, Sanjari MJ, Gharehpetian GB (2014) Hyper-spherical search (hss) algorithm: a novel meta-heuristic algorithm to optimize nonlinear functions. Neural Comput Appl 25(6):1455–1465
43. Salimi H (2015) Stochastic fractal search: a powerful metaheuristic algorithm. Knowl-Based Syst 75:1–18
44. Nematollahi AF, Rahiminejad A, Vahidi B (2020) A novel meta-heuristic optimization method based on golden ratio in nature. Soft Comput 24(2):1117–1151
45. Mirjalili S (2016) Sca: a sine cosine algorithm for solving optimization problems. Knowl-Based Syst 96:120–133
46. Gabis AB, Meraihi Y, Mirjalili S, Ramdane-Cherif A (2021) A comprehensive survey of sine cosine algorithm: variants and applications. Artif Intell Rev 54(7):5469–5540
47. Ahmadianfar I, Heidari AA, Gandomi AH, Chu X, Chen H (2021) Run beyond the metaphor: an efficient optimization algorithm based on Runge Kutta method. Expert Syst Appl 181:115079
48. Abualigah L, Diabat A, Mirjalili S, Elaziz MA, Gandomi AH (2021) The arithmetic optimization algorithm. Comput Methods Appl Mech Eng 376:113609
49. Yang X-S (2009) Harmony search as a metaheuristic algorithm. In: Music-inspired harmony search algorithm. Springer, pp 1–14
50. Atashpaz-Gargari E, Lucas C (2007) Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. In: 2007 IEEE congress on evolutionary computation. IEEE, pp 4661–4667
51. Dai C, Zhu Y, Chen W (2007) Seeker optimization algorithm. In: Computational intelligence and security: international conference, CIS 2006. Guangzhou, China, November 3–6, 2006. Revised Selected Papers. Springer, pp 167–176
52. Tan Y, Zhu Y (2010) Fireworks algorithm for optimization. In: International conference in swarm intelligence. Springer, pp 355–364
53. Venkata RR, Savsani Vimal J, Vakharia DP (2011) Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems. Comput Aided Des 43(3):303–315
54. Kashan AH (2014) League championship algorithm (LCA): an algorithm for global optimization inspired by sport championships. Appl Soft Comput 16:171–200
55. Shi Y (2011) Brain storm optimization algorithm. In: Advances in swarm intelligence: 2nd international conference, ICSI 2011, Chongqing, China, June 12–15, 2011, Proceedings, Part I 2. Springer, pp 303–309
56. Moosavian N, Roodsari BK (2014) Soccer league competition algorithm: a novel meta-heuristic algorithm for optimal design of water distribution networks. Swarm Evol Comput 17:14–24
57. Sadollah A, Bahreininejad A, Eskandar H, Hamdi M (2013) Mine blast algorithm: a new population based algorithm for solving constrained engineering optimization problems. Appl Soft Comput 13(5):2592–2612
58. Braik M, Ryalat MH, Al-Zoubi H (2022) A novel meta-heuristic algorithm for solving numerical optimization problems: Ali baba and the forty thieves. Neural Comput Appl 34(1):409–455
59. Askari Q, Younas I, Saeed M (2020) Political optimizer: a novel socio-inspired meta-heuristic for global optimization. Knowl-Based Syst 195:105709
60. Fadakar E, Ebrahimi M (2016) A new metaheuristic football game inspired algorithm. In: 2016 1st conference on swarm intelligence and evolutionary computation (CSIEC). IEEE, pp 6–11
61. Moosavi SH, Bardsiri VK (2019) Poor and rich optimization algorithm: a new human-based and multi populations algorithm. Eng Appl Artif Intell 86:165–181
62. Ghorbani N, Babaei E (2014) Exchange market algorithm. Appl soft Comput 19:177–187
63. Al-Betar MA, Alyasseri ZAA, Awadallah MA, Doush IA (2021) Coronavirus herd immunity optimizer (chio). Neural Comput Appl 33:5011–5042
64. Dorigo M, Di Caro G (1999) Ant colony optimization: a new meta-heuristic. In: Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406), vol 2. IEEE, pp 1470–1477
65. Kennedy J, Eberhart R (1995) Particle swarm optimization. In: Proceedings of ICNN'95-international conference on neural networks, vol 4. IEEE, pp 1942–1948
66. Yang X-S (2009) Firefly algorithms for multimodal optimization. In: International symposium on stochastic algorithms. Springer, pp 169–178
67. Yang X-S, Deb S (2009) Cuckoo search via lévy flights. In: 2009 World congress on nature & biologically inspired computing (NaBIC). IEEE, pp 210–214
68. Karaboga D (2010) Artificial bee colony algorithm. Scholarpedia 5(3):6915
69. Yang X-S, Gandomi AH (2012) Bat algorithm: a novel approach for global engineering optimization. Eng Comput 29(5):464–483
70. Dorigo M, Di Caro G (2012) Krill herd: a new bio-inspired optimization algorithm. Commun Nonlinear Sci Numer Simul 17(12):4831–4845
71. Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. Adv Eng Softw 69:46–61
72. Mirjalili S (2015) Moth-flame optimization algorithm: a novel nature-inspired heuristic paradigm. Knowl-Based Syst 89:228–249
73. Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67
74. Mirjalili S (2016) Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems. Neural Comput Appl 27(4):1053–1073
75. Meraihi Y, Ramdane-Cherif A, Acheli D, Mahseur M (2020) Dragonfly algorithm: a comprehensive review and applications. Neural Comput Appl 32:16625–16646
76. Askarzadeh A (2016) A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm. Comput Struct 169:1–12
77. Meraihi Y, Gabis AB, Ramdane-Cherif A, Acheli D (2021) A comprehensive survey of crow search algorithm and its applications. Artif Intell Rev 54(4):2669–2716
78. Mirjalili SZ, Mirjalili S, Saremi S, Faris H, Aljarah I (2018) Grasshopper optimization algorithm for multi-objective optimization problems. Appl Intell 48:805–820

79. Meraihi Y, Gabis AB, Mirjalili S, Ramdane-Cherif A (2021) Grasshopper optimization algorithm: theory, variants, and applications. IEEE Access 9:50001–50024
80. Wang G-G, Deb Suash, dos S Coelho Leandro (2015) Elephant herding optimization. In: 2015 3rd international symposium on computational and business intelligence (ISCBI). IEEE, pp 1–5
81. James JQ, Li VOK (2015) A social spider algorithm for global optimization. Appl Soft Comput 30:614–627
82. MiarNaeimi F, Azizyan G, Rashki M (2021) Horse herd optimization algorithm: a nature-inspired algorithm for high-dimensional optimization problems. Knowl-Based Syst 213:106711
83. Zervoudakis K, Tsafarakis S (2020) A mayfly optimization algorithm. Comput Ind Eng 145:106559
84. Pierezan J, Coelho LD (2018) Coyote optimization algorithm: a new metaheuristic for global optimization problems. In: 2018 IEEE congress on evolutionary computation (CEC). IEEE, pp 1–8
85. Meraihi Y, Gabis AB, Ramdane-Cherif A, Acheli D (2022) Advances in coyote optimization algorithm: variants and applications. In: Advances in computational intelligence and communication: selected papers from the 2nd EAI international conference on computational intelligence and communications (CICom 2021). Springer, pp 99–113
86. Mirjalili S (2015) The ant lion optimizer. Adv Eng Softw 83:80–98
87. Shadravan S, Naji HR, Bardsiri VK (2019) The sailfish optimizer: a novel nature-inspired metaheuristic algorithm for solving constrained engineering optimization problems. Eng Appl Artif Intell 80:20–34
88. Hashim FA, Houssein EH, Hussain K, Mabrouk MS, Al-Atabany W (2022) Honey badger algorithm: new metaheuristic algorithm for solving optimization problems. Math Comput Simul 192:84–110
89. Abdollahzadeh B, Gharehchopogh FS, Khodadadi N, Mirjalili S (2022) Mountain gazelle optimizer: a new nature-inspired metaheuristic algorithm for global optimization problems. Adv Eng Softw 174:103282
90. Braik M, Hammouri A, Atwan J, Al-Betar MA, Awadallah MA (2022) White shark optimizer: a novel bio-inspired metaheuristic algorithm for global optimization problems. Knowl-Based Syst 243:108457
91. Hashim FA, Hussien AG (2022) Snake optimizer: a novel meta-heuristic optimization algorithm. Knowl-Based Syst 242:108320
92. Abdollahzadeh B, Gharehchopogh FS, Mirjalili S (2021) African vultures optimization algorithm: a new nature-inspired metaheuristic algorithm for global optimization problems. Comput Ind Eng 158:107408
93. Mirjalili S, Gandomi AH, Mirjalili SZ, Saremi S, Faris H, Mirjalili SM (2017) Salp swarm algorithm: a bio-inspired optimizer for engineering design problems. Adv Eng Softw 114:163–191
94. Faramarzi A, Heidarinejad M, Mirjalili S, Gandomi AH (2020) Marine predators algorithm: a nature-inspired metaheuristic. Expert Syst Appl 152:113377
95. Li S, Chen H, Wang M, Heidari AA, Mirjalili S (2020) Slime mould algorithm: a new method for stochastic optimization. Fut Gener Comput Syst 111:300–323
96. Abdollahzadeh B, Gharehchopogh FS, Mirjalili S (2021) Artificial gorilla troops optimizer: a new nature-inspired metaheuristic algorithm for global optimization problems. Int J Intell Syst 36(10):5887–5958
97. Zamani H, Nadimi-Shahraki MH, Gandomi AH (2022) Starling murmuration optimizer: a novel bio-inspired algorithm for global and engineering optimization. Comput Methods Appl Mech Eng 392:114616
98. Heidari AA, Mirjalili S, Faris H, Aljarah I, Mafarja M, Chen H (2019) Harris hawks optimization: algorithm and applications. Fut Gener Comput Syst 97:849–872
99. Wang X (2025) Draco lizard optimizer: a novel metaheuristic algorithm for global optimization problems. Evol Intell 18(1):1–20
100. Wang X (2024) Artificial meerkat algorithm: a new metaheuristic algorithm for solving optimization problems. Phys Scr 99(12):125280
101. Wang X (2024) Eurasian lynx optimizer: a novel metaheuristic optimization algorithm for global optimization and engineering applications. Phys Scr 99(11):115275
102. Sang-To T, Le-Minh H, Wahab MA, Thanh C-L (2023) A new metaheuristic algorithm: shrimp and goby association search algorithm and its application for damage identification in large-scale and complex structures. Adv Eng Softw 176:103363
103. Ahmadi B, Giraldo JS, Hoogsteen G (2023) Dynamic hunting leadership optimization: algorithm and applications. J Comput Sci 69:102010
104. Minh H-L, Sang-To T, Theraulaz G, Wahab MA, Cuong-Le T (2023) Termite life cycle optimizer. Expert Syst Appl 213:119211
105. Zhou G, Wang D, Zhou G, Jiaxuan D, Guo J (2024) A rhinopithecus swarm optimization algorithm for complex optimization problem. Sci Rep 14(1):15628
106. Abualigah L, Yousri D, Elaziz MA, Ewees AA, Al-Qaness MAA, Gandomi AH (2021) Aquila optimizer: a novel meta-heuristic optimization algorithm. Comput Ind Eng 157:107250
107. Fatani A, Dahou A, Al-Qaness MAA, Songfeng L, Elaziz MA (2021) Advanced feature extraction and selection approach using deep learning and aquila optimizer for iot intrusion detection system. Sensors 22(1):140
108. Wang S, Jia H, Abualigah L, Liu Q, Zheng R (2021) An improved hybrid Aquila optimizer and Harris Hawks algorithm for solving industrial engineering optimization problems. Processes 9(9):1551
109. Mahajan S, Abualigah L, Pandit AK, Altalhi M (2022) Hybrid aquila optimizer with arithmetic optimization algorithm for global optimization tasks. Soft Comput 26(10):4863–4881
110. Elaziz MA, Dahou A, Alsaleh NA, Elsheikh AH, Saba AI, Ahmadein M (2021) Boosting covid-19 image classification using mobilenetv3 and aquila optimizer algorithm. Entropy 23(11):1383
111. AlRassas AM, Al-qaness MAA, Ewees AA, Ren S, Elaziz MA, Damaševičius R, Krilavičius T (2021) Optimized anfis model using aquila optimizer for oil production forecasting. Processes 9(7):1194
112. Zhang Y-J, Yan Y-X, Zhao J, Gao Z-M (2022) Aoaao: the hybrid algorithm of arithmetic optimization algorithm with aquila optimizer. IEEE Access 10:10907–10933
113. Ma C, Huang H, Fan Q, Wei J, Yiming D, Gao W (2022) Grey wolf optimizer based on aquila exploration method. Expert Syst Appl 205:117629
114. Ekinci S, Izci D, Eker E, Abualigah L (2023) An effective control design approach based on novel enhanced aquila optimizer for automatic voltage regulator. Artif Intell Rev 56(2):1731–1762
115. Nadimi-Shahraki MH, Taghian S, Mirjalili S, Abualigah L (2022) Binary aquila optimizer for selecting effective features from medical data: a covid-19 case study. Mathematics 10(11):1929
116. Sasmal B, Hussien AG, Das A, Dhal KG (2023) A comprehensive survey on aquila optimizer. Arch Comput Methods Eng 30(7):4449–4476
117. Youfa F, Liu D, Shengwei F, Chen J, He L (2024) Enhanced aquila optimizer based on tent chaotic mapping and new rules. Sci Rep 14(1):3013

118. Zhao J, Gao Z-M, Chen H-F (2022) The simplified aquila optimization algorithm. IEEE Access 10:22487–22515
119. Li L, Pan JS, Zhuang Z, Chu SC (2022) A novel feature selection algorithm based on aquila optimizer for covid-19 classification. In: International conference on intelligent information processing. Springer, pp 30–41
120. Abd Amr A, El-Mageed Amr A, Abohany AE (2023) Effective feature selection strategy for supervised classification based on an improved binary aquila optimization algorithm. Comput Ind Eng 181:109300
121. Yildizdan G, Bas E (2024) A new binary coati optimization algorithm for binary optimization problems. Neural Comput Appl 36(6):2797–2834
122. Alawad NA, Abed-alguni BH, Shakhatreh AM (2025) Ebao: an intrusion detection framework for wireless sensor networks using an enhanced binary aquila optimizer. Knowl-Based Syst 312:113156
123. Cavlak Y, Ateş A, Abualigah L, Elaziz MA (2023) Fractional-order chaotic oscillator-based aquila optimization algorithm for maximization of the chaotic with lLrentz oscillator. Neural Comput Appl 35(29):21645–21662
124. Kujur S, Dubey HM, Salkuti SR (2023) Demand response management of a residential microgrid using chaotic aquila optimization. Sustainability 15(2):1484
125. Guo H, Wang JG, Liu Y (2023) Multi-threshold image segmentation algorithm based on aquila optimization. Vis Comput 40(4):1–28
126. Turgut OE, Turgut MS, Kırtepe E (2024) Chaotic aquila optimization algorithm for solving phase equilibrium problems and parameter estimation of semi-empirical models. J Bionic Eng 21(1):486–526
127. Suqian W, Liu J, He B, Lin C, Yang J, Wei W (2025) An enhanced dv-hop localization algorithm based on hop distance correction and multi-strategy modified aquila optimizer in hwsns. Clust Comput 28(2):106
128. Cui H, Xiao Y, Hussien AG, Guo Y (2024) Multi-strategy boosted aquila optimizer for function optimization and engineering design problems. Clust Comput 27(6):1–52
129. Guo H, Wang J, Liu Y (2024) Multi-threshold image segmentation algorithm based on aquila optimization. Vis Comput 40(4):2905–2932
130. Gopi S, Mohapatra P (2024) Chaotic aquila optimization algorithm for solving global optimization and engineering problems. Alex Eng J 108:135–157
131. Gao B, Shi Y, Fengqiu X, Xianze X (2022) An improved aquila optimizer based on search control factor and mutations. Processes 10(8):1451
132. Pashaei E (2022) Mutation-based binary aquila optimizer for gene selection in cancer classification. Comput Biol Chem 101:107767
133. Zeng L, Li M, Shi J, Wang S (2023) Spiral aquila optimizer based on dynamic gaussian mutation: Applications in global optimization and engineering. Neural Process Lett 55(8):11653–11699
134. Pang Z, Yang B, Chen R, Zhang Z, Mo F (2023) A multi-phase scheduling method for reconfigurable flexible job-shops with multi-machine cooperation based on a scout and mutation-based aquila optimizer. CIRP J Manuf Sci Technol 46:116–134
135. Duan J, Zuo H, Bai Y, Chang M, Chen X, Wang W, Ma L, Chen B (2023) A multistep short-term solar radiation forecasting model using fully convolutional neural networks and chaotic aquila optimization combining wrf-solar model results. Energy 271:126980
136. Subha B, Jeyakumar V, Deepa SN (2024) Gaussian aquila optimizer based dual convolutional neural networks for identification and grading of osteoarthritis using knee joint images. Sci Rep 14(1):7225
137. Rouhi A, Pira E (2024) A surrogate model-based aquila optimizer for solving high-dimensional computationally expensive problems. J Comput Secur 11(1):1–18
138. Ni L, Li Y, Zhang L, Wang G (2024) A modified aquila optimizer with wide plant adaptability for the tuning of optimal fractional proportional-integral-derivative controller. Soft Comput 28(7):6269–6305
139. Li X, Mobayen S (2022) Optimal design of a pemfc-based combined cooling, heating and power system based on an improved version of aquila optimizer. Concurr Comput: Pract Exp 34(15):e6976
140. Mahdad B (2023) Towards sustainable integration of statcom and dgs based radial distribution systems using dynamic adaptive aquila optimizer. Process Integr Optim Sustain 7(1–2):381–405
141. Alkhalaf S, Alturise F, Bahaddad AA, Elamin BM, Elnaim SS, Abdel-Khalek S, Mansour RF (2023) Adaptive aquila optimizer with explainable artificial intelligence-enabled cancer diagnosis on medical imaging. Cancers 15(5):1492
142. Zhang Y, Xiping X, Zhang N, Zhang K, Dong W, Li X (2023) Adaptive aquila optimizer combining niche thought with dispersed chaotic swarm. Sensors 23(2):755
143. Guda S, Duggirala SR (2023) Adaptive aquila optimized relay selection and power allocation in cr-noma model. Comput Netw 232:109848
144. Al-Selwi SM, Hassan MF, Abdulkadir SJ, Ragab MG, Alqushaibi A, Sumiea EH (2024) Smart grid stability prediction using adaptive aquila optimizer and ensemble stacked bilstm. Results Eng 24:103261
145. Gul F, Mir I, Abualigah L (2024) Adaptive aquila optimizer for centralized mapping and exploration. Pattern Anal Appl 27(4):125
146. Chahal A, Gulia P, Gill NS, Sultana N (2024) Aquila optimizer-based hybrid predictive model for traffic congestion in an iot-enabled smart city. Int J Intell Syst 1:5577278
147. Tarek Z, Gafar M, Sarhan S, Shaheen AM, Alwakeel AS (2024) Integrating reconfigurable intelligent surface and modified aquila optimisation for enhancing wireless communication capacity. IEEE Internet of Things J 12(8):10012–10031
148. Wang S, Ma J, Li W, Khayatnezhad M, Rouyendegh BD (2022) An optimal configuration for hybrid sofc, gas turbine, and proton exchange membrane electrolyzer using a developed aquila optimizer. Int J Hydr Energy 47(14):8943–8955
149. Chaudhari SV, Dhipa M, Ayoub S, Gayathri B, Siva M, Banupriya V (2022) Modified aquila optimization based route planning model for unmanned aerial vehicles networks. In: 2022 international conference on automation, computing and renewable systems (ICACRS). IEEE, pp 370–375
150. Ramamoorthy R, Ranganathan R, Ramu S (2024) An improved aquila optimization with fuzzy model based energy efficient cluster routing protocol for wireless sensor networks. Yanbu J Eng Sci 19(1):51–61
151. Abualigah L, Ahmed SH, Almomani MH, Zitar RA, Alsoud AR, Abuhaija B, Hanandeh ES, Jia H, Elminaam DS, Elaziz MA (2024) Modified aquila optimizer feature selection approach and support vector machine classifier for intrusion detection system. Multimedia Tools Appl 83(21):1–27
152. Ma L, Li J, Zhao Y (2021) Population forecast of china's rural community based on cfangbm and improved aquila optimizer algorithm. Fractal Fract 5(4):190
153. Kandan M, Anbazhagan Krishnamurthy S, Selvi AM, Sikkandar MY, Aboamer MA, Tamilvizhi T (2022) Quasi oppositional aquila optimizer-based task scheduling approach in an iot enabled cloud environment. J Supercomput 78(7):10176–10190
154. Ali MH, Salawudeen AT, Kamel S, Salau HB, Habil M, Shouran M (2022) Single-and multi-objective modified aquila optimizer

for optimal multiple renewable energy resources in distribution network. Mathematics 10(12):2129
155. Al-qaness MAA, Ewees AA, Fan H, AlRassas AM, Elaziz MA (2022) Modified aquila optimizer for forecasting oil production. Geo-Spat Inf Sci 25(4):519–535
156. Huangjing Yu, Jia H, Zhou J, Hussien A (2022) Enhanced aquila optimizer algorithm for global optimization and constrained engineering problems. Math Biosci Eng 19(12):14173–14211
157. Hou X, Wang M (2022) and Jian Dong (2022) Antennas optimal design using opposition-based learning and altruistic aquila optimizer algorithm. In: IEEE MTT-S international wireless symposium (IWS) vol 1. IEEE, pp 1–3
158. Perumalla S, Chatterjee S, Kumar AS (2023) Modelling of oppositional aquila optimizer with machine learning enabled secure access control in internet of drones environment. Theor Comput Sci 941:39–54
159. Dhal KG, Rai R, Das A, Ray S, Ghosal D, Kanjilal R (2023) Chaotic fitness-dependent quasi-reflected aquila optimizer for superpixel based white blood cell segmentation. Neural Comput Appl 35(21):15315–15332
160. Wang Y, Zhang Y, Yan Y, Zhao J, Gao Z (2023) An enhanced aquila optimization algorithm with velocity-aided global search mechanism and adaptive opposition-based learning. Math Biosci Eng 20(4):6422–6467
161. Kumar R, Sharma SC (2023) Hybrid optimization and ontology-based semantic model for efficient text-based information retrieval. J Supercomput 79(2):2251–2280
162. Ekinci S, Izci D, Abualigah L, Zitar RA (2023) A modified oppositional chaotic local search strategy based aquila optimizer to design an effective controller for vehicle cruise control system. J Bionic Eng 20(4):1828–1851
163. Gopi S, Mohapatra P (2024) Fast random opposition-based learning aquila optimization algorithm. Heliyon 10(4):e26187
164. Guo H, Wang JG, Liu Y, Zhang Y (2024) Eao: enhanced aquila optimizer for solving optimization problem. J Intell Fuzzy Syst 46(2):1–20
165. Deng B (2024) Aquila optimizer with dynamic group strategy for global optimization tasks. Concurr Computn: Pract Exp 36(7):e7971
166. Zhang J, Gao Z, Li S, Zhao J (2025) An improved aquila optimizer with local escaping operator and its application in uav path planning. Recent Adv Comput Sci Commun 18(1):E250424229337
167. Al-qaness MA, Ewees AA, Thanh HV, AlRassas AM, Abd Elaziz M (2022) An optimized neuro-fuzzy system using advance nature-inspired aquila and salp swarm algorithms for smart predictive residual and solubility carbon trapping efficiency in underground storage formations. J Energy Storage 56:106150
168. Zahariah J et al (2024) Hybrid aquila arithmetic optimization based anfis for harmonic mitigation in grid connected solar fed distributed energy systems. Electr Power Syst Res 226:109898
169. Zhao J, Gao Z-M (2022) The heterogeneous aquila optimization algorithm. Math Biosci Eng 19:5867–5904
170. Li X, Ma Y, Li Y, Li H, Zuo H, Sun W (2022) Improved aquila optimizer optimization algorithm based on multi-strategy fusion. In: 2022 2nd international conference on computer science, electronic information engineering and intelligent control technology (CEI). IEEE, pp 757–760
171. Alangari S, Obayya M, Gaddah A, Yafoz A, Alsini R, Alghushairy O, Ashour A, Motwakel A (2022) Wavelet mutation with aquila optimization-based routing protocol for energy-aware wireless communication. Sensors 22(21):8508
172. Gul F, Mir I, Mir S (2023) Aquila optimizer with parallel computation application for efficient environment exploration. In: AIAA SCITECH 2023 Forum, p 1655
173. Zhang Y, Sun W, Hou J, Li Q (2023) Hybrid multi-strategy improvements for the aquila optimizer. In: 2023 IEEE intl conf on dependable, autonomic and secure computing, intl conf on pervasive intelligence and computing, intl conf on cloud and big data computing, intl conf on cyber science and technology congress (DASC/PiCom/CBDCom/CyberSciTech). IEEE, pp 0549–0556
174. Utama DM, Sanafa N et al (2023) A modified aquila optimizer algorithm for optimization energy-efficient no-idle permutation flow shop scheduling problem. J Sistem Manajemen Ind 7(2):95–115
175. Ekinci S, Izci D, Abualigah L (2023) A novel balanced aquila optimizer using random learning and nelder-mead simplex search mechanisms for air-fuel ratio system control. J Braz Soc Mech Sci Eng 45(1):68
176. Huang C, Huang J, Jia Y, Jiazhong X (2023) A hybrid aquila optimizer and its k-means clustering optimization. Trans Inst Meas Control 45(3):557–572
177. Kun H, Jiang H, Wang S, Li F (2023) Magnetic force prediction of hybrid magnet with halbach array using generalized regression neural network optimized by a modified aquila optimizer. Int J Appl Electromagnet Mech 71(1):21–44
178. Turgut OE, Turgut MS (2023) Local search enhanced aquila optimization algorithm ameliorated with an ensemble of wavelet mutation strategies for complex optimization problems. Math Comput Simul 206:302–374
179. Guo R, Yi J (2025) Improved aquila optimizer and its applications. Clust Comput 28(4):247
180. Liu X, Wang L, Ma Y, Shao P (2025) Collaborative trajectory planning for stereoscopic agricultural multi-uavs driven by the aquila optimizer. Comput, Mater Contin 82(1):1349–1376
181. Long H, Liu S, Chen T, Tan H, Wei J, Zhang C, Chen W (2022) Optimal reactive power dispatch based on multi-strategy improved aquila optimization algorithm. IAENG Int J Comput Sci 49(4):1249–1267
182. Ali MH, Salawudeen AT, Kamel S, Salau HB, Habil M, Shouran M (2022) Single-and multi-objective modified aquila optimizer for optimal multiple renewable energy resources in distribution network. Mathematics 10(12):2129
183. Nematollahi M, Ghaffari A, Mirzaei A (2024) Task offloading in internet of things based on the improved multi-objective aquila optimizer. SIViP 18(1):545–552
184. Eirgash MA, Togan V (2024) A dual opposition learning-based multi-objective aquila optimizer for trading-off time-cost-quality-co2 emissions of generalized construction projects. Eng Comput 41(8/9):2074–2101
185. Xia Y, Wang J, Zhang Z, Wei D, Cao Z, Li Z (2024) A wind speed point-interval fuzzy forecasting system based on data decomposition and multiobjective optimizer. Appl Soft Comput 165:112084
186. Verma M, Sreejeth M, Singh M, Babu TS, Alhelou HH (2022) Chaotic mapping based advanced aquila optimizer with single stage evolutionary algorithm. IEEE Access 10:89153–89169
187. Wang T-T, Chu S-C, Chia-Cheng H, Jia H-D, Pan J-S (2022) Efficient network architecture search using hybrid optimizer. Entropy 24(5):656
188. Utama DM, Primayesti MD (2022) A novel hybrid aquila optimizer for energy-efficient hybrid flow shop scheduling. Results Control Optim 9:100177
189. Ait-Saadi A, Meraihi Y, Soukane A, Ramdane-Cherif A, Gabis AB (2022) A novel hybrid chaotic aquila optimization algorithm

with simulated annealing for unmanned aerial vehicles path planning. Comput Electr Eng 104:108461
190. Alweshah M, Alessa M, Alkhalaileh S, Kassaymeh S, Abu-Salih B (2024) Hybrid aquila optimizer for efficient classification with probabilistic neural networks. Multiagent Grid Syst 20(1):41–68
191. Peng L, Zhang X, Li J, Ru X, Hu X (2024) Illumination correction of dyed fabrics method using the kernel extreme learning machine based on the improved aquila optimizer. Text Res J 00405175241269180
192. Abualigah L, Elaziz MA, Khodadadi N, Forestiero A, Jia H, Gandomi AH (2022) Aquila optimizer based pso swarm intelligence for iot task scheduling application in cloud computing. In: Integrating meta-heuristics and machine learning for real-world optimization problems. Springer, pp 481–497
193. Sasmal B, Das A, Dhal KG, Ray S (2023) Aquila-particle swarm based cooperative search optimizer with superpixel techniques for epithelial layer segmentation. Appl Soft Comput 149:110947
194. Song D, Yan J, Zeng H, Deng X, Yang J, Xilong Q, Rizk-Allah RM, Snášel V, Joo YH (2023) Topological optimization of an offshore-wind-farm power collection system based on a hybrid optimization methodology. J Mar Sci Eng 11(2):279
195. Liu X (2023) Hybrid integrated aquila optimizer for efficient service composition with quality of service guarantees in cloud computing. Int J Adv Comput Sci Appl 14(10):893–901
196. Suqian W, He B, Zhang J, Chen C, Yang J (2024) Psao: an enhanced aquila optimizer with particle swarm mechanism for engineering design and uav path planning problems. Alex Eng J 106:474–504
197. Hosseinzadeh M, Ionescu-Feleaga L, Ionescu B-S, Sadrishojaei M, Kazemian F, Rahmani AM, Khan F (2022) A hybrid delay aware clustered routing approach using aquila optimizer and firefly algorithm in internet of things. Mathematics 10(22):4331
198. Satyanarayana P, Diwakar G, Priyanka Brahmaiah V, Marlin S, Phani Sai Kumar NV, Gopalakrishnan S (2024) Multi-objective-derived efficient energy saving in multipath routing for mobile ad hoc networks with the modified aquila-firefly heuristic strategy. Eng Optim 1–36
199. Soni M, Sunil G, Rajesh N, Alsalami Z, Dutta P (2024) Firefly and aquila optimization based clustering and routing in iot assisted wireless sensor network. In: 2024 2nd international conference on networks, multimedia and information technology (NMITCON). IEEE, pp 1–5
200. Varshney M, Kumar P, Ali M, Gulzar Y (2024) Using the grey wolf aquila synergistic algorithm for design problems in structural engineering. Biomimetics 9(1):54
201. Ewees AA, Algamal ZY, Abualigah L, Al-qaness MAA, Yousri D, Ghoniem RM, Elaziz MA (2022) A cox proportional-hazards model based on an improved aquila optimizer with whale optimization algorithm operators. Mathematics 10(8):1273
202. Anup Kumar K, Vanmathi C (2022) Optimization driven model and segmentation network for skin cancer detection. Comput Electr Eng 103:108359
203. Bousmaha R (2022) A novel hybrid aquila optimizer with whale optimziation algorithm for global optimization, feature selection and optimizing svm parameters. In: 2022 4th international conference on pattern analysis and intelligent systems (PAIS). IEEE, pp 1–8
204. Singh JP, Gupta AK (2022) An optimized routing technique in wireless sensor network using aquila optimizer. Int J Intel Eng Syst 12(4):10–22266
205. Abualigah L, Almotairi KH (2022) Dynamic evolutionary data and text document clustering approach using improved aquila optimizer based arithmetic optimization algorithm and differential evolution. Neural Comput Appl 34(23):20939–20971
206. Kharrich M, Abualigah L, Kamel S, AbdEl-Sattar H, Tostado-Véliz M (2022) An improved arithmetic optimization algorithm for design of a microgrid with energy storage system: case study of El Kharga Oasis, Egypt. J Energy Storage 51:104343
207. Liu H, Zhang X, Zhang H, Li C, Chen Z (2023) A reinforcement learning-based hybrid aquila optimizer and improved arithmetic optimization algorithm for global optimization. Expert Syst Appl 224:119898
208. Sangeetha J et al (2023) A conceptual aquila merged arithmetic optimization (aiao) integrated auto-encoder based long short term memory (aue-lstm) for sentiment analysis. J Appl Eng Technol Sci (JAETS) 5(1):213–228
209. Ahmadipour M, Othman MM, Bo R, Javadi MS, Ridha HM, Alrifaey M (2024) Optimal power flow using a hybridization algorithm of arithmetic optimization and aquila optimizer. Expert Syst Appl 235:121212
210. Singla MK, Muhammed Ali SA, Kumar R, Jangir P, Khishe M, Gulothungan G, Mahmoud HA (2025) Revolutionizing proton exchange membrane fuel cell modeling through hybrid aquila optimizer and arithmetic algorithm optimization. Sci Rep 15(1):5122
211. Zhang YJ, Zhao J, Gao ZM (2022) Hybridized improvement of the chaotic harris hawk optimization algorithm and aquila optimizer. In: International conference on electronic information engineering and computer communication (EIECC 2021), vol 12172. SPIE, pp 327–332
212. Yao J, Sha Y, Chen Y, Zhang G, Xinyu H, Bai G, Liu J (2022) Ihssao: an improved hybrid salp swarm algorithm and aquila optimizer for UAV path planning in complex terrain. Appl Sci 12(11):5634
213. Xiao Y, Guo Y, Cui H, Wang Y, Li J, Zhang Y (2022) Ihaoavoa: an improved hybrid aquila optimizer and african vultures optimization algorithm for global optimization problems. Math Biosci Eng 19(11):10963–11017
214. Liu Q, Kosarirad H, Meisami S, Alnowibet KA, Hoshyar AN (2023) An optimal scheduling method in iot-fog-cloud network using combination of aquila optimizer and African vultures optimization. Processes 11(4):1162
215. Raghavender Reddy KL, Lathigara A, Aluvalu R, Viswanadhula UM (2023) Scheduling the tasks and balancing the loads in cloud computing using african vultures-aquila optimization model. In: International conference on intelligent computing and networking. Springer, pp 197–219
216. Thulasi V, Lakshmi P, Sangeetha S (2024) Design of hybrid optimized pi controller for power conditioning circuit of piezoelectric energy harvester. Meas Sci Technol 35(12):126114
217. Abd El-Mageed AA, Abohany AA, Ali AH, Hosny KM (2024) An adaptive hybrid African vultures-aquila optimizer with xgb-tree algorithm for fake news detection. J Big Data 11(1):41
218. Al-Qaness MAA, Ewees AA, Thanh HV, AlRassas AM, Dahou A, Elaziz MA (2023) Predicting co2 trapping in deep saline aquifers using optimized long short-term memory. Environ Sci Pollut Res 30(12):33780–33794
219. Al-qaness MAA, Ewees AA, Elaziz MA, Samak AH (2022) Wind power forecasting using optimized dendritic neural model based on seagull optimization algorithm and aquila optimizer. Energies 15(24):9261
220. Wang S, Jia H, Hussien AG, Abualigah L, Lin G, Wei H, Lin Z, Dhal KG (2024) Boosting aquila optimizer by marine predators algorithm for combinatorial optimization. J Comput Des Eng 11(2):37–69

221. Aribowo W, Suryoatmojo H, Pamuji FA (2024) Novel hybrid of marine predator algorithm-aquila optimizer for droop control in dc microgrid. Int J Electr Comput Eng 14(4):2088–8708
222. Nagapavithra S, Umamaheswari S (2023) Detection and classification of sugarcane billet damage using aquila sailfish optimizer based deep learning. Artif Intell Rev 56(Suppl 2):2183–2206
223. Natesan G, Konda S, de Prado RP, Wozniak M (2022) A hybrid mayfly-aquila optimization algorithm based energy-efficient clustering routing protocol for wireless sensor networks. Sensors 22(17):6405
224. Elaziz MA, Dahou A, El-Sappagh S, Mabrouk A, Gaber MM (2022) Aha-ao: artificial hummingbird algorithm with aquila optimization for efficient feature selection in medical image classification. Appl Sci 12(19):9710
225. Hamoodi YA, Mitras BA (2023) Improved chaotic aquila optimization algorithm based on artificial hummingbird algorithm. In: 2023 international conference on engineering, science and advanced technology (ICESAT). IEEE, pp 52–58
226. Zitouni F, Harous S, Lagrini S, Cheradid A, Guerfi S, Frihi FS (2023) Apdo: a hybrid aquila optimizer and prairie dog optimization metaheuristic algorithm for global, optimization. In: 2023 computer applications & technological solutions (CATS). IEEE, pp 1–6
227. Varshney M, Kumar P, Abualigah L (2024) Hybridizing remora and aquila optimizer with dynamic oppositional learning for structural engineering design problems. J Comput Appl Math 462:116475
228. Zhang Y, Yan Y, Zhao J, Gao Z (2021) Chaotic map enabled algorithm hybridizing hunger games search algorithm with aquila optimizer. In: ICMLCA 2021; 2nd international conference on machine learning and computer application. VDE, pp 1–5
229. Nirmalapriya G, Agalya V, Belsam RR, Ananth JM (2023) Fractional aquila spider monkey optimization based deep learning network for classification of brain tumor. Biomed Signal Process Control 79:104017
230. Mohamed AA, Abualigah L, Alburaikan A, Khalifa HA (2023) Aoeho: a new hybrid data replication method in fog computing for iot application. Sensors 23(4):2189
231. Gupta J, Pathak S, Kumar G (2022) Aquila coyote-tuned deep convolutional neural network for the classification of bare skinned images in websites. Int J Mach Learn Cybern 13(10):3239–3254
232. Akyol S (2023) A new hybrid method based on aquila optimizer and tangent search algorithm for global optimization. J Ambient Intell Hum Comput 14(6):8045–8065
233. Wang Y, Xiao Y, Guo Y, Li J (2022) Dynamic chaotic opposition-based learning-driven hybrid aquila optimizer and artificial rabbits optimization algorithm: framework and applications. Processes 10(12):2703
234. Rathod V, Tiwari A, Kakde OG (2022) Aquila-eagle-based deep convolutional neural network for speech recognition using eeg signals. Int J Swarm Intell Res (IJSIR) 13(1):1–28
235. Verma M, Sreejeth M, Singh M (2021) Application of hybrid metaheuristic technique to study influence of core material and core trench on performance of surface inset PMSM. Arab J Sci Eng 47:3037–3053
236. Gupta J, Pathak S, Kumar G (2022) A hybrid optimization-tuned deep convolutional neural network for bare skinned image classification in websites. Multimedia Tools Appl 81(18):26283–26305
237. Selim H, Haikal AY, Labib LM, Saafan MM (2024) Mchiao: a modified coronavirus herd immunity-aquila optimization algorithm based on chaotic behavior for solving engineering problems. Neural Comput Appl 36(22):13381–13465
238. Farahani MS, Babaei S, Kharazan ZS, Bai A, Rahmati Z, Ghasemi G, Alipour F, Farrokhi-Asl H (2024) Hybrid metaheuristic algorithm methods and econometric models in prediction of dogecoin price. J Model Manag
239. Nirmalapriya G, Maram B, Lakshmanan R, Navaneethakrishnan M (2023) Asca-squeeze net: Aquila sine cosine algorithm enabled hybrid deep learning networks for digital image forgery detection. Comput Secur 128:103155
240. Al-Majidi SD, Alturfi AM, Al-Nussairi MK, Hussein RA, Salgotra R, Abbod MF (2025) A robust automatic generation control system based on hybrid aquila optimizer-sine cosine algorithm. Results Eng 25:103951
241. Reddy S, Soma S (2025) Honey badger aquila optimization-based deep learning with multi-kernel shape index histograms for diabetic macular edema classification. Biomed Signal Process Control 100:106894
242. Hu G, Wang S, Houssein EH (2024) Multi-strategy hybrid coati optimizer: a case study of prediction of average daily electricity consumption in China. J Bionic Eng 21(5):1–29
243. Subba Reddy T, Harikiran J, Enduri MK, Hajarathaiah K, Almakdi S, Alshehri M, Naveed QN, Rahman MH (2022) Hyperspectral image classification with optimized compressed synergic deep convolution neural network with aquila optimization. Comput Intell Neurosci 2022:6781740
244. Obayya M, Hassine SBH, Alazwari S, Nour MK, Mohamed A, Motwakel A, Yaseen I, Zamani AS, Abdelmageed AA, Mohammed GP (2022) Aquila optimizer with bayesian neural network for breast cancer detection on ultrasound images. Appl Sci 12(17):8679
245. Jnr EO-N, Ziggah YY, Rodrigues MJ, Relvas S (2022) A hybrid chaotic-based discrete wavelet transform and aquila optimisation tuned-artificial neural network approach for wind speed prediction. Results Eng 14:100399
246. Namala Narasimhulu R, Naidu K, Falkowski-Gilski P, Divakarachari PB, Roy U (2022) Energy management for pv powered hybrid storage system in electric vehicles using artificial neural network and aquila optimizer algorithm. Energies 15(22):8540
247. Yousif NR, Balaha HM, Haikal AY, El-Gendy EM (2023) A generic optimization and learning framework for Parkinson disease via speech and handwritten records. J Ambient Intell Hum Comput 14(8):10673–10693
248. Amudha V, Vidhya Lakshmi S et al (2023) Automated groundwater quality index classification using adaptive aquila optimizer with deep learning. In: 2023 4th international conference on smart electronics and communication (ICOSEC). IEEE, pp 1063–1069
249. Mhmood AA, Ergül Ö, Rahebi J (2023) Detection of cyber-attacks on smart grids using improved vgg19 deep neural network architecture and aquila optimizer algorithm. Signal, Image Video Process 18(2):1–15
250. Lu J, Singh V, Singh S, Kumar A, Pandey S, Verma DK, Kaushik VD (2023) Predicting student performance with adaptive aquila optimization-based deep convolution neural network 82(11):1152–1164
251. Balaha HM, Antar ER, Saafan MM, El-Gendy EM (2023) A comprehensive framework towards segmenting and classifying breast cancer patients using deep learning and aquila optimizer. J Ambient Intell Hum Comput 14(6):7897–7917
252. Alahmari S, Yonbawi S, Suneetha Racharla E, Lydia L, Ishak MK, Alkahtani HK, Aljarbouh A, Mostafa SM (2023) Hybrid multi-strategy aquila optimization with deep learning driven crop type classification on hyperspectral images. Comput Syst Sci Eng 47(1):375–391
253. Qiao X, Peng T, Sun N, Zhang C, Liu Q, Zhang Y, Wang Y, Nazir MS (2023) Metaheuristic evolutionary deep learning model based on temporal convolutional network, improved aquila

optimizer and random forest for rainfall-runoff simulation and multi-step runoff prediction. Expert Syst Appl 229:120616
254. Barfungpa SP, Sarma HKD, Samantaray L (2023) An intelligent heart disease prediction system using hybrid deep dense aquila network. Biomed Signal Process Control 84:104742
255. Honnashamaiah A, Rathnakara S (2023) ECG signal classification using CNN & LSTM with aquila optimization technique. Tuijin Jishu/J Propuls Technol ISSN 44:1001–4055
256. Ayshwarya B, Logeswari T, Divyashree D, Suhaas KP (2024) Hybrid neural network method using aquila optimization algorithm for detection of lung cancer in ct images. SN Comput Sci 5(7):903
257. Panda A (2024) Digital channel equalizer using functional link artificial neural network trained with quantum aquila optimizer. SN Comput Sci 5(4):326
258. Soundararajan S, Tapas Bapu BR, Sargunavathi S, Poonguzhali I (2024) Self-attention based generative adversarial network with aquila optimization algorithm espoused energy aware cluster head selection in WSN. Int J Commun Syst 37(5):e5690
259. Luo X, Cai C, Zhao H (2024) Study on the evolutionary characteristics of spatial and temporal patterns and decoupling effect of urban carbon emissions in the yangtze river delta region based on neural network optimized by aquila optimizer with nighttime light data. Land 14(1):51
260. Li Z, Wang Q, Zhu B, Wang B, Zhu W, Dai Y (2022) Thermal error modeling of high-speed electric spindle based on aquila optimizer optimized least squares support vector machine. Case Stud Therm Eng 39:102432
261. Ajay V, Praveen Kumar Reddy Burla, Rajendra Tarale Pratik et al (2022) An aquila-optimized svm classifier for diabetes prediction. In: 2022 international conference on artificial intelligence and data engineering (AIDE). IEEE, pp 29–34
262. Dele-Afolabi TT, Masoud Ahmadipour MA, Azmah Hanim AA, Oyekanmi MA, Sikiru S, Kumar N (2024) Performance assessment of sn-based lead-free solder composite joints based on extreme learning machine model tuned by aquila optimizer. J Alloy Compd 970:172684
263. Duhayyim MA, Alabdulkreem E, Tarmissi K, Aljebreen M, Khier BSIAE, Zamani AS, Yaseen I, Eldesouki MI (2022) Aquila optimization with transfer learning based crowd density analysis for sustainable smart cities. Appl Sci 12(21):11187
264. Mumenin KM, Prapti Biswas Md, Khan A-M, Alammary AS, Nahid A-A (2023) A modified aquila-based optimized xgboost framework for detecting probable seizure status in neonates. Sensors 23(16):7037
265. Ramachandran A, Gayathri K, Alkhayyat A, Malik RQ (2023) Aquila optimization with machine learning-based anomaly detection technique in cyber-physical systems. Comput Syst Sci Eng 46(2):2177–2194
266. Ma J, Wang X (2021) Compound fault diagnosis of rolling bearing based on acmd, gini index fusion and ao-lstm. Symmetry 13(12):2386
267. Grace M, Sughasiny M (2022) Malware detection for android application using aquila optimizer and hybrid lstm-svm classifier. EAI Endorsed Trans Scalab Inf Syst 10(1):1–11
268. Almasoud Ahmed S, Alshahrani Hala J, Hassan Abdulkhaleq QA, Sharaf AN, Abdelwahed M (2023) Modified aquila optimizer with stacked deep learning-based sentiment analysis of covid-19 tweets. Electronics 12(19):4125
269. Li L, Li Y (2023) Research on a photovoltaic power prediction model based on an iao-lstm optimization algorithm. Processes 11(7):1957
270. Adnan RM, Mo W, Ewees AA, Heddam S, Kisi O, Zounemat-Kermani M (2024) Enhancing streamflow prediction accuracy: a comprehensive analysis of hybrid neural network models with Runge-Kutta with aquila optimizer. Int J Comput Intell Syst 17(1):1–23
271. Sherin A, Jasmine SelvakumariJeya I, Deepa SN (2024) Enhanced aquila optimizer combined ensemble bi-lstm-gru with fuzzy emotion extractor for tweet sentiment analysis and classification. IEEE Access 12:141932–141951
272. Ge Z, Wang H (2023) Integrated optimization of blocking flowshop scheduling and preventive maintenance using a q-learning-based aquila optimizer. Symmetry 15(8):1600
273. Jamazi C, Manita G, Chhabra A, Manita H, Korbaa O (2024) Mutated aquila optimizer for assisting brain tumor segmentation. Biomed Signal Process Control 88:105089
274. Ren Y, Xia L, Wang Y (2024) An improved gm (1, 1) forecasting model based on aquila optimizer for wind power generation in sichuan province. Soft Comput 28(15):8785–8805
275. Singh JP, Gupta AK (2022) Energy aware cluster head selection and multipath routing using whale-based tunicate swarm algorithm (wtsa) for wireless sensor network. New Rev Inf Netw 27(1):1–29
276. Taha AA, Abouroumia HO, Mohamed SA, Amar LA (2022) Enhancing the lifetime and energy efficiency of wireless sensor networks using aquila optimizer algorithm. Fut Int 14(12):365
277. Yang Fan, Ding Mingzhu (2022) An improved dv-hop algorithm using hop distance correction and aquila optimization. In: 2022 international conference on artificial intelligence and computer information technology (AICIT). IEEE, pp 1–4
278. Agarwal N, Gokilavani M, Nagarajan S, Saranya S, Alsolai H, Dhahbi S, Abdelaziz AS (2023) Intelligent aquila optimization algorithm-based node localization scheme for wireless sensor networks. Comput, Mater Contin 74(1):141–152
279. Hemavathi S, Latha B (2023) Hflfo: hybrid fuzzy levy flight optimization for improving qos in wireless sensor network. Ad Hoc Netw 142:103110
280. Abualkishik AZ, Alwan AA et al (2022) Trust aware aquila optimizer based secure data transmission for information management in wireless sensor networks. J Cybersecur Inf Manag 9(1):40–51
281. Rajinikanth V, Aslam SM, Kadry S, Thinnukool O (2022) Semi/fully-automated segmentation of gastric-polyp using aquila-optimization-algorithm enhanced images. CMC-Comput Mater Contin 70:4087–4105
282. Sonthi VK, Nagarajan S, Krishnaraj N (2021) Automated telugu printed and handwritten character recognition in single image using aquila optimizer based deep learning model. Int J Adv Comput Sci Appl 12(12):597–604
283. Nguyen H, Hoang N-D (2022) Computer vision-based classification of concrete spall severity using metaheuristic-optimized extreme gradient boosting machine and deep convolutional neural network. Autom Constr 140:104371
284. Shankar K, Kumar S, Dutta AK, Alkhayyat A, Jawad AJM, Abbas AH, Yousif YK (2022) An automated hyperparameter tuning recurrent neural network model for fruit classification. Mathematics 10(13):2358
285. Balaha HM, Shaban AO, El-Gendy EM, Saafan MM (2024) Prostate cancer grading framework based on deep transfer learning and aquila optimizer. Neural Comput Appl 36(14):7877–7902
286. Khamees AK, Abdelaziz AY, Ali ZM, Alharthi MM, Ghoneim SSM, Eskaros MR, Attia MA (2022) Mixture probability distribution functions using novel metaheuristic method in wind speed modeling. Ain Shams Eng J 13(3):101613
287. Li W, Zhang S, Can L (2022) Exploration of China's net co2 emissions evolutionary pathways by 2060 in the context of carbon neutrality. Sci Total Environ 831:154909
288. Guan F, Yang Z, Zhang X, Huang J (2022) Motorized buoy path following based on improved los algorithm and aquila optimizer

algorithm. In: 2022 IEEE international conference on mechatronics and automation (ICMA). IEEE, pp 376–381
289. Aarthi B, Chelliah BJ (2022) Deep recurrent neural network-based aquila optimization-based online shaming emotion analysis. Concurr Comput: Pract Exp 34(11):e6882
290. Karmouni H, Chouiekh M, Motahhir S, Dagal I, Oufettoul H, Qjidaa H, Sayyouri M (2022) A novel mppt algorithm based on aquila optimizer under PSC and implementation using raspberry. In: 2022 11th international conference on renewable energy research and application (ICRERA). IEEE, pp 446–451
291. Nematollahi M, Ghaffari A, Mirzaei A (2023) Task offloading in internet of things based on the improved multi-objective aquila optimizer. Signal, Image Video Process 18(1):1–8
292. Wenchao R, Zhang L, Liu D, Sun N, Li M, Faiz MA, Li T, Cui S, Khan MI (2024) New approach for regional water-energy-food nexus security assessment: enhancing the random forest model with the aquila optimizer algorithm. Agric Water Manag 301:108946
293. Zhong J, Liu Z, Bi X (2024) Partial discharge signal denoising algorithm based on aquila optimizer-variational mode decomposition and k-singular value decomposition. Appl Sci 14(7):2755
294. Muhammad Swaileh A, Alzaidi AA, Hassan AQA, Ebad SA, Sultan HA, Alliheedi MA, Aljubailan AA, Alzahrani KA (2025) Enhanced automated text categorization via aquila optimizer with deep learning for arabic news articles. Ain Shams Eng J 16(1):103189
295. Wang X, Fan J, Deng S, Zhengxing W, Zhou C, Yaming O, Han Y (2022) An underwater structured light vision calibration method considering unknown refractive index based on aquila optimizer. IEEE Trans Instrum Meas 72:1–12
296. Aribowo W, Suryoatmojo H, Pamuji FA (2022) Optimalization droop control based on aquila optimizer algorithm for dc microgrid. In: 2022 international seminar on intelligent technology and its applications (ISITIA). IEEE, pp 460–465
297. Mehmood K, Chaudhary NI, Khan ZA, Raja MAZ, Cheema KM, Milyani AH (2022) Design of aquila optimization heuristic for identification of control autoregressive systems. Mathematics 10(10):1749
298. Abou El-Ela Adel A, El-Sehiemy Ragab A, Shaheen Abdullah M, Shalaby Ayman S (2022) Aquila optimization algorithm for wind energy potential assessment relying on weibull parameters estimation. Wind 2(4):617–635
299. Korich B, Bakria D, Gozim D, Mohammedi RD, Elbar M, Teta A (2023) Shifting of nonlinear phenomenon in the boost converter using aquila optimizer. J Eng Exact Sci 9(3):15744–01e
300. Bankole AT, Bello-Salau H, Haruna Z (2023) Aquila-based model predictive control of an adapted fridge display case model for vaccine preservation. Eng Proc 37(1):99
301. Ren L, Wang D, Zhang Y (2024) Optimal control of fsbb converter with aquila optimizer-based pid controller. Micromachines 15(10):1277
302. Gupta DK, Dei G, Soni AK, Jha AV, Appasani B, Bizon N, Srinivasulu A (2024) Fractional order pid controller for load frequency control in a deregulated hybrid power system using aquila optimization. Results Eng 23:102442
303. Aljumah AS, Alqahtani MH, Shaheen AM, Elsayed AM (2024) Enhanced aquilla optimizer for economic environmental dispatch with cubic fuel cost and emission models. IEEE Access 12:135929–135960
304. Huang H, Li H, Wang M, Wu Y, He X (2022) Multi-uav cooperative path planning based on aquila optimizer. In: International conference on autonomous unmanned systems. Springer, pp 2005–2014
305. Bao T, Zhao J, Liu Y, Guo X, Chen T (2024) Mixed multi-strategy improved aquila optimizer and its application in path planning. Mathematics 12(23):3818
306. Chowdhury A, Roy R, Mandal KK (2024) Enhancement of technical, economic & environmental benefits in multi-point pv & wind-based dg integrated radial distribution network using aquila optimizer. Expert Syst Appl 252:124307
307. Khamees AK, Abdelaziz AY, Eskaros MR, El-Shahat A, Attia MA (2021) Optimal power flow solution of wind-integrated power system using novel metaheuristic method. Energies 14(19):6117
308. Sharma H, Arora K, Mahajan R, Ansarullah SI, Amin F, AlSalman H (2024) Improved aquila optimizer for swarm-based solutions to complex engineering problems. Sci Rep 14(1):30714
309. Varshney M, Kumar P, Ali M, Gulzar Y (2024) Dynamic random walk and dynamic opposition learning for improving aquila optimizer: solving constrained engineering design problems. Biomimetics 9(4):215
310. Mohamed A, Salah M, Eldefrawi M (2024) Code quality improvement using aquila optimizer. J Softw: Evolut Process 36(4):e2559
311. Zhou Y, Chen Z, Gong Z, Chen P, Razmjooy S (2024) The improved aquila optimization approach for cost-effective design of hybrid renewable energy systems. Heliyon 10(6):e27281
312. Nkc H, Inkollu SR, Patil R, Janamala V (2022) Aquila optimizer based optimal allocation of soft open points for multi objective operation in electric vehicles integrated active distribution networks. Int J Intell Eng Syst 15(4):269–278
313. Samal P, Panigrahy D (2023) A novel technique based on aquila optimiser algorithm for optimal integration of distributed generations in the distribution system. Process Integr Optim Sustain 7(1–2):127–136
314. Rawandale Ujjwala S, Ganorkar Sanjay R, Kolte Mahesh T (2023) Aquila based adaptive filtering for hearing aid with optimized performance. Int J Intell Eng Syst 16(3):151–161
315. Hussan MR, Sarwar MI, Sarwar A, Tariq M, Ahmad S, Mohamed ASN, Khan IA, Khan MMA (2022) Aquila optimization based harmonic elimination in a modified h-bridge inverter. Sustainability 14(2):929
316. Xing Q, Wang J, Haiyan L, Wang S (2022) Research of a novel short-term wind forecasting system based on multi-objective aquila optimizer for point and interval forecast. Energy Convers Manage 263:115583
317. Utama DM, Rubiyanti S, Wardana RW (2023) Optimization multi-item lot sizing model involve transportation and capacity constraint under stochastic demand using aquila optimizer. J Tekn Ind 24(1):31–50
318. Liu C, Zhen J (2023) Diagonal loading beamforming based on aquila optimizer. IEEE Access 11:69091–69100
319. Badhe N, Neve RP, Yele VP, Abhang S, Dhule KM, Mali D. An optimized system for predicting energy usage in smart grids using temporal fusion transformer and aquila optimizer. Front Artif Intell 8:1542320
320. Baş E (2023) Binary aquila optimizer for 0–1 knapsack problems. Eng Appl Artif Intell 118:105592
321. Jamei M, Karbasi M, Malik A, Abualigah L, Abu Reza Md, Islam T, Yaseen ZM (2022) Computational assessment of groundwater salinity distribution within coastal multi-aquifers of bangladesh. Sci Rep 12(1):11165
322. Maaram KK, Chandre S (2024) Aquila optimizer based arithmetic optimization algorithm using feature selection for alzheimer's disease classification. Int J Intell Eng Syst 17(6):1136–1148

323. Aribowo W, Supari S, Suprianto B (2022) Optimization of pid parameters for controlling dc motor based on the aquila optimizer algorithm. Int J Power Electron Drive Syst 13(1):216
324. Guo Z, Yang B, Han Y, He T, He P, Meng X, He X (2022) Optimal pid tuning of pll for pv inverter based on aquila optimizer. Front Energy Res 9:812467