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TOPICAL REVIEW

A Systematic Review of Wind Driven Optimization Algorithms and Their Variants

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ABSTRACT Wind Driven Optimization (WDO) Algorithm is a novel metaheuristic algorithm inspired by the continuous flow of air resulting from differences in air pressure until the air reaches a state of pressure balance. Owing to its simple structure, few parameters, intuitive nature, and straightforward programming, WDO has garnered increasing attention from scholars since its inception. WDO's novelty lies in its utilization of aerodynamic principles to orchestrate the search process, WDO draws on the dynamics of wind and atmospheric pressure differences to propel the search for optimal solutions. However, WDO has limitations such as sensitivity to algorithm parameters and premature convergence. Consequently, various WDO variants have been proposed to overcome the limitations of the original WDO. To identify potential avenues for further research and to develop WDO for future investigation. This article systematically reviews WDO and its variants from multiple perspectives. Initially, the principle of WDO is outlined. Subsequently, the impact of modifications to the WDO on its overall effectiveness is investigated. Furthermore, the distinctive characteristics of WDO variants and their practical applications are analyzed. Moreover, the conclusions of the review are summarized, and future research directions for WDO variants and their applications are described.

INDEX TERMS Wind driven optimization, metaheuristic algorithm, optimization, convergence, algorithm.

I. INTRODUCTION

Optimization is a foundational discipline within mathematics, which revolves around the task of identifying the most favorable solution from a given set of feasible solutions. It has broad applications across various disciplines, such as engineering design and maintenance [1], finance [2], [3], business [4], economics [5], [6] and computer science [7].

There are two broad categories of optimization methods, which are deterministic optimization and stochastic optimization [8]. Specifically, deterministic optimization is relatively more mature, but engineering conditions are often demanding, and it is difficult to handle large-scale problems, which has led to the rapid development of metaheuristic optimization algorithms. As a result, metaheuristic algorithms have attracted considerable attention from researchers [9], [10], [11], [12]. These algorithms derive inspiration from the behavior observed in biological or physical systems in nature [13], they represent advanced and versatile strategies for conducting searches, capable of effectively addressing specific optimization problems [14]. The two most predominant and successful classes or directions in bio-inspired algorithms involve evolutionary-based methods and swarm-based methods, which are inspired by natural evolution and collective behavior in animals, respectively. However, this has been further refined to classify

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algorithms based on their specific area of inspiration from nature, thereby enhancing a broader perspective within the domain, they are broadly classified into three categories: ecology-based methods, evolutionary-based methods, and swarm-based methods [15].

Natural ecosystems offer a rich array of mechanisms that can inspire and inform the design and resolution of challenging problems in engineering and computer science. These systems include both living organisms and the non-living components of their environment, such as air, soil, and water, with which they interact. The interactions within these ecosystems can be intricate and diverse, occurring both between different species and within the same species. The nature of these interactions can range from cooperative to competitive, adding layers of complexity to the dynamics of ecosystems. Ecology-based methods are based on the methodology proposed in natural ecosystems. Ecology-based methods include Biogeography-Based Optimization(BBO) [16], Invasive Weed Colony Optimization(IWCO) [17], Flower Pollination Algorithm(FPA) [18], Turbulent Flow of Water-based Optimization(TFWO) [19], Wild Geese Algorithm(WGA) [20], Circulatory System Based Optimization (CSBO) [21], Ivy algorithm (IVYA) [22], Lung performance-based optimization (LPO) [23], and others.

Evolutionary-based methods are grounded in the principles of biological evolution, which have shaped the design of all living beings on Earth, as well as the strategies they employ to interact with one another. In evolutionary-based methods, organisms evolve mainly through selection and mutation, with popular algorithms including Genetic Algorithm (GA) [24], Paddy Field Algorithm (PFA) [25], and Differential Evolution(DE) [26], Harmony search algorithm (HSA) [27].

Swarm-based methods represent a recent and emerging paradigm in bio-inspired computing, employed for implementing adaptive systems. Swarm-based methods the utilization of collective intelligence exhibited by groups of simple agents, drawing inspiration from the behavior of real-world insect swarms, as a problem-solving tool. Well-known examples include Particle Swarm Optimization (PSO) [28], [29], [30], Shuffled Frog Leaping Algorithm(SFLA) [31], [32], Cuckoo Search (CS) [33], [34], [35], [36], [37], [38], Bat algorithm(BA) [39], Dragonfly Algorithm(DA) [40], Sparrow Search Algorithm(SSA) [41], and others. The details are revealed, as shown in Figure 1. WDO has demonstrated successful applications in real-world engineering optimization problems, particularly in domains such as electromagnetic devices [42], photovoltaic power generation systems [43], reservoir operation [44], segmentation and extraction of a carotid ultrasound image in medicine [45], the path planning of mobile robot [46], among others, and it has demonstrated remarkable results. It demonstrates exceptional practicability throughout the research and experimental processes, which can be implemented in any domain and application that uses GA, PSO or any evolutionary strategy [47]. WDO has some unique advantages: (1) Clear physical significance: The update equations of WDO are based on the simulation of a simplified model of the forceful motion of an air mass. It combines Newton's second law and the ideal gas equation of state to derive the update equations for the velocity and position of the air mass at each iteration, which makes the algorithm physically meaningful. (2) Strong global search capability: WDO automatically compensates for atmospheric pressure imbalances by modeling atmospheric flow. It can effectively explore the potential optimal solution in the search space and has a faster convergence speed. (3) Easy to understand and implement: WDO has a clear concept and is easy to understand and implement [44], [48], it also has high search accuracy [49], and it does not require complex parameter settings. Since its inception, WDO has garnered considerable scholarly attention and rapidly developed and applied recently [50].

Ezugwu et al. [51] compiled a comprehensive table of 209 metaheuristic algorithms, documented in the literature as of 2021, categorized by their respective impact factors. This data reveals that WDO possesses an impact factor of 83, placing it 97_{th} in the ranking. PSO possesses an impact factor of 14588, placing it 3rd in the ranking. However, in contrast to the PSO, WDO has actual physical significance. WDO, as its name implies, is inspired by the dynamics of wind, specifically the movement of air parcels within the Earth's atmosphere. This natural phenomenon has been effectively translated into a computational model designed to navigate the search space in optimization problems. Analogous to the PSO approach, WDO conceptualizes air parcels as particles, each characterized by a position vector and a velocity vector. These particles are engaged in an iterative optimization process, during which their velocities and positions are continuously updated. A key distinction between WDO and PSO lies in the specific equation governing the update of the particles' velocities. In WDO, this equation is meticulously derived from a physical model that accurately reflects the dynamics of wind movement. This differentiation not only underscores the unique nature of WDO but also enhances its capability to effectively mimic the complex patterns of air movement in solving optimization problems. The integration of such physical principles into the algorithm's core design is a testament to its innovative approach in the realm of computational optimization. The potential lies in refining the abstraction of its foundational physical model, which could significantly enhance its capability to devise more effective search strategies [52]. Therefore, WDO has potential for further in-depth research and study.

One of the highlights of WDO is the process of generating new solutions, i.e., the population-based solution construction method, where new solutions are constructed by stochastic operations to avoid being trapped in local optima, which improves the construction of high-quality solutions across the population [53]. WDO, compared to other heuristic algorithms such as GA and PSO, can implement constraints within the search area, in WDO, air particles

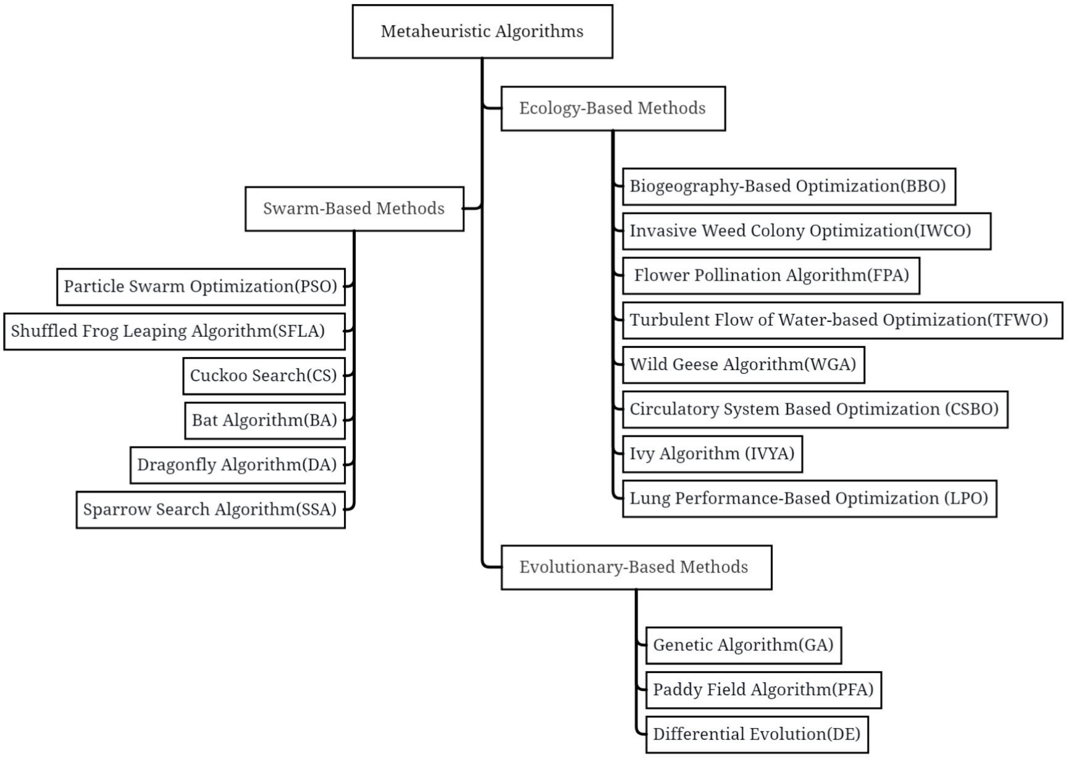

FIGURE 1. Different metaheuristic algorithms.

are characterized by their position and velocity, which correspond to a candidate solution and the degree of position displacement, respectively. However, WDO distinguishes itself by incorporating additional elements in the velocity update equation, notably gravitational and Coriolis forces. The gravitational force acts as a beneficial perturbation, assisting air particles in avoiding prolonged entrapment at the search space's boundaries and aiding in their reintegration into the search area. Conversely, the Coriolis force uniquely influences a specific dimension of an air particle based on a different dimension of another member within the population. WDO is like other natural heuristics, but WDO's code is simpler and easier to run than the other algorithms, and it requires fewer control variables to be adjusted [54].

WDO was initially introduced by Bayraktar et al. in 2010. The algorithm draws inspiration from the dynamic airflow patterns observed on earth, which arise from variations in air pressure and gradually tend towards equilibrium. WDO is an efficient population-based iterative metaheuristic global optimization algorithm [55], [56]. Although it is comparatively simple to implement, in contrast to other nature-inspired optimization algorithms, it is not exempt from limitations. One such limitation is its increased vulnerability to premature convergence when confronted with complex optimization problems [42], [57], and its accuracy is relatively low [58], [59]. Additionally, the no free lunch theorem [60], implies that a metaheuristic algorithm cannot solve all optimization problems [48], [61]. Given these limitations, the literature has introduced several variants of WDO to enhance its performance and mitigate its shortcomings. These variants have been applied in different fields and have yielded better results. For instance, some variants of WDO have focused on enhancing the algorithm's parameters, while others have aimed to hybrid WDO with other metaheuristic algorithms to improve its performance.

II. RESEARCH METHODOLOGY

Derived from the principal objective of the literature review, the research questions are elucidated in Table 1.

To ameliorate potential research bias and elevate the academic robustness of the research methodology this section articulates the review protocol, encompassing critical components such as the search strategy, paper selection criteria, and related methodologies.

A. SEARCH STRATEGY FOR THE PRIMARY STUDY

Six scientific databases were meticulously chosen as the primary resources for comprehensive exploration, and their details are elucidated in Table 2. The delineation of search terms is as follows:(1) WDO, (2) WDO variant, (3) improved WDO, (4) WDO parameter improvement, (5) hybrid WDO, (6) adaptive WDO, (7) binary WDO, (8) real-world applications of WDO, (9) theoretical applications of WDO, and (10) review of WDO.

TABLE 1. Research questions for the literature review.

RQ1: What are the fundamental principles and characteristics of WDO?
RQ2: What are the main limitations and shortcomings of the basic WDO in solving optimization problems?
RQ3: How have researchers proposed improvements and variants to address the limitations of the basic WDO?
RQ4: What are the key parameters and mechanisms that have been modified or introduced in the improved variants of WDO?
RQ5: How to verify the validity of WDO variants?
RQ6: What are the real-world applications and domains where WDO and its variants have been successfully applied?
RQ7: How do the improved variants of WDO compare to the basic algorithm and other metaheuristic algorithms in terms of performance and convergence?
RQ8: What can be discovered from cited papers?
RQ9: What are the future research directions and potential areas for further improvement and application of WDO and its variants?

TABLE 2. Resource of reviewed articles.

Scientific Source	Uniform resource location
ACM	https://dl.acm.org
IEEE	https://ieeexplore.ieee.org
SCOPUS	https://www.scopus.com
Science direct	http://www.sciencedirect.com
Springer	https://www.springer.com
Wiley Online Library	https://onlinelibrary.wiley.com

B. PAPER SELECTION CRITERIA

In addressing the extensive corpus of research on WDO, this paper employs a targeted selection criterion, adhering to the methodological guidelines delineated in [62] and [63]. The primary sources for this literature review are ACM, IEEE, SCOPUS, Science direct, springer and Wiley Online Library, with a focus on a comprehensive range of search keywords. The range of publication years was determined to be from 2010 to 2023, including both conference and journal papers. From the preliminary search, a huge number of research papers were found. The distribution of papers within the database is succinctly outlined in Table 3.

The quality of the papers was assessed based on the title, abstract, introduction, experiments and results as delineated in Table 4.

The key contributions of this review article are summarized as follows:

1. A thorough and critical examination of WDO and its variants are presented. This review identifies the limitations inherent in current WDO variants and offers insightful recommendations to address these shortcomings. Additionally, the paper provides clear guidance, outlining the essential steps necessary for developing robust, novel WDO variants.

2. This paper endeavors to deliver an exhaustive review of the applications of WDO, given their critical significance in the field of artificial intelligence. This comprehensive approach ensures a robust and detailed understanding of WDO's development, advancements, and multifaceted applications across various disciplines.

3. Five promising research directions are proposed to further augment the optimization efficacy of WDO.

The remainder of this paper is structured as follows: Section II describes the research method used in this paper. Section III presents an in-depth description of the standard WDO, encompassing its inspirations, primary parameters, and algorithmic steps outlined in the flowchart. Section IV elaborates on the various improvements of WDO. Section V explores the diverse applications of WDO in numerous research domain. Section VI provides the discussion of the findings and limitations of the current research on WDO and its variants. Finally, Section VII offers concluding remarks on the potential of WDO for practical applications and suggests future research directions.

III. BASIC CONCEPTS OF WDO

In this section, the fundamentals, main parameters, mathematical model of WDO are described, which will answer the research question, RQ1.

A. FUNDAMENTALS OF WDO

The fundamentals of WDO are derivations of velocity and position update equations during the movement of air particles. Specifically, the determination of a starting point for an air particle necessitates the application of Newton's Second Law of Motion. This law states that the total force exerted on an air particle is directionally proportional to its acceleration. The simplified form of Newton's Second Law is as follows:

$$\rho \boldsymbol{a} = \sum \boldsymbol{F}_i \tag{1}$$

where $\boldsymbol{a}$ is the acceleration, ρ is the air density of a very small air particles, and $\boldsymbol{F}_i$ is the force acting on the air particles. To equate the air pressure with the density and temperature of the air particles, we will also use the ideal gas law equation:

$$P = \rho RT \tag{2}$$

where P is the pressure, R is the ideal gas constant, and T is the temperature.

The motion of the atmosphere occurs under a combination of forces, the most important of which include the gravitational $\boldsymbol{F}_G$, pressure gradient force $\boldsymbol{F}_{PG}$, Coriolis force $\boldsymbol{F}_C$ and the four forces of friction $\boldsymbol{F}_F$. Among them, gravity generally refers to the force pointing vertically to the center of the earth, and if the problem is mapped to the N-dimensional space, gravity points to the center of the coordinate system; the air pressure gradient force is the force formed due to the difference in the pressure of each region, and its direction is directed from high-pressure regions to low-pressure regions; the Coriolis force refers to the rotation of the earth, and the

TABLE 3. Distribution of papers in resources with given search terms.

Search terms	ACM	SCOPUS	IEEE	Science direct	Springer	Wiley online library
WDO	182	199	57	1457	639	323
WDO variant	299621	5	1	112	157	245
Improved WDO	311735	32	16	449	411	94
WDO parameter improvement	389560	7	4	193	236	115
Hybrid WDO	55181	35	11	205	277	61
Adaptive WDO	179775	14	5	240	220	99
Binary WDO	95055	29	7	116	200	40
Real-world applications of WDO	424814	4	0	151	158	205
Theoretical applications of WDO	410054	1	0	88	164	107
Review of WDO	166812	3	1	911	313	183

TABLE 4. Assessment criteria.

Assessment indicators	Inclusion criteria	Exclusion criteria
Title	Exemplary keywords, including WDO, WDO variant,improved WDO, WDO parameter improvement, hybrid WDO, adaptive WDO, binary WDO, applications of WDO, and review of WDO	Keywords not provided
Abstract	Discusses the background of the study, the problem, the proposed methodology, and the assessment with clear logic	Abstract lacks strong logic
Introduction	Highlights literature review, research methodology and research findings	Lack of proper discussion of literature review, methodology and contributions
Experiment	The experiment can demonstrate the effectiveness of the proposed approach	Lack of properly designed experiments
Result	Results have efficient evaluation criteria	Lack of proper discussion of literature review, methodology and contributions

position and speed of the air particles point in the current dimension are affected by any other dimension. The physical equations for these four forces are as follows:

$$\boldsymbol{F}_G = \rho\delta V \boldsymbol{g} \tag{3}$$

$$\boldsymbol{F}_{PG} = -\nabla P\delta V \tag{4}$$

$$\boldsymbol{F}_C = -2\Omega \times \boldsymbol{u} \tag{5}$$

$$\boldsymbol{F}_F = -\rho\alpha\boldsymbol{u} \tag{6}$$

where δV represents the finite volume of air particle, $\boldsymbol{g}$ represents the gravitational acceleration, ∇P represents the air particle pressure gradient, Ω is the angular velocity of rotation of the earth, $\boldsymbol{u}$ represents the velocity vector of the wind, and α is the coefficient of friction.

By substituting these four forces into Equation (1), the resulting equation is as shown in Equation (7):

$$\rho\frac{\Delta\boldsymbol{u}}{\Delta t} = (\rho\delta V\boldsymbol{g}) + (-\nabla P\delta V) + (-2\Omega \times \boldsymbol{u}) + (-\rho\alpha\boldsymbol{u}) \tag{7}$$

where the acceleration $\boldsymbol{a}$ in Equation (1) is replaced with $\frac{\Delta\boldsymbol{u}}{\Delta t}$. For simplification purposes, we set $\Delta t = 1$. For a very small air particle, we define $\delta V = 1$. The simplified form of Equation(7) is as follows:

$$\rho\Delta\boldsymbol{u} = (\rho\boldsymbol{g}) + (-\nabla P) + (-2\Omega \times \boldsymbol{u}) + (-\rho\alpha\boldsymbol{u}) \tag{8}$$

Based on Equation (2), the density ρ can be replaced according to the pressure, so that Equation (8) can be written:

$$\Delta\boldsymbol{u} = \boldsymbol{g} + (-\nabla P\frac{RT}{P_{cur}}) + (\frac{-2\Omega \times \boldsymbol{u}RT}{P_{cur}}) + (-\alpha\boldsymbol{u}) \tag{9}$$

Herein, P_{cur} represents the pressure value at the current position. It is assumed that during the execution of WDO, each iteration in the population will result in changes to both its position and velocity.

Therefore, $\Delta\boldsymbol{u}$ can be replaced by $\Delta\boldsymbol{u} = \boldsymbol{u_{new}} - \boldsymbol{u_{cur}}$. where $\boldsymbol{u_{new}}$ represents the velocity of the air particles at the next iteration, and $\boldsymbol{u_{cur}}$ represents the current velocity of the air particles. $\boldsymbol{g}$ and ∇P are vectors that can be divided into direction and magnitude by equations such as $\boldsymbol{g} = |g|(0 - \boldsymbol{x}_{cur})$, $-\nabla P = \left|P_{opt} - P_{cur}\right|(\boldsymbol{x}_{opt} - \boldsymbol{x}_{cur})$. Where P_{opt} denotes the optimal point of the pressure so far, and $\boldsymbol{x}_{opt}$ denotes the optimal position so far, and $\boldsymbol{x}_{cur}$ is the current position, substituting the above two equations to update Equation (9) gives Equation (10).

$$\begin{aligned}\boldsymbol{u}_{new} &= (1-\alpha)\boldsymbol{u}_{cur} - g\boldsymbol{x}_{cur} \\ &\quad + \left(\frac{RT}{P_{cur}}\left|P_{opt} - P_{cur}\right|(\boldsymbol{x}_{opt} - \boldsymbol{x}_{cur})\right) \\ &\quad + \left(\frac{-2\Omega \times \boldsymbol{u}RT}{P_{cur}}\right)\end{aligned} \tag{10}$$

There are three additional replacements. Firstly, the velocity of the air particles $\boldsymbol{u}$ is replaced by this velocity $\boldsymbol{u}_{cur}^{other\ dim}$. Secondly, all constants are combined and expressed as $c = -2\,|\Omega|\,RT$. Thirdly, since in some cases the pressure values may become extremely large, the velocity will also become meaningless due to being too large, which will directly lead to a less efficient operation of WDO. Therefore, the actual value of the pressure is replaced by an ordering based on the pressure value of the air particles, so that the velocity is updated as in Equation (11) and the position is updated as in Equation (12).

$$u_{new} = (1-\alpha)u_{cur} - g x_{cur} + (RT\left|1-\frac{1}{i}\right|(x_{opt}-x_{cur})) + (\frac{c u_{cur}^{other}}{i}) \tag{11}$$

$$x_{new} = x_{cur} + (u_{new} \times \Delta t) \tag{12}$$

where i denotes the ranking of the pressure value of this air particle among all air particles and x_{new} denotes the new position for the next iteration.

Based on Equation(11), the term one indicates that the air particles persist in their trajectory along the previous path, albeit encountering resistance from the frictional force. The term two represents the gravitational force, which exerts an attraction on the air particles towards the center of the coordinate system. The term three delineates the force acting on air particles, propelling them towards the location of highest pressure. This highest-pressure point symbolizes the global best position in the context of WDO optimization problem. The term four represents the Coriolis force, which acts as a deflecting force in WDO. This force influences the movement of air particles in one direction based on their movement in another direction, contributing to the complexity of their trajectories in the optimization process.

B. MAIN PARAMETERS

WDO aims to replicate the movement of air resulting from differences in air pressure across different locations, ultimately leading to an equilibrium of air pressure. The algorithm involves a small number of parameters that are easy to implement and fine-tune for different optimization topologies [55]. R stands for universal gas constant and T for temperature. The range of values for RT is generally [1.0,2.0], $c = -2|\Omega| RT$,and it generally takes values in the range [0.6,0.7]. The parameter g represents the acceleration of gravity and typically assumes values within the range of [0.6,0.7], which influences the gravitational force magnitude and serves the purpose of preventing air particles from persisting at the boundaries for prolonged durations by pulling them back into the search space. The parameters c and g are carefully fine-tuned to enhance robustness and offer additional degrees of freedom for fine-tuning diverse optimized topologies. α is the coefficient of friction, the range of values is generally [0.8,0.9], and it influences the magnitude of the frictional force.

C. MATHEMATICAL MODELING

WDO commences by initializing key parameters, including the number of air particles, the maximum number of iterations, and other relevant factors such as c, g, α, RT and u_{max}. Subsequently, the positions and speeds of each air particle are assigned randomly, and a pressure function is formulated to direct the movement of the air particles. This function enables the air particles to move randomly at different positions and velocities and evaluates the pressure value of each air particle at its current position. The population is subsequently ranked based on these pressure values. In each iteration, the velocity and position of each air particle is adjusted to move toward the optimal position. The algorithm continues to iterate until reaching the final cycle, which represents the optimal solution. To execute WDO, there are three main phases, initialization of the algorithm, updating the local optimal position, and finalization of the global optimal position. Figure 2 presents a flowchart depicting the sequential steps of WDO. The main steps of the algorithm can be summarized as follows:

1) DEFINE THE PROBLEM AND INITIALIZE PARAMETER VALUES

The main goal of the optimization process is to determine the maximum or minimum value of the objective function. For instance, in the case of seeking the minimum value, the objective function takes the following form:

$$\begin{cases} min\ f(x) \\ s.t. x_i \in X_i,\ i = 1,2,3,\ldots,N \end{cases} \tag{13}$$

The objective function is denoted by $f(x)$, where x represents the solution vector consisting of decision variables $x_1, x_2, x_3, \ldots, x_N (i.e., i = 1,2,3,\ldots,N)$, and the value range of each decision variable is represented by X_i.

The initialization process of WDO involves initializing each parameter to their respective values. These parameters include the population size (N), the maximum number of generations (G), the gravitational acceleration (g), the constant (c), the coefficient of friction (α), the maximum allowed speed (u_{max}),and RT coefficient (RT).

2) INITIALIZE THE POPULATION

An initial population of N air particles is generated, where each particle possesses D dimensions. Random locations and velocities are assigned to each particle. Subsequently, the pressure for each air particle is evaluated. This population can be represented by a matrix denoted as:

$$P(N,D) = \begin{bmatrix} k_1^1 & k_1^2 & \ldots & k_1^D \\ k_2^1 & k_2^2 & \ldots & k_2^D \\ \ldots & \ldots & \ldots & \ldots \\ k_N^1 & k_N^2 & \ldots & k_N^D \end{bmatrix} \tag{14}$$

3) GENERATE A NEW SOLUTION

To generate a new solution $X_i = (x_1, x_2, x_3, \ldots, x_N)$, velocity updates are performed using four distinct parameters, namely: c, g, α and RT. Based on Equation (11), each new velocity is generated using one of these parameters and the resulting position update equation is based on Equation (12).

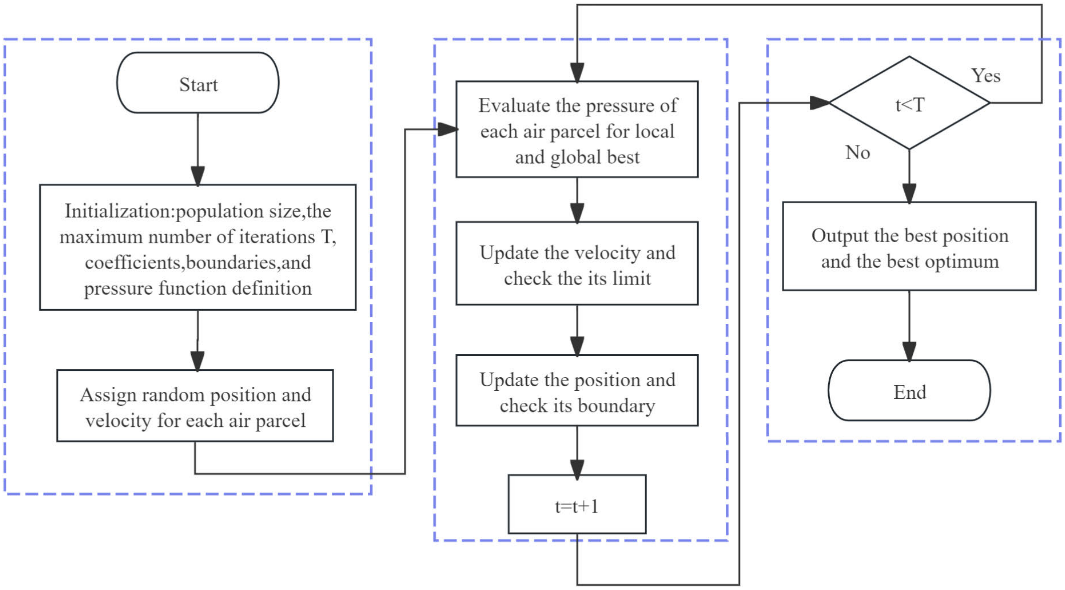

FIGURE 2. Flowchart of WDO.

4) UPDATE LOCATION

To prevent excessive movement of the search position of the air particles during each iteration, it is crucial to limit the position of the air particle within the range of $[-1, 1]$. Additionally, it is necessary to restrict the update speed, which is calculated based on Equation (15).

$$u_{new}^{*} = \begin{cases} u_{max} & u_{new} > u_{max} \\ -u_{max} & u_{new} < -u_{max} \end{cases} \tag{15}$$

where u_{max} and $-u_{max}$ represent the upper and lower limits of air particle speed, respectively.

5) CHECK THE ALGORITHM TERMINATION CONDITION

If the algorithm reaches the maximum number of iterations, the computation will be terminated. However, if it does not reach the maximum number, the algorithm will continue generating new solutions until convergence is attained.

This section introduces a new, iterative heuristic approach to global optimization known as WDO. Drawing inspiration from the atmospheric phenomena observed on Earth, where wind flows from areas of high pressure to those of low pressure, aiming to achieve a balance in air pressure. In WDO, the motion and positioning of air parcels, influenced by the dynamics of wind, are continuously adjusted in accordance with the physical principles that govern atmospheric activity.

IV. IMPROVEMENTS OF WDO

In this section, the limitations of the basic WDO are presented, improvements to the basic WDO are discussed, the mainstream methods of improving WDO is shown in Figure 3, and steps to verify the validity of WDO variants are presented, this will answer questions RQ2-RQ5.

A. HYBRIDIZED WDO

A wide range of metaheuristic algorithms has been proposed and applied in diverse fields such as engineering, industry, and science applications [64]. These metaheuristics, include GA, PSO, Cuckoo Search(CS) [65], and WDO. However, no single optimization algorithm among these heuristics can stand out from the large family of nature metaheuristics, each metaheuristic has its strengths and weaknesses.

In recent years, due to the limitations of using single heuristic algorithms in certain applications, researchers have combined these algorithms based on their respective characteristics to achieve complementary advantages, improve algorithm performance, and apply them to practical problems. These hybrid algorithms have demonstrated higher efficiency and effectiveness in tackling complex optimization problems [66], [67], [68]. For instance, hybrid algorithms based on GA and PSO are applied to the design of recurrent neural networks and fuzzy neural networks [69]. In the domain of robotics, a hybrid algorithm combining Attractive Potential Field (APF) and improved ACO was used for collaborative multi-robot formation control and global path optimization, demonstrating the combination of different heuristic algorithms to achieve optimal solutions in robotics [70]. Additionally, in the context of vehicle routing problems, a study explored the synergy between GA and ACO, demonstrating the potential of combining different heuristic algorithms to address complex problems [71].This section highlights the combined utilization of WDO with other outstanding metaheuristic algorithms.

WDO also has its limitations, it may suffer from rapid convergence, leading to premature convergence to a local optimum. This limitation needs to be addressed to enhance the performance of WDO when dealing with complex

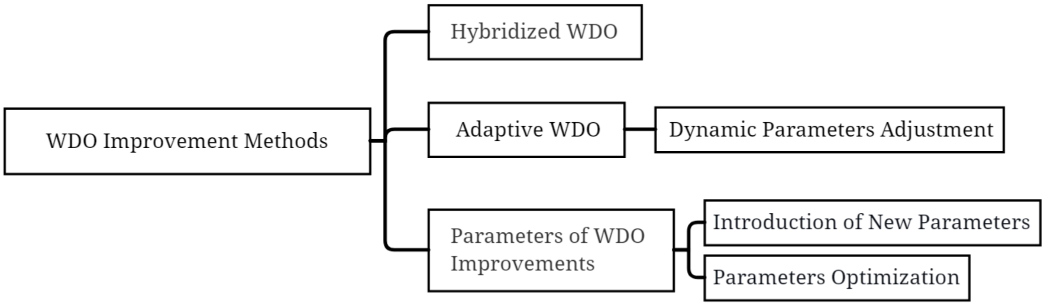

FIGURE 3. WDO mainstream improvement methods.

optimization problems. WDO update equations contain numerous inherent parameters that require careful fine-tuning by the user to achieve optimal performance.

In [57], Bao et al. have proposed a novel hybrid algorithm called WDO-DE, WDO-DE, a two-population evolutionary strategy, half of the population particles are run using WDO, which generates velocity according to Equation (11) and position according to Equation (12), the other half of the population particles are run using the DE, which performs a mutation operation according to one of the Equations (16-20), a crossover operation according to Equation (21), after the mutation operation is completed, DE will utilize crossover operation to generate a vector $U_{i,G} = (u^1_{i,G}, u^2_{i,G}, u^3_{i,G}, \ldots, u^D_{i,G})$, then a selection operation according to Equation (22).

$$V_{i,G} = X_{r^i_1,G} + F \cdot (X_{r^i_2,G} - X_{r^i_3,G}) \tag{16}$$

$$V_{i,G} = X_{best,G} + F \cdot (X_{r^i_1,G} - X_{r^i_2,G}) \tag{17}$$

$$V_{i,G} = X_{i,G} + F \cdot (X_{best,G} - X_{i,G}) + F \cdot (X_{r^i_1,G} - X_{r^i_2,G}) \tag{18}$$

$$V_{i,G} = X_{best,G} + F \cdot (X_{r^i_1,G} - X_{r^i_2,G}) + F \cdot (X_{r^i_3,G} - X_{r^i_4,G}) \tag{19}$$

$$V_{i,G} = X_{r^i_1,G} + F \cdot (X_{r^i_2,G} - X_{r^i_3,G}) + F \cdot (X_{r^i_4,G} - X_{r^i_5,G}) \tag{20}$$

where $r^i_1, r^i_2, r^i_3, r^i_4, r^i_5$ are unique integers, each distinctly exclusive of the other, and they lie within the specified range bounded by $[1, NP]$ and F is the scale factor of difference vector.

$$u^j_{i,G} = \begin{cases} V^j_{i,G} & if\ rand_j[0,1) \le CR\ or (j = j_{rand}) \\ x^j_{i,G} & others \end{cases} \tag{21}$$

where $CR \in [0, 1]$ it is a crossover constant. j_{rand} is a random integer within the range $[1, D]$.

$$X_{i,G+1} = \begin{cases} U_{i,G} & if\ f(U_{i,G}) \le f(X_{i,G}) \\ X_{i,G} & others \end{cases} \tag{22}$$

Mutation, crossover, and selection operations of DE ensure population diversity, and WDO-DE combines WDO and DE, with individuals of the DE guiding the evolution of individuals of WDO to reduce the risk of falling into local optima. This collaboration between the DE and WDO ensures that the WDO-DE maintains population diversity, thereby improving search performance and robustness. Although they tested the performance of the WDO-DE using 15 benchmark functions, which include unimodal, multimodal, low dimensional and high dimensional unconstrained test functions, their performance on realistic optimization problems was not investigated.

Zhou et al. [72] introduced a new optimization algorithm called quantum WDO (QWDO) for solving the path planning problem of unmanned combat air vehicles (UCAVs). The algorithm incorporates quantum rotation gate and quantum non-gate strategies to enable individual variation within the population. Comparative analysis with other algorithms demonstrates that QWDO outperforms them in terms of performance, making it a promising approach for UCAVs path planning, but QWDO has only tested two test instances, the QWDO was not thoroughly tested using other benchmark functions to prove its effectiveness.

Mahto and Choubey [73] introduced a novel hybrid optimization algorithm combining Invasive Weed Optimization (IWO) and WDO for nulling pattern synthesis in antenna arrays. The focus is on achieving minimal side lobe level (SLL) and beam width in uniform linear arrays (ULA) and non-uniform circular array (NUCA). The paper proposed a hybrid IWO/WDO. The innovation lies in integrating the strengths of IWO (good exploration and diversity properties) with the systematic and directed search capabilities of WDO.

The initial positions of the algorithm's solutions, referred to as seeds, are distributed throughout the search space in a manner akin to the established Invasive Weed Optimization approach, ensuring a uniform spread across the potential solution domain, as shown in Equation (23):

$$\sigma_{new} = \left(\frac{iter_{max} - iter}{iter_{max}}\right)^n \cdot (\sigma_{initial} - \sigma_{final}) + \sigma_{final} \tag{23}$$

The position of the new seed is determined as:

$$\boldsymbol{x}_{new} = \boldsymbol{x}_{temp} + \text{rand} \cdot \sigma_{new} \tag{24}$$

where rand is uniformly distributed between zero and one.

WDO guides the initial seed position using its velocity and position equations, while IWO dictates the further progression of the algorithm. The algorithm has improved performance in synthesizing broad nulls, minimizing SLL, controlling beam width, and achieving faster convergence compared to other evolutionary algorithms like GA, PSO, and BFO. Results were validated against six standard benchmark functions, showing that the IWO/WDO converges faster and more effectively than the other algorithms considered. However, the IWO/WDO needs more to be tested on high dimensional problems.

Mahto and Choubey [74] presented a hybrid algorithm integrating IWO and WDO for antenna array pattern synthesis, the specific hybrid algorithmic process is the same as article [73], the location updates for the feasible options are based on Equation (23) and Equation (24). The main contribution lies in the algorithm's ability to synthesize array patterns with minimal SLL and controlled beamwidth, enhancing interference minimization. The experimental results show significant improvements in SLL reduction and null control compared to conventional methods. The application is pertinent to antenna design in communication systems, where interference minimization is critical. The IWO/WDO performs well in terms of convergence, However, the IWO/WDO needs more to be tested on high dimensional problems.

To solve the 0-1 knapsack problem, Zhou et al. [75] introduced a complex-valued encoding method and a greedy strategy to WDO, compared to a range of established algorithms such as the complex-valued CS, greedy GA, WDO, binary CS, BA, and PSO, the CWDO demonstrates superior performance, stability, and robustness. Empirical simulation results indicate that the CWDO is an effective and feasible approach for addressing the complexities of the 0-1 knapsack problem. The test functions used by Zhou et al. are three types of test cases with 10 instances of each test function. The CWDO needs to test thoroughly using other benchmarking functions to prove its effectiveness.

Yahia and Elkamchouchi [76] introduced a combined nature-inspired optimization algorithm—Gravitational Search Algorithm(GSA), IWO, and WDO—targeting accurate real antenna array calibration. The algorithm aims to optimize the array pattern synthesis and null control while minimizing the beam width, side lobe level, and interference. The algorithm's efficacy is demonstrated through simulations, showing improvements in performance metrics like side lobe level minimization and null control, compared to existing methods. However, the GSA/IWO/WDO is untested on diverse benchmarking functions, it also needs to be tested on high dimensional problems.

In the refined algorithm, the gravitational constant g, a pivotal parameter in WDO, is substituted with the iterative acceleration a_{cur} of the i_{th} seeds, as shown in Equation (25), a concept derived and adapted from the GSA.

$$u_{\text{new}} = (1-\alpha)u_{\text{cur}} + a_{\text{cur}}(t)x_{\text{cur}} + RT\left|\frac{1}{z}-1\right|(x_{\text{opt}}-x_{\text{cur}}) + \frac{cu_{\text{cur}}^{otherdim}}{z} \tag{25}$$

where the variable z is defined as the index denoting the position of the pressure (fitness) value in its current state.

To address the challenge of managing energy consumption more efficiently in smart grid systems. Javaid et al. [77] introduced a novel hybrid algorithm called GWD, which combines the principles of WDO and GA. In GWD, the velocity update process of global air pressure is replaced by crossover and mutation operations from the genetic algorithm. The experimental results reported in their study demonstrate that the proposed GWD outperforms other heuristic algorithms based on the selected performance indicators. The GWO verified its superior performance compared to other heuristics, but the GWO was not thoroughly investigated using other benchmarking functions to prove its effectiveness.

To improve global search capability and prevent being trapped in local optima. Sinha and Choubey [78] presented an enhanced version of WDO combined with GA for adaptive filtering in digital signal processing, specifically for Adaptive Channel Equalizer (ACE) and System Identification (SI). The method shows superior performance over the original WDO, GA, and the Least Mean Square (LMS) algorithm in terms of convergence speed and error rates, particularly in handling inter-symbol interference and random noise.

To address Demand Side Management (DSM) in the Smart Grid. Qureshi et al. [79] proposed hybrid Enhanced Differential Harmony WDO (EDHWADO). EDHWADO incorporates the characteristics of the Harmony Search Algorithm (HSA), Enhanced Differential Evolution (EDE), and WDO. In their proposed algorithm, the initial population is generated following the procedure of HSA. The initial harmony is created according to the following Equation (26).

$$X_{i,j} = L_j + \text{randb}()\cdot(U_j - L_j) \tag{26}$$

In the equation referenced above, $X_{i,j}$ represents the element located in the i_{th} row and j_{th} column of the initial population matrix. U signifies the upper bound limit, which has a maximum value of 1, while L denotes the lower bound limit, with a minimum value of 0. Generating the initial population in accordance with the HSA guarantees that the population values are confined within the boundaries set by U and L.

They substitute component u_{new} in Equation (11) with the mutation and crossover techniques from EDE, as specified in the following equation.

$$V_{i,G+1} = X_{r1,G} + F\cdot(X_{r2,G} - X_{r3,G}) \tag{27}$$

They select the best possible solution from five generated vectors or solutions, in accordance with the criteria set out in the equation below.

$$U_{j,i,G+1} = \begin{cases} V_{j,i,G} & if \ \text{rand}(j) \leq 0.3 \\ x_{j,i,G} & others \end{cases} \quad (28)$$

$$U_{j,i,G+1} = \begin{cases} V_{j,i,G} & if \ \text{rand}(j) \leq 0.6 \\ x_{j,i,G} & others \end{cases} \quad (29)$$

$$U_{j,i,G+1} = \begin{cases} V_{j,i,G} & if \ \text{rand}(j) \leq 0.9 \\ x_{j,i,G} & others \end{cases} \quad (30)$$

$$U_{j,i,G+1} = \text{randb}(j) \cdot x_{j,i,G} \quad (31)$$

$$U_{j,i,G+1} = \text{randb}(j) \cdot v_{j,i,G} + (1 - \text{randb}(j)) \cdot x_{j,i,G} \quad (32)$$

EDHWADO can effectively reduce costs while controlling Peak Average Ratio (PAR), WDO, and HSA are proven to be cost effective for PAR, while EDE is effective for PAR control. The EDHWADO verifies superior performance on real-world problems compared to other heuristics, but the EDHWADO has not been thoroughly investigated using other benchmarking functions to prove its effectiveness.

Sawant and Manoharan [80] introduced a novel band selection approach for hyperspectral images using a modified WDO(MWDO). This approach addresses the curse of dimensionality and aims to improve classification accuracy by effectively selecting optimal bands and feeding them into a deep learning architecture. The MWDO is designed to prevent premature convergence and balance exploration-exploitation in the search process. The method demonstrated high classification accuracy on three standard datasets, indicating its potential for hyperspectral image processing. However, MWDO increases the computational cost and has not been thoroughly tested on high dimensional problems.

To increase population diversity, the particle swarm algorithm was used to dynamically compute air particle origins, as shown in Equation(33).

$$\begin{aligned} u_{\text{new}} &= (1-\alpha)u_{\text{cur}} - g(x_{\text{or}} - x_{\text{curr}}) \\ &\quad + \left[RT \left| 1 - \frac{1}{i} \right| (x_{\text{new}} - x_{\text{curr}}) \right] \\ &\quad + \left[\frac{-cu_{\text{curr}}^{otherdim}}{i} \right] \end{aligned} \quad (33)$$

where x_{or} signifies the origin point of an air particle, its position meticulously determined by employing Equation (34).

$$x_{new} = x_j + v_{jnew} \quad (34)$$

The velocity of each particle can be updated as:

$$v_{jnew} = w \cdot v_j + c_1 r_1 (P_{best} - x_j) + c_2 r_2 (g_{best} - x_j) \quad (35)$$

where w represents the inertia weight, confined within the range [0, 1], ensuring a balanced momentum during the search process. Both r_1 and r_2 are random variables uniformly distributed in the interval [0, 1], introducing stochastic elements to the search. Meanwhile, c_1 and c_2 serve as cognitive and social learning rates respectively, guiding the particles through the problem space by blending personal insights with collective experience.

Sinha et al. [81] showcased the Hybrid IWO/WDO's application in synthesizing linear array antennas by optimizing key parameters like excitation amplitude, position, and complex weight. The specific hybrid algorithmic process is the same as article [74], the location updates for the feasible options are based on Equation (23) and Equation (24). It emphasizes placing single and multiple nulls strategically to reduce interference. The algorithm aligns with modern communication demands by ensuring high gain, low SLL, minimal beam width, and directed nulls. The efficiency of this hybrid approach is validated through four examples, with results favorably compared to other soft computing optimization techniques reported in the literature. However, the IWO/WDO needs to test thoroughly using diverse benchmarking functions and high dimensional problems to prove its effectiveness.

To address the issue of WDO getting trapped in local optima during the early stages, Gao et al. [82] proposed a hybrid approach that combines quantum computation of single coding with WDO, known as the Quantum WDO (QWDO). Furthermore, to solve the nonlinear optimization problem of three-dimensional (3D) Time-Difference-of-Arrival (TDOA) cooperative location, they incorporated the Chan algorithm into the QWDO framework, resulting in the Chan-QWDO. The probability amplitude of a qubit is utilized to represent the position of an air particle. To update this position, they employ a quantum rotation gate strategy, which is intricately combined with a quantum rotation angle and a chaotic equation. This approach significantly enhances the diversity of the population and effectively prevents premature convergence. However, the Chan-QWDO needs to test thoroughly using diverse benchmarking functions and high dimensional problems to prove its effectiveness.

Initiate the process by establishing the set of quantum air particles. Subsequently, determine an initial quantum position in accordance with the Chan algorithm. Following this, allocate the remaining initial positions and velocities in a random manner. Proceed to update the quantum position for each quantum air particle. This paper employs two distinct strategies to facilitate the updating of quantum positions.

The first approach involves the quantum rotation gate strategy, with the update process unfolding as follows:

$$u_{i,j}^{t+1} = \text{abs}(u_{i,j}^{t+1} \cos(v_{i,j}^{t+1}) + \sqrt{1 - (u_{i,j}^{t})^2} \sin(v_{i,j}^{t+1})) \quad (36)$$

The second strategy employs a quantum rotation angle method, which is intricately combined with a chaotic equation. The update equation for the quantum rotation angle is expressed as follows:

$$\theta_{ij}^{t+1} = c_1 s_{i,j}^{t} (u_{g,j}^{t} - u_{i,j}^{t}) + c_2 s_{i,j}^{-t} (b_j^{t} - u_{i,j}^{t}) \quad (37)$$

c_1 and c_2 represent constants that indicate the extent of influence exerted by the global optimal quantum position and the local optimal quantum position on quantum air particles, respectively. $u^t_{g,j}$ denotes the global optimal quantum position, while b^t_j refers to the local quantum position. The chaotic variables, designated $s^t_{i,j}$ an $s^{-t}_{i,j}$, respectively adhere to the chaotic equations $s^t_{i,j} = 4s^{t-1}_{i,j}(1 - s^{t-1}_{i,j})$ and $s^{-t}_{i,j} = 4s^{-t-1}_{i,j}(1 - s^{-t-1}_{i,j})$.

The procedure for updating the quantum position of an air particle, which involves the use of the quantum rotation angle in conjunction with a chaos equation, unfolds as follows:

$$u^{t+1}_{i,j} = \text{abs}(u^t_{i,j}\cos(\theta^{t+1}_{i,j}) + \sqrt{1-(u^t_{i,j})^2}\sin(\theta^{t+1}_{i,j})) \quad (38)$$

Compared to the Chan, GA, and PSO algorithms, the Chan-QWDO demonstrates greater effectiveness in finding solutions. This method is both reliable and practical for solving the 3D cooperative Time Difference of Arrival (TDOA) location problem involving multiple Unmanned Aerial Vehicles (UAVs). However, the Chan-QWDO has not been thoroughly investigated using other benchmarking functions to prove its effectiveness.

Despite their strong search capabilities and minimal control parameters, both WDO and CS algorithms are susceptible to premature convergence due to the loss of population diversity. Sawant and Manoharan [83] proposed WDOMCS, which combines WDO and CS with a Chaotic map, the proposed methodology utilizes the Chebyshev chaotic map for initializing the population at the initial stage, according to the following equation.

$$X_{t+1} = \cos(a.\cos^{-1}(X_t)) \quad (39)$$

Subsequently, the population is segmented into two distinct subgroups. For each subgroup, WDO and CS strategies are independently implemented.

Half of the population particles are run using WDO, which generates velocity according to Equation (11) and position according to Equation (12), the other half of the population particles are run using the modified version of CS, which performs an operation according to the Equation (40).

$$X_i(t+1) = X_i(t) + \alpha_i(t+1) \oplus levy(\lambda) \quad (40)$$

where, α is finite constant.

This bifurcation allows the subgroups to exchange pertinent information and leverage each other's strengths, thereby mitigating premature convergence and facilitating the attainment of the optimal solution. Moreover, in the CS algorithm, the Levy flight step size is adaptively adjusted, considering the fitness value and the current iteration number. This adjustment significantly enhances the convergence speed of the algorithm, and this algorithm can avoid premature convergence and obtain the optimal solution. Although the WDOMCS algorithm was tested on standard benchmark hyperspectral datasets, Indian pines, Pavia University and Botswana for comparison with GA, PSO, GWO, WDO, and CS with good results, it has led to improved optimization performance and robustness, WDOMCS still needs to be investigated using diverse benchmarking functions and high dimensional problems to prove its effectiveness.

The research introduced a dual-objective optimization model focusing on enhancing wind and solar absorption rates and ensuring reliable operation by aligning the interests of Battery Swapping Stations (BSS) and DC distribution entities. A hybrid algorithm combining Genetic Algorithm GA and WDO is proposed by Wang et al. [84], employing CPLEX and GA-WDO for solving upper and lower models, respectively. Results indicate that the model significantly reduces operational costs and increases renewable energy utilization, demonstrating its practical efficacy and validity. However, GA-WDO only compared with WDO and GA, it still needs to be investigated using diverse benchmarking functions and high dimensional problems to prove its effectiveness.

Singh et al. [85] introduced a Hybrid WDO (HWDO), which designs to generate a reliable workflow schedule while maintaining the budget within specified limits. The algorithm's performance was evaluated using WorkflowSim with real-world scientific applications. The results demonstrate that the HWDO achieves a 9%–17% improvement in schedule reliability compared to other algorithms, all the while adhering to the budget constraints. However, to prove the effectiveness of HWDO thoroughly, it needs to be investigated using diverse benchmarking functions and high dimensional problems.

To address the challenge of accurately modeling the performance of photovoltaic (PV) modules, Ibrahim et al. [86] proposed a hybrid wind driven-based fruit fly optimization algorithm(WDFO), FO optimized the four hyper parameters of WDO, Firstly, the air particles' velocity and position are updated using Equation (11) and Equation (12), respectively. In each iteration, the hyper-parameters of the WDFO are meticulously tuned and updated in accordance with the requirements of the subsequent phase. Secondly, the update of the direction and distance toward the optimal values of the hyper-parameters is governed by Equation (41) and Equation (42). Once the minimum error threshold is achieved, these optimal values are then applied in a subsequent cycle to initiate a re-evaluation of the air parcels, thereby refining the preceding results. The iterative process of updating both the hyper-parameters and the modeled velocities and positions is brought to a halt upon meeting a predetermined termination criterion. Notably, the strategic adjustment of the hyper-parameters plays a pivotal role in balancing the global and local search capabilities, thereby facilitating a more expedient attainment of the optimal solution, the WDFO improved the convergence speed and accuracy of WDO, but it still needs to be investigated using diverse benchmarking functions and high dimensional problems to prove its effectiveness.

$$X^{new}_{axis} = X(bestIndex) \quad (41)$$
$$Y^{new}_{axis} = Y(bestIndex) \quad (42)$$

where bestIndex is obtained from the following Equations (43)-(50).

$$X_{axis}^{new} = \text{rand}(LR) \tag{43}$$

$$Y_{axis} = \text{rand}(LR) \tag{44}$$

$$X_i = X_{axis} + \text{rand}(LR) \tag{45}$$

$$Y_i = Y_{axis} + \text{rand}(LR) \tag{46}$$

$$dis_i = \sqrt{X_i^2 + Y_i^2} \tag{47}$$

$$S_i = \frac{1}{dis_i} \tag{48}$$

$$Smell_i = \text{fitness}(S_i) \tag{49}$$

$$[bestSmell, bestIndex] = \min(Smell) \tag{50}$$

To addresses the problem of premature convergence and getting trapped in local optima, which are common issues in WDO, Tang et al. [87] introduced an innovative selection strategy, founded on a fitness-distance balance, to supplant the conventional selection method in WDO. Additionally, it incorporates a chaotic local search mechanism, which intelligently selects a chaotic map based on a memory component, thereby significantly enhancing the algorithm's search efficacy. Remarkably, the proposed algorithm maintains the same computational time complexity as the standard WDO. In their rigorous analysis, optimal parameter settings for the new algorithm were determined. Comparative experiments were conducted using the CEC 2017 benchmark functions to assess the algorithm's effectiveness. The results from these experiments unequivocally demonstrate that the newly proposed algorithm exhibits superior performance in comparison to the traditional WDO, particularly noted in its ability to achieve gradual convergence in function optimization tasks. Furthermore, the practical applicability, the robustness and versatility of the algorithm are substantiated through its deployment on six real-world optimization problems. However, in higher-dimensional scenarios, CFDBWDO does not exhibit a marked superiority over AWDO. To prove the effectiveness of HWDO thoroughly, it needs to be investigated using diverse benchmarking functions.

Athira and Sasikala [88] presented a security framework for distributed cloud computing, focusing on secure Data Deduplication (DD) and Data Portability (DP). The proposed method enhances data security by dividing files into blocks, selecting optimal Cloud Servers (CS) using a Hybrid Forest Genetic Algorithm based on file and CS attributes, and employing the Whirlpool algorithm for hash code generation and deduplication through hash chaining. The framework further secures data using the Levy Flight-WDO(LF-WDO) algorithm for DP. In the LF-WDO approach, the introduction of the Levy Flight Distribution (LFD) replaces traditional randomness, resulting in more efficient DP processes. In the LF-WDO, the position (x) and velocity (v) of air parcels are determined based on the LFD are shown in equations.

$$\mathrm{L}(x) = \mathrm{t}(-x) \ \ 0 < x \leq 2 \tag{51}$$

$$\mathrm{L}(x) = \mathrm{t}(-v) \ \ 0 < v \leq 2 \tag{52}$$

where, L(•) signifies the LFD, t indicates the time of task completion. Subsequently, the velocity of each air parcel is updated as follows:

$$\begin{aligned} \hat{v}_{\text{new}} = (1-\lambda)\cdot \mathrm{L}(v) - g\mathrm{L}(x) \\ + \left(\alpha T\left|\frac{1}{r}-1\right|(\mathrm{L}'(x)-\mathrm{L}(x))\right) \\ + \left(\frac{c\cdot v}{r}\right) \end{aligned} \tag{53}$$

where $\hat{v}_{new}$ denotes the velocity at iteration $s+1$, g denotes gravitational acceleration, $\mathrm{L}'(x)$ denotes the air parcel's optimal location, and represents the parcel's rank among the entire group as well as c indicates the coefficient.

Following the velocity update, the position of each air parcel is recalibrated as:

$$\hat{x}_{new} = \mathrm{L}(x) + \hat{v}_{new}\cdot s \tag{54}$$

where, $\hat{x}_{new}$ denotes the updated position.

Experimental results demonstrate the efficacy of the proposed approach in enhancing data security in distributed cloud environments. However, to prove the effectiveness of LF-WDO, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems. The different Hybridized WDO and their limitations are shown in Table 5.

B. IMPROVEMENTS IN ADAPTIVE WDO

Boulesnane and Meshoul [52] proposed an adjustment to the gravitational parameter in their study. They introduced an automatic adaptive mechanism for setting the gravitational parameter, where the value of the gravitational parameter is randomly selected from the range [0,1]. The improved algorithm MWDO exhibits superior performance in terms of accuracy and robustness compared to the original algorithm. However, the performance of MWDO on practical engineering problems has not been studied.

Suzuki et al. [47] changed the way four inherent terms of c, g, α and RT through these two methods. In the first method, the values of the four terms are randomized at each iteration by selecting a value from a uniform distribution in the range of [0, 1].The second method is to utilize the Covariance Matrix Adaptation Evolution Strategy (CMAES) [89], [90] to optimize the values of the parameters c, g, α and RT at each iteration, a new group of values is assigned for the next iteration. The population size of CMAES should be identical to that of WDO, and four parameters in WDO need to be adaptive, so CMAES will apply to these four parameters and the dimensions should be limited to four, so that WDO implementation can be a parameter-free adaptive optimization algorithm. AWDO utilizes four renowned numerical benchmark functions, namely Sphere, Rastrigin, Griewank, and Rosenbrock. Numerical tests indicate that the proposed algorithm exhibits faster convergence and yields superior results, thereby enhancing overall performance. However, AWDO does not consider constrained real-world optimization problems, and its performance on realistically

TABLE 5. Hybridized WDO and their limitations.

Researchers /Year/Refs.	Hybrid Strategy	Description	Statistical tests	Performance	Limitations
Bao et al. (2015) [57]	DE	DE is used to maintain population diversity	ANOVA	Improve optimization performance and robustness	Need to be tested on real-world problems
Zhou et al. (2015) [72]	Quantum rotation gate and quantum non-gate strategies	Improve the diversity of population and avoid premature convergence	None	The QWDO demonstrates exceptional efficacy and practicality as a method	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Mahto et al. (2016) [73]	IWO	IWO has good exploration and diversity properties	None	IWO/WDO converges faster and more effectively	Need more to be tested on high dimensional problems
Mahto et al. (2016) [74]	IWO	IWO has good exploration and diversity properties	None	IWO/WDO converges faster and more effectively	Need more to be tested on high dimensional problems
Zhou et al. (2017) [75]	complex-valued encoding and greedy strategy	The implementation of these strategies effectively enhances the diversity within the population, thereby mitigating the risk of premature convergence	ANOVA	Improve performance	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Yahia et al. (2017) [76]	GSA and IWO	IWO offers good exploration and diversity properties. GSA has the high exploration for optimized solution	None	Improve performance	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Javaid et al. (2017) [77]	GA	GA is well-suited for handling multi-objective optimization problems and offers flexibility in terms of constraints and parameters	ANOVA	Improve performance	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Sinha et al. (2017) [78]	GA	GA is leveraged to introduce diversity in the population of WDO and to enhance the search process and avoid the probability of the algorithm getting trapped in local optima.	None	Improve performance	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
T. N. Qureshi et al. (2018) [79]	HAS and EDE	HSA is cost effective, and EDE is effective in controlling PAR	None	Improve performance	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Sawant et al. (2019) [80]	PSO	PSO demonstrates a proficient balance in managing the trade-off between local and global search capabilities	None	Improve high classification accuracy	Computationally expensive Need to be tested on high dimensional problems
Sinha et al. (2019) [81]	IWO	IWO offers good exploration and diversity properties.	None	Improve performance	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Gao et al. (2020) [82]	Quantum computation and Chan algorithm	Quantum computation is used to improve global search, and Chan algorithm is used to improve accuracy	MSE	Improve the convergence speed and accuracy	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Sawant et al. (2021) [83]	CS and Chaotic map	CS share suitable information to avoid premature convergence Chaotic map maintains population diversity and avoids premature convergence	None	Better optimization performance and robustness algorithm convergence speed	Untested on diverse benchmarking functions Need to be tested on high dimensional problems

TABLE 5. ***(Continued.)*** **Hybridized WDO and their limitations.**

Researchers /Year/Refs.	Hybrid Strategy	Description	Statistical tests	Performance	Limitations
Y. Wang et al. (2020) [84]	GA	GA-WDO improved the search ability and the search speed	None	Increase renewable energy utilization	Untested on diverse benchmarking functions Need to be tested on high dimensional problems Compared with WDO and GA only
Singh et al. (2021) [85]	HWDO	HWDO	Mean	Minimize failure factors and execution time to generate reliable workflow tables	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Ibrahim et al. (2022) [86]	FO	FO is used to optimize the four parameters c , g , α and RT	MAPE,nRMSE, SD	Improve the convergence speed and accuracy	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Tang et al. (2022) [87]	Chaotic local search and fitness-distance balance strategy.	This research introduces an innovative selection strategy, predicated on a fitness-distance balance. Furthermore, it incorporates an advanced chaotic local search component	Mean, SD, Wilcoxon rank-sum test	Improve performance	In higher-dimensional scenarios, CFDBWDO does not exhibit a marked superiority over AWDO.
Athira et al. (2022) [88]	Levy Flight	In LF-WDO, use the levy flight distribution in place of the randomness to acquire effective DP	None	The security of the file data experienced a rapid enhancement	Untested on diverse benchmarking functions Need to be tested on high dimensional problems

constrained optimization problems needs further investigation.

Bayraktar and Komurcu [91] proposed an adaptive WDO to achieve multi-objective, this algorithm still uses CMAES optimize the values of the parameters c, g, α and RT at each iteration. While the MO-AWDO has showcased efficient performance across five multi-objective numerical benchmark functions with varying dimensions, its applicability to all benchmark functions remains incomplete. Further investigation is necessary, particularly in assessing its performance on real engineering problems.

In their study, Xia et al. [92] introduced a modified version of WDO called MWDO. MWDO select the optimal control coefficients in WDO with Levy distribution and uniform distribution The coefficient values are specified as follows:

$$\alpha = 0.1 * \text{rand\_}L \tag{55}$$

$$RT = 0.1 * \text{rand\_}L \tag{56}$$

$$g = 0.1 * \text{rand\_}L \tag{57}$$

$$c = 2.5 * \text{rand\_}U \tag{58}$$

where the random number rand_U follows a uniform distribution between 0 and 1, while the random number rand_L adheres to a Levy distribution.

$$f(x;\mu;\gamma) = \sqrt{\frac{\gamma}{2\pi}}\frac{e^{-\gamma/2(x-\mu)}}{(x-\mu)^{3/2}} \tag{59}$$

where μ represents the location parameter and γ represents the scale parameter. $\mu = 0$ and $\gamma = 0.001$.

An advanced implementation algorithm for GRFT is presented, leveraging the innovative BMWDO (BSSL Learning-Based MWDO) framework, which is itself grounded in the principles of MWD. Central to the BMWDO method is the integration of a BSSL learning procedure, specifically designed to effectively address the challenges posed by BSSL phenomena. When benchmarked against the conventional BPSO, this novel approach exhibits enhanced detection capabilities, achieving superior performance while maintaining a computational cost that is on par with its predecessor. The efficacy of this method is further substantiated through a series of comprehensive numerical experiments, underscoring its practical viability and robustness. However, the proposed variants still need to be thoroughly investigated using other benchmarking functions to prove their validity. The proposed variant still needs to be thoroughly investigated using other benchmarking functions to prove its validity.

Shaheen et al. [93] represented these parameters of c, g, α and RT as uniformly distributed pseudo-random numbers within a specified range as follows Table 6.

TABLE 6. **Parameter range.**

Parameter	c	g	α	RT
Range	[0.2,0.4]	[0.1,0.2]	[0.2,0.4]	[2.4,3.0]

The simulation outcomes vividly demonstrate the effectiveness of the proposed MWDO in addressing the ORPD problem. Its performance not only surpasses that of the standard WDO but also outshines various other methodologies documented in the literature, particularly in the context of minimizing power loss. This superiority is a testament to the advanced capabilities and efficiency of the MWDO approach in optimizing power systems. However, MWDO was not studied using other benchmarking functions.

Nagar et al. [94] presented a comprehensive analysis and application of the Adaptive WDO (AWDO), comparing it to the classical WDO in continuous-valued electromagnetic problems. The main contribution lies in AWDO's ability to automatically determine inherent parameters, making it a self-adaptive and efficient algorithm that outperforms WDO without requiring a priori knowledge of optimal parameter values. The AWDO integrates the classical WDO with the Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES), enhancing performance and ease of use. The CMA-ES is configured to maintain a population size identical to that of WDO. The scope of the optimization problem is confined to a four-dimensional parameter space, specifically defined by the inherent parameters: c, g, α and RT. In every iteration, CMA-ES systematically generates and returns a novel set of values for these inherent parameters, corresponding to each member within WDO population. The effectiveness of AWDO is demonstrated through its superior performance in optimizing a linear antenna array problem compared to WDO, highlighting its potential in complex, real-world engineering problems. However, the AWDO only compared with WDO, it needs to be compared with other heuristic algorithms. To prove the effectiveness of AWDO, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems.

Madipalli et al. [95] presented a fully automatic technique for segmenting the Intima Media Complex (IMC) in ultrasound images of the Common Carotid Artery (CCA) using Adaptive WDO(AWDO). It introduces an innovative denoising and enhancement process in the preprocessing stage, followed by a robust segmentation method. The AWDO adaptively selects parameters to improve the segmentation process, this process is facilitated by the CMAES algorithm. The proposed method's effectiveness is demonstrated through a comparative analysis with state-of-the-art methods, showing superior results in segmenting the IMC. However, to prove the effectiveness of AWDO, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems.

Bayraktar [96] introduced Adaptive WDO (AWDO), a nature-inspired, metaheuristic method, applied to training feedforward artificial neural networks for digit classification using the MNIST dataset. The main contribution lies in integrating AWDO with a black-box solver, the CMAES, to adaptively tune parameters, this resulted in the formation of a versatile, adaptive algorithm. First successful application of AWDO to numerical classification.

Ibrahim et al. [97] introduced an Adaptive WDO (AWDO), aiming to enhance parameter extraction for single-diode PV cell models. The AWDO integrates the CMAES, strategically tailoring the optimization process to suit the specific characteristics of each problem. This methodical selection of inherent terms significantly enhances the algorithm's adaptability and precision in tackling diverse optimization challenges. The algorithm's design aims to accurately identify global parameter values under varying conditions and solve complex multi-modal and multi-dimensional optimization problems. The main contribution lies in AWDO's ability to adaptively handle parameter extraction with improved accuracy and computational efficiency, compared to traditional methods. However, to prove the effectiveness of AWDO thoroughly, it needs to be investigated using diverse benchmarking functions and high dimensional problems.

Wang et al. [98] introduced and evaluates the Adaptive WDO(AWDO) algorithm for parameter estimation in single-diode PV cell models. It stands out for its adaptability and efficiency in parameter extraction, especially under varying weather conditions. The AWDO, integrating CMAES, showcases enhanced convergence and accuracy compared to traditional methods. AWDO still needs to be investigated using diverse benchmarking functions and high dimensional problems to prove its effectiveness.

Ibrahim et al. [53] presented the development and application of an Improved WDO (IWDO) algorithm for identifying parameters of a triple-diode photovoltaic (PV) cell model. The IWDO enhances WDO by CMAES. This results in a more accurate and faster method for finding the global optimum, balancing exploration, and exploitation. The algorithm's performance is demonstrated using data from commercial photovoltaic technologies and is validated against other optimization methods, showing improved accuracy, convergence speed, and feasibility. IWDO still needs to be investigated using diverse benchmarking functions and high dimensional problems to prove its effectiveness.

Liu et al. [43] introduced an enhanced Maximum Power Point Tracking (MPPT) method for photovoltaic systems using an Adaptive WDO(AWDO). It addresses the inefficiencies of traditional MPPT methods by improving tracking speed, accuracy, and stability in varying environmental conditions. The AWDO dynamically adjusts its parameters, offering a significant improvement over the standard WDO by reducing oscillations at the Maximum Power Point (MPP) and ensuring fast and precise tracking. The effectiveness of the AWDO is validated through MATLAB/Simulink simulations, demonstrating superior performance in tracking accuracy and stability compared to traditional methods. To prove the effectiveness of AWDO, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems.

The adaptive weights are introduced in the gravity and Coriolis force expressions, and the adaptive weight expressions are given in the following equations.

$$\lambda_1 = \lambda_2 = \frac{\left|x_{opt} - x_{cur}\right|}{x_{opt}} \times \frac{1}{100} \tag{60}$$

$$u_{\text{new}} = (1-\alpha)u_{\text{cur}} - \lambda_1 g x_{\text{cur}} + \left(\frac{\lambda_2 c u_{\text{cur}}^{otherdim}}{i}\right) + \left(RT\left|1-\frac{1}{i}\right|(x_{\text{opt}} - x_{\text{cur}})\right) \tag{61}$$

In [99], an innovative method for estimating solar PV parameters i.e. WDO combined with CMAES is introduced. To determine the reliability, timeliness, and dynamics of the process, they used three different datasets. The performance of solar PV models characterized by single and double diode parameters was carefully evaluated. The results show that the proposed method can compute the solar PV parameters efficiently and effectively. To prove the effectiveness of proposed method thoroughly, it still needs to be investigated using diverse benchmarking functions.

Abd El-Mageed et al. [100] presents an Improved Binary Adaptive WDO (iBAWDO) for Feature Selection (FS) in supervised classification tasks. iBAWDO integrates evolutionary crossover techniques and SA with WDO to enhance feature selection efficiency. The algorithm's effectiveness is validated across 18 benchmark datasets and compared with 11 other meta-heuristic approaches. Statistical validation is conducted using Wilcoxon's rank-sum test, confirming iBAWDO's significant effectiveness on both small and large-dimensional datasets. To prove the effectiveness of iBAWDO thoroughly, it still needs to be investigated using diverse benchmarking functions.

Mathew et al. [101] presented a novel approach for parameter estimation of organic photovoltaic (OPV) cells using a three-diode model combined with an adaptive WDO. The work primarily addresses the challenge of accurately modeling OPV cells to replicate their I-V characteristics, particularly the kink effect. The main contribution is the effective use of WDO for parameter estimation, which outperforms traditional methods by achieving precise parameter values with fast convergence and minimal error. The hybrid algorithm's efficacy is demonstrated through extensive testing under various conditions, showing its superiority in terms of accuracy and computational efficiency. However, to prove the effectiveness of adaptive WDO, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems.

Based on the reviewed literature, we summarize the improvement process of the adaptive WDO algorithm, which focuses on adapting one to four parameters in the speed update formula of the WDO. Figure 4 illustrates the flowchart of the adaptive WDO. Table 7 shows the improvements and limitations in adaptive WDO.

C. IMPROVEMENTS OF PARAMETERS AND INTRODUCTION OF NEW PARAMETERS

Bayraktar et al. [55] detailed a numerical study for parameter tuning and employs statistical methods to evaluate algorithm performance, suggesting WDO's suitability for both discrete and continuous optimization problems. They proposed parameter ranges based on a numerical study conducted on unimodal and multi-modal test functions, as shown in Table8. However, to prove the effectiveness of the method they proposed, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems.

Segundo et al. [102] presented an enhanced WDO, incorporating Lévy flights for global continuous optimization, dubbed WDOLE. It demonstrates the algorithm's superior performance over the standard WDO by comparing their results on benchmark functions. The hybridization with Lévy flights allows for better exploration and exploitation, leading to faster convergence and improved solutions. This approach significantly outperforms the classical WDO, particularly in avoiding local optima and achieving closer to optimal solutions. However, the performance of WDOLE on practical engineering problems has not been studied. They changed the way the four inherent terms of c, g, α and RT through these equations. Details are shown as follows:

$$\alpha = (0.7\frac{a_{ij}}{\max it} + 0.9)\sqrt{\frac{2.4}{2\pi}}\exp\left(\frac{-2.4}{(\text{rand.} - 10^{-6})^{2.5}}\right) \tag{62}$$

$$RT = 4(0.4\frac{a_{ij}}{\max it} + 0.5)\sqrt{\frac{2.4}{2\pi}}\exp\left(\frac{-2.4}{(\text{rand.} - 10^{-6})^{2.5}}\right) \tag{63}$$

$$g = \sqrt{\frac{L}{2\pi}}\exp\left(\frac{-2.4}{(\text{rand.} - 10^{-6})^{2.5}}\right) \tag{64}$$

$$- 2\Omega RT \begin{cases} 4\sqrt{\frac{3.4}{2\pi}}\exp\left(\frac{-3.4}{(\text{rand.} - 10^{-6})^{2.5}}\right); \\ \quad \text{rand.} > 0.5 \\ 4\left(0.4\frac{a_{ij}}{\max it} + 0.2\right); \\ \quad \text{any other value of rand.} \end{cases} \tag{65}$$

where max it represents the maximum number of iterations, and L represents the step lengths. The step lengths (L) are drawn from a Levy distribution with $L > 0$.

$$L = \sqrt{\frac{\gamma}{2\pi}} e^{\frac{-\gamma}{2(s-\mu)^{3.5}}} \tag{66}$$

where γ represents a scale factor with values $\gamma > 0$, μ represents a shift parameter, and this distribution is valid for large steps $0 < \mu < s < \infty$.

The optimization of WDO has been enhanced by introducing new parameters by researchers. For example, Boulesnane and Meshoul [52] proposed the modified WDO (MWDO). In Equation (61), the velocity update equation incorporates a rank-based term to express pressure, but this approach

TABLE 7. Improvements and limitations in adaptive WDO.

Researchers /Year/Refs.	Adaptive algorithm	Description	Statistical tests	Performance	Limitations
Boulesnane et al. (2015) [52]	MWDO	The gravitational term is automatically and adaptively determined	Wilcoxon rank-sum test	Improve performance	Need to be tested on real-world problems
Bayraktar et al. (2016) [47]	AWDO	1.Replace c, g, α and RT values with uniformly distributed random numbers. 2.Optimize c, g, α and RT with CMAES	None	Improve performance	Need to be tested on real-world problems
Bayraktar et al. (2016) [91]	MO-WDO	Optimize c, g, α and RT with CMAES	None	Improve performance	Need to be tested on real-world problems
Xia et al. (2016) [92]	MWDO	Random distribution tuning for these parameters c, g, α and RT	None	Improve performance	Untested on diverse benchmarking functions , need to be tested on high dimensional problems
Shaheen et al. (2018) [93]	MWDO	Automatic adjust the control parameters with a uniformly distributed pseudorandom number	None	Improve convergence	Untested on diverse benchmarking functions , need to be tested on high dimensional problems
Nagar, J.et al. (2018) [94]	AWDO	Optimize c, g, α and RT with CMA-ES	None	The convergence efficacy of the AWDO outperforms that of WDO	Untested on diverse benchmarking functions, need to be tested on high dimensional problems Compared with WDO only
Madipalli et al. (2018) [95]	AWDO	Optimize c, g, α and RT with CMAES	Mean difference	AWDO works better than other methods	Untested on diverse benchmarking functions , need to be tested on high dimensional problems
Bayraktar et al. (2019) [96]	AWDO	Optimize c, g, α and RT with CMAES	None	AWDO is the first application to digital identification	Gradient descent method converges faster than AWDO
Ibrahim et al. (2020) [97]	AWDO	Optimize c, g, α and RT with CMAES	RMSE	AWDO is better than PSO, BBO, BFO	Untested on diverse benchmarking functions , need to be tested on high dimensional problems
Wang et al. (2020) [98]	Otsu-AWDO	Optimize c, g, α and RT with CMAES	RMSE	Otsu-AWDO obtain more accurate results for IMT measurement	Untested on diverse benchmarking functions , need to be tested on high dimensional problems
Ibrahim et al. (2020) [53]	IWDO	Enhances WDO by CMAES	RMSE,MAPE, nRMSE,nMBE, MBE, R^2	IWDO is improved in finding the global optimum of the identified parameters with better accuracy and convergence speed	Untested on diverse benchmarking functions, need to be tested on high dimensional problems
H. P. Liu et al. (2021) [43]	AWDO	Introduce the adaptive weights into the gravity and Coriolis force expressions	None	Improve convergence	Untested on diverse benchmarking functions , need to be tested on high dimensional problems
Mathew et al. (2020) [99]	AWDO	Optimize c, g, α and RT with CMAES	RMSE	AWDO works better than other methods	Untested on diverse benchmarking functions, need to be tested on high dimensional problems
Abd El-Mageed et al. (2022) [100]	iBAWDO	Combine SA, evolutionary crossover technique and CMAES and binarize it	Wilcoxon rank-sum test	iBAWDO is significantly effective on both small and large dimensional datasets	Untested on diverse benchmarking functions, need to be tested on high dimensional problems
Mathew et al. (2022) [101]	AWDO	Optimize c, g, α and RT with CMAES	RMSE, IAE	AWDO is demonstrated through extensive testing under various conditions	Untested on diverse benchmarking functions, need to be tested on high dimensional problems

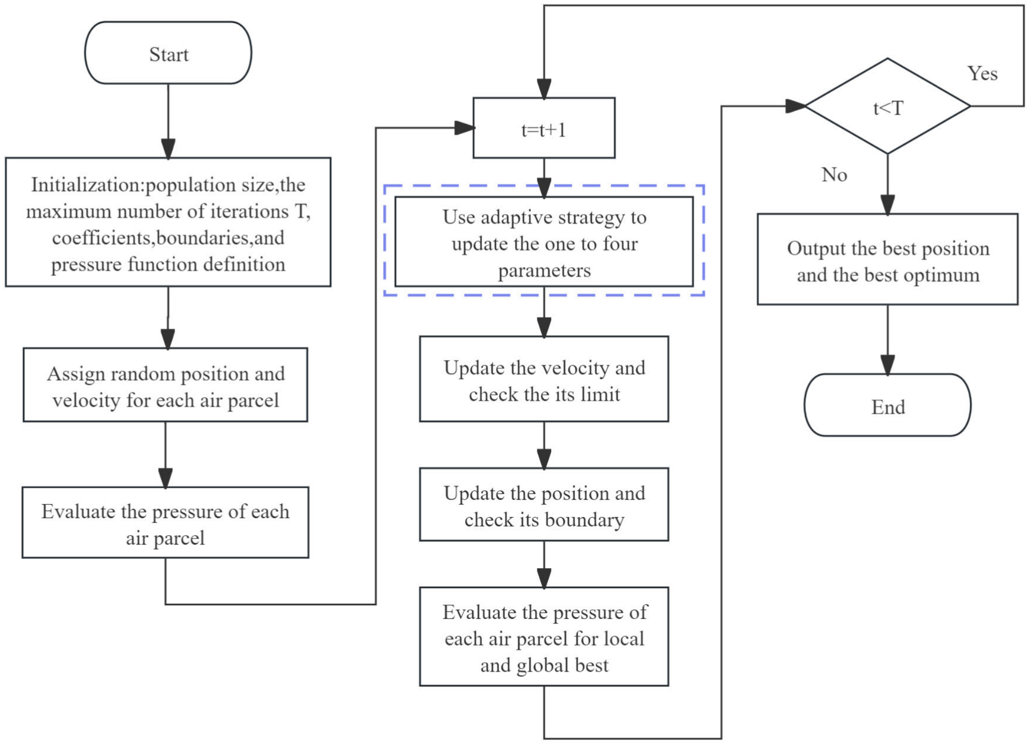

FIGURE 4. Flowchart of the adaptive WDO.

TABLE 8. Recommended parameter range.

Parameter	α	g	c	RT
Range	[0.8,0.9]	[0.6,0.7]	[0.05,3.6]	[1.0,2.0]

may not be suitable when there is a large number of airborne particles, potentially impacting the Coriolis force negatively. To further improve the algorithm's search capability, in the model equation, they replaced the rank-based term with a pressure-based term, as depicted in the following equation. The MWDO exhibits superior performance in terms of accuracy and robustness compared to the original algorithm. However, the performance of MWDO on practical engineering problems has not been studied.

$$\begin{aligned} u_{t+1}^{i} = (1-\alpha)u_t^i - g x_t^i \\ + \left(RT \left| \frac{P_{\text{best}}}{P_i} - 1 \right| (x_{\text{opt}} - x_t^i) \right) \\ + \left(\frac{c u_t^{\text{other dim}}}{P_i} \right) \end{aligned} \tag{67}$$

That is, i is replaced by P_{best} and P_i in Equation (67). Where P_i is the following equation:

$$P_i = \exp(-D * \frac{f(x_i) - f_{worst}}{sum}) \tag{68}$$

$$And\ sum = \sum_{j=1}^{N} \left(f(x_j) - f_{worst} \right) + (f_{best} - f_{worst}) \tag{69}$$

where f_{best} is the best value of objective function achieved up to now, and D represents the problem dimension.

$$f_{worst} = \max(\max(f(x_1), f(x_2), f(x_3), \ldots, f(x_N)), f_{best}) \tag{70}$$

f_{worst} is the worst value of test function achieved up to now, N represents the number of particles.

D. IMPROVEMENTS OF WDO USING BINARY ALGORITHM

According to the limited research, WDO is a continuous optimization method, most of the research on WDO mainly focuses on the optimization of continuous space, and only a few studies on binary problems.

To address the issue of emitted beamforming in opportunistic array radar, Zhang et al. [103] performed a novel binary version of the multi objective WDO for beamforming in opportunistic array radar, framing it as a multi objective optimization problem. It proposes a new definition of position vectors and integrates grey relational grade (GRG) to evaluate similarity between solutions, optimizing for a balance between main beam width and sidelobe level. The method outperforms conventional PSO in reducing sidelobe levels and computational time. However, to prove the effectiveness of the proposed method, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems. In the binary WDO the velocity updating is similar to the standard WDO, but position updating in the binary WDO is based on the sigmoid function, the subsequent equation demonstrates the stated relationship.

$$S(u_{new}) = \frac{1}{(1+\exp(-u_{new}))} \tag{71}$$

$$X_{new} = \begin{cases} 0 & if\ S(u_{new}) \le \text{rand};\ 0 \le \text{rand} \le 1 \\ 1 & if\ S(u_{new}) > \text{rand};\ 0 \le \text{rand} \le 1 \end{cases} \tag{72}$$

Zhou et al. [75] introduced a novel complex-valued encoding WDO (CWDO) with a greedy strategy for solving the 0-1 knapsack problem. They integrated a complex value encoding method to enhance global optimization and a greedy strategy to improve local search efficiency. This hybrid approach is designed to increase population diversity and avoid premature convergence. Through experimental validation across standard, small-scale, and large-scale test cases, CWDO demonstrated superior performance, stability, and robustness compared to existing algorithms like complex-valued CS, greedy GA, binary CS, BA, and PSO. The statistical methodology utilized to evaluate the algorithm's effectiveness included ANOVA tests, showcasing the CWDO's efficacy in solving the 0-1 knapsack problem with better search performance. However, to prove the effectiveness of the CWDO, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems.

Ranjan et al. [104] introduced a novel binary WDO applied to the design of a six-band ultra-thin, polarization-insensitive pixelated metamaterial absorber. The research focuses on synthesizing the unit cell structure of the metamaterial absorber by optimizing the presence of each unit pixel in a Frequency Selective Surface (FSS). The optimization demonstrates six distinct absorption bands with absorptivity over 90% at frequencies ranging from 7.6 GHz to 16.7 GHz. The novel approach includes a reinterpretation of the velocity vector in the binary WDO, incorporating "memory" to enhance optimization by considering the current binary state in updates. The study validates the design through numerical simulations and experimental results, showing a close match between the two. The methodology employs Finite Element Method (FEM)-based solver interfacing with MATLAB for simulation, highlighting the absorber's effectiveness across a wide angle of incidence and its polarization insensitivity. However, to prove the effectiveness of the proposed method, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems. They give a redefinition of velocity in binary WDO, the velocity of the air particle represents the probability that the current binary state will change to its complement. In this way the velocity in the binary WDO has the property of memory, influenced by the previous velocity state, and plays a crucial role in the renewal of air particles, as shown in the following equation:

$$\mathrm{S}(V_{mn,t}) = \frac{1}{1+\exp(-V_{mn,t})} \tag{73}$$

The function $\mathrm{S}(V_{mn,t})$ in its space domain, is defined as $[-\mathrm{V}_{max}, V_{min}]$.

$$\mathrm{S}(V_{mn,t}) = \begin{cases} \dfrac{1}{1+\exp(V_{mn,t})} = 0, & if\ V_{mn,t} \to -V_{max} \\ \dfrac{1}{2}, & if\ V_{mn,t} = 0 \\ \dfrac{1}{1+\exp(-V_{mn,t})} = 1, & if\ V_{mn,t} \to V_{max} \end{cases} \tag{74}$$

The value of $\mathrm{S}(V_{mn,t})$ obtained by Equation (74) is subset of (0,1). A uniformly distributed random number is generated within (0,1) and it is compared to $\mathrm{S}(V_{mn,t})$. The n_{th} bit of the m_{th} air particle, is updated according to:

$$X_{mn,t} = \begin{cases} X_{mn,t-1} & if\ r_{mn,t} \ge \mathrm{S}(V_{mn,t}) \\ \overline{X_{mn,t-1}} & if\ r_{mn,t} < \mathrm{S}(V_{mn,t}) \end{cases} \tag{75}$$

where, $\overline{X_{mn,t-1}}$ is complement binary state of $X_{mn,t-1}$. This new definition of position update brins memory to the optimization method, as next binary state of position is dependent on its present state.

For the given $r_{mn,t}$, the probability that the n_{th} bit equals to its complement binary state is:

$$P(X_{mn,t} = X_{mn,t-1}) = \mathrm{S}(V_{mn,t}) \tag{76}$$

Ranjan et al. [105] presented the synthesis of two wideband metamaterial cross-polarizers (MCPs) using the binary WDO(BWDO). This advanced technique modifies the traditional wind-driven optimization to suit electromagnetic (EM) problems requiring binary solutions. Two MCP models were developed, exhibiting high polarization conversion ratios (PCR) across broad bandwidths, achieved through meticulous optimization iterations. The study emphasizes the binary adaptation of WDO for pixelated structures, interfacing MATLAB with Ansys HFSS for efficient design and simulation. Experimental validation confirms the simulated performance, highlighting the BWDO's effectiveness in synthesizing wideband MCPs for potential X-band applications. However, the BWDO still needs to be investigated using diverse benchmarking functions and high dimensional problems to prove its effectiveness. In BWDO, the air particle's location can be represented by binary values "1" or "0", and its velocity indicates the likelihood of this binary state. The relationship between the position and velocity of the air particles is defined by the following equation. Additionally, the probability that it remains in its current binary state is:

$$P(X_{mn,t} = \overline{X_{mn,t-1}}) = 1 - \mathrm{S}(V_{mn,t}) = \mathrm{S}(-V_{mn,t}) \tag{77}$$

where $\mathrm{S}(V_{mn,t})$ is the Equation (73). From Equations (68) and (70), it is evident that the probability of a bit being flipped is higher when it differs from the corresponding bit in the global best solution.

Within the limitation of $\mathrm{S}(V_{mn,t}) \in -[-V_{max}, V_{max}]$ and expressed as Equation (74).

The value of $S(V_{mn,t})$ is evaluated by Equation (78). Consider the m_{th} air particle $x_{mn,t}$,the position of the n_{th} bit is upgraded as:

$$X_{mn,t} = \begin{cases} 0 & if\ r_{mn,t} \geq S(V_{mn,t}) \\ 1 & if\ r_{mn,t} < S(V_{mn,t}) \end{cases} \tag{78}$$

where $r_{mn,t}$ is defined as the threshold value. Robustness of BWDO on optimization problems is experimentally demonstrated.

When a given data set has a large number of characteristics of a given data set, traditional methods usually difficult to find a good solution to improve the overall classification accuracy, Abd El-Mageed et al. [100] presented an Improved Binary Adaptive WDO (iBAWDO) for feature selection in supervised classification, integrating evolutionary crossover and simulated annealing to enhance search capability and solution quality. This approach significantly reduces feature dimensionality while maintaining or improving classification accuracy, tested on 18 benchmark datasets against 11 binary meta-heuristic methods. The iBAWDO's effectiveness is confirmed through statistical analysis, including Wilcoxon's rank-sum test, demonstrating its superiority in handling both small and large-dimensional datasets for feature selection.

Ranjan et al. [106] presented the synthesis of two wideband metamaterial cross-polarizers (MCPs) utilizing the Binary WDO (BWDO) technique. The BWDO, an advanced version of WDO, is specifically adapted for electromagnetic problems with binary string variables. The main contributions include the successful synthesis of two wideband MCP models, each exhibiting high polarization conversion ratios (PCR) over broad frequency ranges. The research demonstrates the effectiveness of the BWDO technique in optimizing pixelated unit cell structures, providing a more efficient alternative to traditional trial-and-error methods. However, to prove the effectiveness of the BWDO, it needs to be investigated thoroughly using diverse benchmarking functions and high dimensional problems.

The improvements of WDO using binary algorithm are presented in Table 9.

E. SUMMARY OF IMPROVEMENTS OF WDO

Each heuristic algorithm has its own limitations, and so does WDO. Complex optimization problems can cause premature convergence. WDO has several parameters that need to be adjusted by the user according to the specific problem. This section evaluates the enhancement of WDO through various approaches, including parameter refinement, integration of other heuristics and mechanisms, utilization of adaptive methods, introduction of new parameters, and adoption of binary coding. WDO has gained increasing attention from scholars who have made two major improvements: a) introducing other strategic mechanisms and combining them with other metaheuristics, b) enhancing the algorithm's performance by adjusting its parameters. This section reviews recent and historical WDO variants and identifies their limitations.

Table 10 provides a comprehensive overview of the published papers corresponding to each improved method of WDO. It is summarized that the following steps are required to verify the validity of WDO variants:

1) INNOVATIVE APPROACH DEVELOPMENT

Facilitates the creation of a novel methodology, incorporating groundbreaking concepts, strategic parameter adjustments, or hybridization techniques. Ensures a balance between exploration and exploitation by integrating diverse heuristic algorithms and strategies and modifies control parameters for optimal algorithm performance.

2) BENCHMARK FUNCTION TESTING OF NEW WDO VARIANTS

Selects a range of standardized benchmark optimization functions such as CEC2023 test suite, unimodal, multi-modal, and composite benchmarking functions to assess the effectiveness of the new WDO variants. Evaluates the quality and efficiency of the algorithm's solutions through rigorous testing, examining various aspects of algorithmic performance.

3) REAL-WORLD ENGINEERING PROBLEM TESTING

Identifies relevant problem domains in engineering where WDO variants can be applied. Implements these algorithms in actual engineering scenarios to verify their practical utility and efficacy in solving complex, real-world problems.

4) COMPARATIVE ANALYSIS WITH ESTABLISHED ALGORITHMS

Conducts comparative evaluations of the new WDO variants against well-known WDO variants and other meta-heuristic approaches. Performs this analysis under uniform testing conditions to ensure fairness and accuracy in benchmarking.

5) PERFORMANCE IN HIGH-DIMENSIONAL TEST

A variant of WDO may exhibit robust performance in tackling low-dimensional problems, yet its efficacy might diminish significantly when applied to high-dimensional challenges. Consequently, it is imperative to rigorously assess the new variant's proficiency across both low and high-dimensional problem scopes. Typically, a WDO variant's performance tends to wane with the escalation of problem dimensions, underscoring the necessity to meticulously evaluate the performance of any new WDO variant, particularly in the context of high-dimensional problems.

6) SENSITIVITY ANALYSIS

Conducts a comprehensive sensitivity analysis to determine the impact of varying algorithmic parameters on the performance of the new WDO variants. Reveals which parameters significantly influence the outcomes, thereby understanding the robustness of the algorithm.

TABLE 9. Improvements of WDO using binary algorithm.

Researchers /Year/Refs.	Binary algorithm	Description	Statistical tests	Performance	Limitations
Zhang et al.(2015) [103]	Bi-MOWDO	By utilizing binary encoding	GRA	Improve performance	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Zhou et al. (2017) [75]	Binary WDO	By utilizing binary encoding	ANOVA	Improve performance	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Ranjan et al. (2018) [104]	Binary WDO	By utilizing binary encoding	None	Improve performance	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Ranjan et al. (2019) [105]	BWDO	By utilizing binary encoding	None	Prove the robustness of the BWDO	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Abd El-Mageed et al. (2022) [100]	iBAWDO	By utilizing binary encoding	Wilcoxon rank-sum test	Improve accuracy	Untested on diverse benchmarking functions Need to be tested on high dimensional problems
Ranjan et al. (2022) [106]	BWDO	By utilizing binary encoding	None	The results almost match the respective simulated results	Untested on diverse benchmarking functions Need to be tested on high dimensional problems

7) CONVERGENCE ANALYSIS

While average fitness and standard deviation are crucial metrics for assessing the performance of an optimization algorithm, conducting a convergence analysis is essential to comprehensively demonstrate the algorithm's capability to avoid local optima and effectively converge towards a global optimum.

8) STATISTICAL ANALYSIS

Applies advanced statistical methods to analyze the data obtained from testing and real-world applications. Utilizes techniques like t-tests, ANOVA, Wilcoxon rank-sum test, Friedman test, and regression analysis to validate the statistical significance and reliability of the results.

V. APPLICATIONS OF WDO AND ITS VARIANTS

The above articles improve on the standard WDO and compensates for its shortcomings, making it more robust and accurate. This section provides an overview of the enhancements made to WDO, including the concepts, mechanisms, and outcomes of these improvements, both in terms of practical and theoretical applications in electromagnetism, computer science and meteorology,as shown in Figure 5. This answers questions RQ6-RQ7. A summary of the different fields of WDO is shown in Table 11-Table 20.

A. ENGINEERING

Bayraktar et al. [56] utilized WDO to address electromagnetics engineering problems and successfully applied it to solve real-world optimization problems. Through experiments, they demonstrated the effectiveness of WDO for solving optimization problems. Furthermore, they validated its effectiveness by employing it in the optimized design of a thin double-sided AMC surface operating at 10 GHz.

In their study, Bayraktar et al. [107] utilized WDO to optimize the antenna geometry, specifically the length, position of stubs, and other design parameters. The results indicated that by applying WDO, an optimized stub-loaded inverted-F antenna (SLIFA) could be achieved, resulting in a lower profile and a notable gain improvement of 8.2 dB.

To address electromagnetism optimization problems, Bayraktar et al. [55] employed WDO. They found that WDO outperformed other algorithms when dealing with problems involving a combination of discrete and real-valued parameters.

Bhandari et al. [108] utilized WDO to select the optimal threshold for optimal multilevel thresholding using Kapur's entropy. This approach resulted in reduced computational costs and improved computational efficiency.

Mahto et al. [109] employed WDO to optimize array antennas for achieving high performance. Experimental results demonstrated that WDO outperformed both the PSO and the comprehensive learning particle swarm optimization (CLPSO) methods in terms of performance. To validate the effectiveness of WDO in electromagnetic field design, Mahto et al. [110] applied WDO to place a broad null at the desired direction in array pattern synthesis, while considering specific design constraints. Comparative analysis

TABLE 10. Improvements in WDO.

Variant	References
Hybridized WDO	Bao et al.(2015) [57] Zhou at al.(2015) [72] Mahto et al. (2016) [73] Mahto et al. (2016) [74] Zhou et al. (2017) [75] Yahia et al. (2017) [76] Javaid et al. (2017) [77] T. N. Qureshi et al. (2018) [79] Sawant et al. (2019) [80] Sinha et al. (2019) [81] Gao et al. (2020) [82] Y. Wang et al. (2020) [84] Sawant et al. (2021) [83] Singh et al. (2021) [85] Ibrahim et al. (2022) [86] Tang et al. (2022) [87] Athira et al. (2022) [88]
Adaptive WDO	Boulesnane et al. (2015) [52] Bayraktar et al.(2016) [47] Bayraktar et al.(2016) [91] Xia et al.(2016) [92] Shaheen et al.(2018) [93] Nagar, J. et al. (2018) [94] Madipalli et al.(2018) [95] Bayraktar et al.(2019) [96] I. A. Ibrahim et al.(2020) [97] Wang et al.(2020) [98] Ibrahim et al. (2020) [53] Mathew et al. (2020) [99] Mathew et al. (2022) [101] H. P. Liu et al. (2021) [43] Abd El-Mageed et al. (2022) [100] Mathew et al. (2022) [101]
WDO with new parameters	Boulesnane et al. (2015) [52] H. P. Liu et al. (2021) [43]
WDO parameter improvements	Bayraktar et al. (2013) [55] Segundo et al. (2014) [102] Xia et al.(2016) [92]
Binary WDO	Zhang et al.(2015) [103] Zhou et al. (2017) [75] Ranjan et al.(2018) [104] Ranjan et al. (2019) [105] Abd El-Mageed et al. (2022) [100] Ranjan et al. (2022) [106]

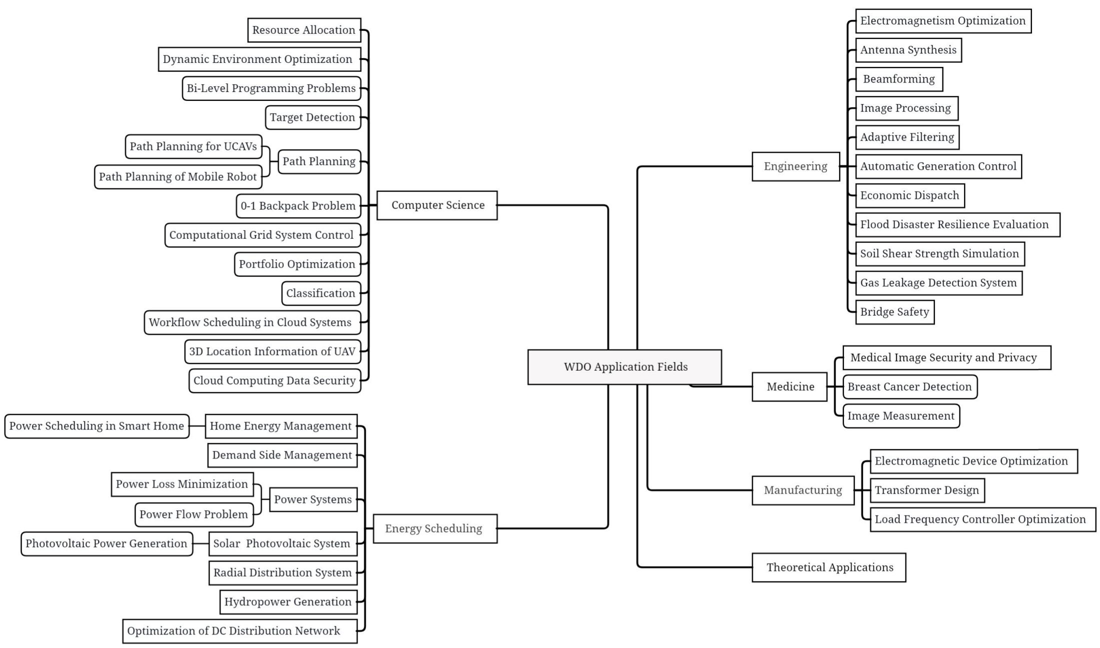

FIGURE 5. WDO application fields.

with other algorithms revealed that WDO outperformed them in terms of achieving a minimum signal-to-noise ratio and exhibiting faster convergence speed. Zhang et al. [103] introduced a binary multi-objective WDO to address the emitted beamforming problem in opportunistic array radar. Through simulations, the results demonstrated that the proposed method outperformed PSO in terms of beam optimization.

The main contribution of paper [73] is the development and application of a novel hybrid IWO/WDO for efficient and effective nulling pattern synthesis in antenna arrays, demonstrating superior performance over existing methods in terms of convergence rate, SLL minimization, and beam width control. Mahto and Choubey [74] introduced a novel optimization algorithm, the IWO/WDO, tailored for the synthesis of linear sparse array patterns with uniformly excited elements. This advanced algorithm aims to minimize interference by adeptly controlling the SLL and beam width through precise element position optimization. Efficacy is demonstrated with three varying element counts, showcasing superior SLL reduction and null depth levels compared to standard algorithms like IWO, WDO, PSO, CLPSO, DE, and BBO. Remarkably, it achieves minimum SLLs of −23.5 dB, −13.22 dB, and −19.7 dB across different element arrays and exhibits rapid convergence within approximately 100 iterations, outperforming six other algorithms in null control, SLL, beam width, and convergence rate.

Yahia and Elkamchouchi [76] proposed unified GSA/IWO/WDO optimization algorithm—a synergy of gravitational search algorithm, invasive weed optimization, and wind-driven optimization—capitalizes on the unique strengths of each nature-inspired component. This fusion not only enhances the calibration accuracy but also significantly improves the synthesis of array patterns and null control, ensuring minimized beam width. Empirical simulations underscore its efficacy, particularly inside lobe level reduction, interference suppression, and beam width minimization, thereby elevating the overall performance of real antenna array systems in terms of pattern synthesis resolution under stringent beam width constraints. To reduce the influence of symbol interference and random noise, Sinha and Choubey [78] combined the advantages of GA to improve WDO and carry out adaptive filtering, and the enhanced WDO demonstrates superior performance compared to other algorithms. Dwivedi et al. [111] emphasized the superiority of WDO in improving the transient performance of automatic generation control in interconnected multi-source power systems, considering various physical constraints like governor dead band and generation rate constraints. The research finds WDO more effective than BSA in optimizing the PI/PID controller parameters for AGC.

Nagar et al. [94] tackled the challenge of manually selecting the inherent parameters of WDO in electromagnetism applications by integrating adaptive strategies with WDO. The adaptive WDO demonstrated comparable or superior performance to the traditional WDO when applied to continuous value electromagnetic problems. Jevtic et al. [112] addressed the combined economic emission dispatch (CEED) problem by integrating adaptive strategies with WDO. Notably, the adaptive WDO does not require manual adjustment of coefficients. Comparative analysis with other algorithms revealed that the adaptive WDO outperformed them in terms of accurately and effectively solving the CEED problem. Sankar et al. [113] focused on utilizing WDO for CEED problems in power systems, aimed to optimize fuel costs while minimizing emissions. The study evaluates WDO against other algorithms across various test systems, emphasizing its efficiency and rapid convergence. Sankar et al. [114] investigated the application of WDO in economic dispatch problems within power systems, aiming to minimize fuel costs. It compares WDO's performance against other algorithms across various test systems, showing its potential to efficiently handle complex optimization problems in the energy sector.

Mahto et al. [115] presented an efficient WDO for the pattern synthesis of uniform linear arrays (ULA). The focus is on achieving maximum sidelobe level (SLL) suppression, constrained on dynamic range ratio (DRR) beam width, and null control by manipulating the amplitude-only and position-only of array elements. WDO, inspired by natural phenomena, is compared with other techniques like PSO, BBO, COA, CSA, CPSO, ILPSO, CLPSO and DE, demonstrating its superior performance in terms of SLL suppression, beam width control, null control, and convergence rate. Sawant and Manoharan [80] presented an enhanced WDO for band selection in hyperspectral image analysis. Additionally, they incorporated a deep learning architecture to further improve the classification accuracy of hyperspectral images. The proposed method achieved impressive overall accuracies of 93.26%, 94.76%, and 95.96% for the Indian Pines, Pavia University, and Salinas datasets, respectively. Sinha et al. [81] presented a hybrid IWO/WDO for optimizing linear array antenna parameters, aiming to enhance antenna design by achieving high gain, minimal side lobe level, and precise null placement. It offers a comprehensive solution to today's communication challenges. The algorithm's efficiency is validated through multiple design examples, showcasing its superiority in parameter optimization and array pattern synthesis. Liu et al. [116] introduced WDO and developed an enhanced prediction pursuit flood disaster resilience evaluation system. This system aimed to establish a suitable evaluation index system for regional flood disaster resilience. Comparative analysis with other algorithms revealed that WDO exhibited faster convergence and superior performance in this context. To enhance the flood control strategy for NamOon Reservoir, Thailand, Kangrang et al. [117] introduced a novel methodology integrating WDO approach with a simulation model. This integrated framework was meticulously designed to minimize the objective function defined as the average excess water. The effectiveness of the proposed approach was rigorously evaluated by determining the optimal flood rule curve for the reservoir. The model was used to determine the optimal flood rule curve for NamOon Reservoir, Thailand, and the results showed that the flood scenario of the optimal flood control rule curve is smaller than its current rule curve both in the present and future.

Moayedi et al. [118] incorporated WDO to enhance the prediction capability of neural networks in soil shear strength simulation. By integrating WDO with neural networks, this approach reduced the training error by 28.25% and demonstrated significant improvements in pattern recognition.

To enhance the accuracy of hyperspectral band identification, Sawant and Manoharan [83] combined WDO with CS and Chaotic map for band selection. The results demonstrated the superiority of this method over the standard WDO and CS approaches in accurately identifying hyperspectral bands. To solve the phased array radar transmit beam problem, Xu and Zhang [119] proposed an Improved WDO (IWDO)algorithm for transmitting beamforming of phased array radar, and this method allows for more accurate peak power. Recioui et al. [120] introduced WDO and applied it to the design of optimized planar antenna arrays. In this paper, the authors used WDO to design an optimized planar antenna array to ensure minimal side flaps and high directivity. By using only multiple excitation types of amplitude, phase, or both, the results of the optimized values show that the different antenna configurations suppress the sidelobe level well while the directivity is no worse than that of a uniform antenna.

Ramli et al. [49] employed WDO to address non-convex economic dispatch problems, aiming to enhance the efficiency of economic scheduling in power systems. Simulation results revealed that WDO successfully determined the optimal generation value with minimal generation cost and reduced power loss, indicating its effectiveness in optimizing economic dispatch. Mezhoud et al. [121] discussed WDO method for solving Optimal Power Flow (OPF) and Emission Index (EI) issues in electric power systems. It aims to minimize an objective function to balance energy production and consumption, considering constraints. The method, tested on IEEE 30-bus and IEEE 57-bus systems, showed promising results, indicating its effectiveness and robustness.

Li et al. [122] detailed the development of a near-infrared H2S leakage detection system utilizing tunable diode laser absorption spectroscopy (TDLAS) and a novel algorithm named WDO-ELM. The system enhances signal-to-noise ratio and telemetry distance for more accurate detection of H2S gas concentrations. It integrates a digital lock-in amplifier with a discrete wavelet transform filter for signal processing and employs WDO-ELM algorithm for global optimization, achieving significant improvements in detection limits and system sensitivity. He et al. [50] introduced a methodology that leverages a Wavelet Neural Network (WNN) as the surrogate model, in conjunction with WDO, for the purpose of updating structural finite element models. This approach was initially applied to the finite element model updating of a continuous beam structure with three equal spans, to evaluate its viability. The outcomes indicate that the WNN proficiently captures the non-linear interplay between the structural responses and their respective parameters, demonstrating superior simulation capabilities. Concurrently, WDO exhibits exceptional optimization prowess, significantly enhancing the efficiency of the model updating process. Subsequently, the methodology was implemented to update an actual bridge model. The results affirm that the finite element model, revised through the integration of WDO and WNN, is effectively applicable to the multi-parameter bridge model updating. This holds substantial practical value in the engineering domain, presenting a method that is not only efficient but also reliable in finite element model updating. Table 11 provides a literature review highlighting the applications of WDO in various engineering domains.

B. MANUFACTURING

Ayala et al. [123] introduced WDO, and its improved version, Lévy WDO (LWDO), which used Lévy flight, and multi-objective LWDO to solve transformer design optimization (TDO) problems. It performs better than standard WDO and the Non-dominated sorting Genetic Algorithm II (NSGA-II), it converges more efficiently and maintains diversity of solutions on the Pareto front. Through simulation experiments, the effectiveness of LWDO in dealing with multi-objective problems is proved, which shows that this method has a promising prospect in such optimization tasks.

Di Barba [124] applied WDO to address multi-objective functions and optimization problems in computational electromagnetics. Using WDO, successful optimization and synthesis of magnet current distribution were achieved, leading to optimal results in the given context.

Ho et al. [125] proposed a method for optimizing the robustness of electromagnetic devices in the presence of interval uncertainty. Their approach utilized a new uncertainty quantization formula and an enhanced version of WDO. By incorporating these advancements, the method successfully obtained the global optimal solution for the design problem under interval uncertainty in a single run.

To address the issue of premature convergence in WDO, Ho and Yang [126] introduced an improved approach. They incorporated a dynamic and random competition mechanism to overcome premature convergence. Additionally, a probabilistic mutation was designed, which utilized the latest information accumulated from the search history to guide the exploration of potential solutions and enhance the convergence of the algorithm.

To optimize the cost function in the design of multilayer microwave absorbers, considering both normal and oblique incidence of waves, Ranjan et al. [127] proposed a specialized cost function. This cost function was designed to provide optimal performance for normal and oblique incidence under various polarization conditions. WDO was employed to obtain improved numerical results in terms of wave thickness and oblique incidence for the optimization problem.

Ranjan et al. [104] utilized WDO to synthesize a six-band Metamaterial Absorber (MA). They optimized the presence of each unit pixel on the pixelated Frequency Selective Surface (FSS) to achieve the desired unit cell structure for the MA, the designed absorber exhibited excellent performance.

The document [128] is a comprehensive study on the application of WDO for Load Frequency Control (LFC) in

TABLE 11. Literature review of WDO application in engineering.

Authors/Year/Refs.	Object	Mechanism	Results	Application
Bayraktar et al. (2010) [56]	To solve the electromagnetism engineering problem	Apply WDO to electromagnetics engineering problems to solve real-world problems	Experiments prove the effectiveness of WDO for optimization problems, and the effectiveness is also proved by applying it to the optimized design of thin double-sided AMC surface of 10GHZ	Electromagnetism optimization problem
Bayraktar et al. (2011) [107]	To determine the optimal length and position of stubs as well as other antenna design parameters	Optimize antenna geometry by applying WDO	The findings indicate that optimizing the SLIFA yields a lower profile and an impressive gain improvement of 8.2dB	Antenna synthesis
Bayraktar et al. (2013) [55]	To solve the electromagnetism optimization problem	Use WDO to solve electromagnetism optimization problems	Compared to other algorithms, WDO is good at handling problems with discrete and real-valued parameters	Electromagnetism optimization problem
Bhandari et al. (2014) [108]	To reduce calculation costs	Optimal threshold selection by WDO using Kapur's entropy for optimal multilevel thresholding	This mothed improve computational efficiency	Image segmentation
Mahto et al. (2015) [109]	To design high performance array antennas	Use WDO to optimize the array antenna	The experimental results demonstrate that WDO outperforms both the PSO and the CLPSO algorithms by a significant margin	Linear array synthesis
Mahto et al. (2015) [110]	To prove the effectiveness of WDO in electromagnetic field design	Use WDO for placing broad null at the desired direction in the array pattern synthesis with specified design constraints	Compared with other algorithms, WDO performs better in terms of minimum signal-to-noise ratio and convergence speed	Linear array synthesis
Zhang et al. (2015) [103]	To solve the problem of emitted beamforming for opportunistic array radar	Propose a binary multi-objective WDO	The simulation results indicate that the proposed method outperforms PSO in terms of beam optimization	Beamforming of opportunistic array radar
Mahto et al. (2016) [73]	To achieve broad nulls, minimal SLL, and controlled beam width	Combine the advantages of IWO to improve WDO	IWO/WDO converges faster and more effectively than the other algorithms considered	Array antenna synthesis
Mahto et al.(2016) [74]	To optimize of side lobe levels and null control within specific beamwidth constraints	Combine the advantages of IWO to improve WDO	IWO/WDO converges faster and more effectively than the other algorithms considered	Interference of linear sparse array
Yahia et al. (2017) [76]	To optimize the array pattern synthesis and null control while minimizing the beam width, side lobe level, and interference	Combine the advantages of GSA and IWO to improve WDO	GSA/IWO/WDO enhances estimation's accuracy of the array parameters	Antenna array system
Sinha et al. (2017) [78]	To reduce the influence of symbol interference and random noise	Combine the advantages of GA to improve WDO and carry out adaptive filtering	The improved WDO performs better than other algorithms	Adaptive filtering
Dwivedi et al. (2017) [111]	To improve the transient performance of automatic generation control	Use WDO for solving	Using WDO has better result in terms of settling times, overshoot and undershoot	Automatic generation control
Nagar et al. (2018) [94]	To solve the problem of selecting the inherent parameters of WDO manually in the electromagnetism application	Combine adaptive strategies with WDO	The performance of the adaptive WDO is comparable to or better than that of WDO for continuous value electromagnetic problems	Electromagnetism optimization problem
JEVTIĆ et al. (2018) [112]	To solve the CEED problem	Combine adaptive strategies with WDO, no manual adjustment of coefficients is required	Compare with other algorithms, the adaptive WDO performs better while being able to solve the CEED problem accurately and effectively	Economic dispatch
Sankar et al. (2018) [113]	To solve the CEED problem	Use WDO for solving	WDO is competitive with PSO, CEP, FCGA	Combined economic and emission dispatch
Sankar et al. (2018) [114]	To solve the non-convex economic dispatch problem	Use WDO for solving	WDO is competitive and robust existing algorithms	Economic dispatch
Mahto et al.(2019) [115]	Use WDO for nulling pattern synthesis having minimum SLL and beam width	Use WDO for solving	WDO has better performance in terms of SLL suppression, beam width control, null control, and convergence rate	Linear array synthesis

TABLE 11. ***(Continued.)*** **Literature review of WDO application in engineering.**

Authors/Year/Refs.	Object	Mechanism	Results	Application
Sawant et al. (2019) [80]	To improve the classification accuracy of hyperspectral images	Propose a modified WDO for band selection, and then further selection through deep learning architecture	The modified WDO achieves remarkable overall accuracies of 93.26%, 94.76%, and 95.96% for the Indian Pines, Pavia University, and Salinas datasets, respectively	Hyperspectral band selection
Sinha et al. (2019) [81]	To optimize the parameters of array elements	Develop IWO/WDO to optimize the parameters of array elements	IWO/WDO demonstrates efficiency and adaptability for positioning multiple nulls precisely within the synthesis of array patterns	Array antenna synthesis
Liu et al. (2019) [116]	To construct the appropriate evaluation index system for regional flood disaster resilience	Introduce WDO and proposed an improved prediction pursuit flood disaster resilience evaluation system	Compare with other algorithms, WDO converges faster and performs better	Prediction flood disaster resilience evaluation system
Kangrang et al. (2019) [117]	To improve the rule curves of reservoir	Introduce WDO and proposed an improved rule curve of reservoir	The optimal flood control rule curve is smaller than its current rule curve both in the present and future	Flood control rule curves optimization
Moayedi et al. (2020) [118]	To improve the prediction ability of the neural network in soil shear strength simulation	Introduce WDO to improve the prediction ability of neural networks	This method reduces the training error by 28.25% and significantly improves pattern recognition	Soil shear strength simulation
Sawant et al. (2021) [83]	To improve the accuracy of finding the hyperspectral band	Use WDO in combination with the CS and chaotic map to find the hyperspectral band	The results show that this method is superior to the standard WDO and CS	Hyperspectral band selection
Xu et al. (2021) [119]	To solve the phased array radar transmit beam problem	Propose IWDO for transmit beamforming of phased array radar	This method allows for more accurate peak power	Transmit beamforming for phased array
Abdelmadjid et al. (2021) [120]	To optimize planar antenna array which ensures minimum side lobes and high directivity	Use WDO to planar antenna array	The different antenna configurations suppress the sidelobe level well	Antenna array optimization
Ramli et al. (2022) [49]	To improve efficiency in economic scheduling issues	Use WDO to solve non-convex economic dispatch problems.	WDO can determine the optimal generation value with minimum generation cost and low power loss	Economic dispatch
Mezhoud et al. (2022) [121]	To achieve optimal multi-reservoir system rule curves	Use WDO for solving	WDO is successfully implemented to find optimum control variables of OPF and EI problems	The optimal power flow and emission index optimization
Li et al. (2023) [122]	To improve the reliability and stability of the system	Combine WDO with the ELM and applied WDO-ELM to H2S leak detection system	It is experimentally demonstrated that WDO-ELM compensated the limitations of ELM algorithm and widened the optimal weights and thresholds	H2S leakage detection system
He et al.(2023) [50]	To ensure the safety and serviceability of bridge structures	Leverage a WNN as the surrogate model, in conjunction with WDO	The finite element model, revised through the integration of WDO and WNN, is effectively applicable to the multi-parameter bridge model updating	Bridge safety

interconnected power systems, considering the nonlinearities of Generation Rate Constraint (GRC) and Governor Dead Band (GDB). The main work involves the development and evaluation of WDO in optimizing LFC, demonstrating its effectiveness compared to other evolutionary algorithms.

Ranjan et al. [105] introduced a novel binary version of WDO, named Binary WDO (BWDO), designed for binary-valued problems like antenna array and metasurface synthesis. The paper validates the BWDO with standard benchmark functions and demonstrates its efficiency through examples of thinned antenna array and metasurface synthesis.

Yang et al. [42] developed a WDO-based vector optimizer to tackle the multi-objective design problem in electromagnetism. Their approach effectively addresses both inverse and optimization problems. Experimental results demonstrate the favorable performance of this method in solving such complex electromagnetic problems.

Ranjan et al. [106] presented the development of two wideband metamaterial cross-polarizers (MCPs), Model-I and Model-II, utilizing the Binary WDO (BWDO) technique. The work's key contributions are the successful design and synthesis of these MCPs with high polarization conversion ratios (PCRs) across a broad frequency range. The hybrid algorithm, BWDO, efficiently optimizes pixelated structures for electromagnetic applications. The performance of the MCPs is validated through close agreement between simulated and experimental results, showcasing the algorithm's effectiveness. Table 12 provides a literature

TABLE 12. Literature review of WDO application in manufacturing.

Authors/Year/Refs.	Object	Mechanism	Results	Application
Ayala et al. (2016) [123]	To present a transformer design optimization methodology using a multi-objective WDO approach	Use WDO to achieve multi-objective optimization	The multi-objective LWDO surpasses both the multi-objective version of WDO and the classical NSGA-II in performance.	Transformer Design
Di Barba et al. (2016) [124]	To solve the multi-objective optimization problem in the field of electromagnetics	Use WDO to achieve multi-objective optimization	The achievement of the optimal synthesis of the current distribution in the magnet has been accomplished	Electromagnetic device optimization
Ho et al. (2017) [125]	To optimize the robustness of electromagnetic devices in the interval uncertainty	Propose a method based on a new uncertainty quantization formula and an improved WDO	The proposed method can identify the global optimal solution for the design problem under interval uncertainty within a single run	Electromagnetic device optimization
Ho et al. (2017) [126]	To overcome the premature convergence of WDO	Introduce a dynamic and random competition mechanism and improve the convergence	It is proved that the method is superior and feasible	Electromagnetic device optimization
Ranjan et al. (2018) [127]	To optimize the cost function in the design of multilayer microwave absorbers in the optimization problem considering the normal and oblique incidence of waves	Propose a cost function that is optimally designed for normal and oblique incidence under polarization conditions	WDO is used to obtain better numerical results in terms of wave thickness and oblique incidence	Electromagnetic device optimization
Ranjan et al. (2018) [104]	To synthesize a six-band MA	Synthesize the unit cell structure of MA by optimizing the presence of each unit pixel on the pixelated FSS	The designed absorber has good performance	Electromagnetic device optimization
Alhelou et al.(2018) [128]	To optimate the LFC controllers' parameters	Use WDO to tune the LFC controllers' parameters	The robustness of WDO has been confirmed	Load frequency controller optimization
Ranjan et al. (2019) [105]	To address binary value problems, such as antenna array and meta surface synthesis	The binary mechanism is introduced into WDO	This method improved the performance	Electromagnetic device optimization
Yang et al. (2019) [42]	To solve the electromagnetism multi-objective design problem	Develop a WDO-based vector optimizer for multi-objective inverse and optimization problems	The experimental results show that this method performs well	Electromagnetic device optimization
Ranjan et al. (2022) [106]	To synthesize metamaterial cross polarizer (MCP) frequency-selective surfaces (FSS)	Use the binary WDO for MCPs synthesis	The proposed MCPs have a monolayer and wider PCR bandwidth, but also a larger unit cell size	Electromagnetic device optimization

review highlighting the applications of WDO in the field of manufacturing.

C. ENERGY SCHEDULING

Naseem et al. [129] discussed the problem of scheduling residential appliances in smart grids to reduce cost and peak to average ratio (PAR) by using four different heuristic algorithms: Bacterial Forging Optimization Algorithm (BFOA), GA, Binary PSO (BPSO) and WDO. The authors compared the performance of these algorithms on a home energy management (HEM) system with 10 different appliances categorized into three groups: shiftable interruptible, shiftable uninterruptible and regular appliances. The authors evaluate the performance of the algorithms in terms of cost reduction, PAR reduction, and computational time. The results concludes that WDO can effectively address the residential load scheduling problem and achieve the objectives of cost reduction, but increase the PAR

To design an efficient Demand Side Management (DSM) controller, Javaid et al. [77] proposed a hybrid genetic wind driven (GWD) approach. The results demonstrate that the GWD scheme reduces the power cost by approximately 10% and 33% compared to the GA and WDO, respectively.

Similarly, to effectively control the Peak Average Ratio (PAR) and minimize costs, Qureshi et al. [79] introduced a hybrid Enhanced Differential Harmony WDO (EDHWDO). This approach combines the characteristics of the Harmony Search Algorithm (HSA), Enhanced DE (EDE), and WDO, resulting in significant cost reduction.

To enhance the performance of the Load Frequency Controller (LFC), Alhelou et al. [128] employed WDO for tuning the LFC parameters. The results demonstrate that this approach significantly improved the performance of the LFC, particularly in terms of maximum deviation and settling time.

To enhance the efficiency of solar photovoltaic (PV) systems, Mathew et al. [130] utilized WDO to optimize the parameters of a twelve-parameter Double Diode Model (12p-DDM) for solar PV systems. Through experimental verification, the authors demonstrated the accuracy and flexibility of the proposed method.

Shaheen et al. [93] introduced a modified WDO (MWDO) algorithm, focusing on optimal reactive power dispatch (ORPD) in power systems to minimize power loss. The MWDO, inspired by atmospheric wind patterns and adapting control parameters dynamically, shows superiority over standard WDO and other methods in literature, achieving significant power loss reduction in test systems like IEEE 14, 30-bus, and West Delta Network. The algorithm's performance is validated through comparative simulations, demonstrating its effectiveness and robustness in optimizing power systems.

Injeti and Kumar [131] focused on optimizing the deployment of Distributed Generators (DGs) and D-STATCOM(DSCs) in radial distribution systems. The main work involves formulating a weighted objective function to minimize daily power loss, improve voltage profiles, and maximize net annual savings. WDO, inspired by the atmospheric motion of wind, is utilized to find optimal locations and sizes for DGs and DSCs. The effectiveness of this methodology is validated by considering various scenarios and conducting a detailed outcome analysis.

Ermis et al. [132] utilized WDO to tackle the optimal power flow problem. The results indicate that WDO is effective in resolving voltage deviations, reducing calculation time, minimizing total active power losses, and optimizing fuel costs associated with the power flow problem.

To improve the efficiency of the global Maximum Power Point Tracking (MPPT) technique of photovoltaics system (PVS), Abdalla et al. [58] used WDO to optimize the MPPT technique, and by comparison, the MPPT technique based on WDO is more efficient.

Ibrahim et al. [97] introduced an Adaptive WDO (AWDO) algorithm for efficiently extracting parameters of the single-diode PV cell model. The results obtained from this approach showed promising performance.

Ibrahim et al. [53] proposed an improved version of WDO by using CMAES. This enhanced algorithm demonstrated improvements in terms of accuracy, convergence speed, and feasibility.

Mathew and Rani [99] presented an innovative approach for parameter estimation of Solar PV models using WDO. The main work involves testing WDO's performance for estimating parameters in single and double diode solar PV models. The algorithm's effectiveness is assessed using three different datasets, including experimental data for specific PV models and manufacturer's datasheet values. The key contribution is the introduction of WDO for solar PV parameter estimation, demonstrating its superiority over existing methods through lower Root Mean Square Error (RMSE) values, indicating higher accuracy and efficient convergence.

Wang et al. [84] presented a novel GA-WDO hybrid algorithm to optimize operations in DC distribution networks with Battery Swapping Stations (BSS). It aims to minimize operational costs while maximizing the utilization of wind and solar energy, addressing the variability and uncertainty in renewable energy sources. The study showcases the model's effectiveness in balancing energy demand, optimizing resource use, and improving system reliability.

Ibrahim et al. [133] introduced a multi-objective WDO to optimize the stand-alone PV power generation system for mobile network base stations. The objective was to determine the optimal number of PV modules and cell capacity. The results of the study demonstrated the effectiveness of the proposed method in achieving good optimization outcomes.

Similarly, to improve the efficiency of the PV power system, Liu et al. [43] introduced a fast and accurate tracking method of the maximum power point, which is the Adaptive WDO(AWDO) algorithm and introduces adaptive weights into gravity and Coriolis force expressions, the results show that this method tracks quickly and accurately, and reduces steady-state oscillations.

Liu et al. [44] proposed an improved WDO, known as IWDO, to optimize reservoir operation. This algorithm incorporated a dynamic adaptive random mutation mechanism and a search space reduction strategy. The application of IWDO resulted in enhanced search efficiency and improved scheduling results in terms of quality.

Makhadmeh et al. [134] discussed the integration of WDO with Smart Home Battery (SHB) systems for optimizing power scheduling in smart homes. The focus is on reducing electricity bills and peak power demand while enhancing user satisfaction. The study demonstrates the effectiveness of WDO in comparison to the Bacterial Foraging Optimization Algorithm (BFOA), showcasing WDO's superior performance in optimizing power scheduling objectives in smart homes.

Senthilkumara et al. [135] presented the application of WDO to solve the Optimal Power Flow (OPF) problem in power systems, specifically focusing on reducing the fuel cost of generation. WDO's efficacy is demonstrated on the IEEE 30 bus test system, achieving significant cost reductions, and showcasing its capability to handle complex optimization problems effectively.

Ibrahim et al. [86] proposed a hybrid approach called wind driven-based fruit fly optimization (WDFO) to identify the unknown parameters of a double-diode PV cell module. The results indicate that the hybrid WDFO algorithm enhances computational accuracy and convergence speed.

Mathew et al. [101] introduced an adaptive WDO for parameter estimation of three-diode organic PV cells. The adaptive WDO is employed to accurately determine the PV parameters. Table 13 presents a literature review of WDO applications in energy scheduling.

D. COMPUTER SCIENCE

To rationalize and efficiently allocate resources and improve utilization, Sun et al. [136] used a combination of auction models, neural networks, and intelligent optimization

TABLE 13. Literature review of WDO application in energy scheduling.

Authors/Year/Refs.	Object	Mechanism	Results	Application
Naseem et al. (2017) [129]	To reduce cost and PAR by scheduling of residential appliances	Use WDO for solving	Using WDO achieves the objectives of cost reduction	Home energy management in smart grid
Javaid et al. (2017) [77]	To design an efficient DSM	WDO is mixed with GA to obtain the hybrid GWD	Use the hybrid GWD algorithm for optimization	DSM in smart grid
T. N. Qureshi et al. (2018) [79]	To effectively control PAR and reduce the cost	Propose a hybrid EDHWDO by combining the HSA, EDE, and WDO	This method helps to reduce the cost significantly	DSM in smart grid
Alhelou et al. (2018) [128]	To enhance the LFC performance	Use WDO for tuning the LFC	This method improved the performance in terms of maximum deviation and settling time	Power systems
Mathew et al. (2018) [130]	To improve the efficiency of solar PV systems	Adopt WDO to optimize the parameter of a 12p-DDM of solar PV	The proposed method experimentally verified the accuracy and flexibility	SolarPV system
Shaheen et al. (2018) [93]	To solve the problem of ORPD and reduce power consumption	Propose a modified WDO that automatically changes the control parameters	The results obtained show the ability of this method to minimize power losses	Power loss minimization in power systems
Injeti et al.(2018) [131]	To determine optimal locations and sizes of DGs and DSCs	Use WDO to solve the optimal locations and sizes of DGs and DSCs	WDO has successfully provided an optimal solution with excellent quality and convergence	Radial distribution system
Ermis et al. (2019) [132]	To solve the optimal power flow problem	Use WDO to solve the optimal power flow problem	The results show that WDO is effective in solving for voltage deviations, calculation time, total active power losses, and fuel costs	Power flow problem
Abdalla et al. (2019) [58]	To improve the efficiency of global MPPT technique of PVS	Use WDO to optimize the MPPT technique	The MPPT technique based on WDO is more efficient	PV power generation
I. A. Ibrahim et al. (2020) [97]	To quickly extract the parameters of the single-diode PV cell model	Propose an AWDO	Improve performance	PV cells
Ibrahim et al. (2020) [53]	To identify the parameters of the PV cell model	Propose the improved WDO by CMAES	Improve accuracy, convergence speed, and feasibility	PV cells
Mathew et al. (2020) [99]	To detect of Solar PV parameters	Use an adaptive WDO which combined with CMAES	WDO achieves low RMSE values with fewer iterations across all types of Solar PV	PV cells
Y. Wang et al. (2020) [84]	Reduce the operation cost of DC distribution network with BSS and improve the utilization rate of wind and light	Propose the hybrid algorithm which is a combination of GA and WDO	Improve the optimization speed	Optimization of DC distribution network
Ibrahim et al. (2021) [133]	To optimize the stand-alone PV power generation system and determine the optimal number of PV modules and cell capacity	Propose a multi-objective WDO for optimization	Obtain good results	PV power generation
H. P. Liu et al. (2021) [43]	To improve the efficiency of the PV power system	Propose a fast and accurate tracking method of the maximum power point, which is the AWDO, and introduce adaptive weights into gravity and Coriolis force expressions	The results show that this method tracks quickly and accurately, and reduces steady-state oscillations	PV power generation
Liu et al. (2021) [44]	To further optimize the reservoir operation	Use an IWDO, which introduced a dynamic adaptive random mutation mechanism and a search space reduction strategy	This method improves the search efficiency and the quality of the scheduling results	Hydropower generation
Makhadmeh et al.(2021) [134]	To optimize power scheduling in smart homes	Adopt WDO to optimize power scheduling in smart homes	Using WDO has reduced electricity costs and enhanced overall user satisfaction	Power scheduling in smart homes
Senthilkumara et al. (2021) [135]	To find OPF solution	Adopt WDO to OPF solution	WDO is a superior solution for resolving the OPF problem	power flow problem
Ibrahim et al. (2022) [86]	To identify the unknown parameters of a double-diode PV cell module	Propose a WDFO	The results show that the computational accuracy and convergence speed of the hybrid WDFO are improved	PV cells
Mathew et al. (2022) [101]	To identify the parameter estimation of a three-diode organic PV cells	Use an adaptive WDO	The adaptive WDO is applied to obtain the exact PV parameters	PV cells

TABLE 14. Literature review of WDO application in computer science.

Authors/Year/Refs.	Object	Mechanism	Results	Application
Sun et al. (2013) [136]	To rationalize and efficiently allocate resources and improve utilization	Use a combination of auction models, neural networks, and intelligent optimization techniques, and use WDO for function optimization	This method can effectively improve resource utilization	Resource allocation
Boulesnane et al. (2014) [137]	Use a new strategy of improved WDO to solve collision avoidance in dynamic environments problem	WDO is introduced with a multi-region concept and a new collision avoidance technique	By utilizing the mobile peak benchmark as an example, it demonstrates superior performance compared to other algorithms	Dynamic environment optimization
Zhou et al. (2015) [72]	Propose a new quantum WDO to solve the path planning problem of UCAV	Introduce quantum rotation gate strategy and quantum non-gate strategy	It exhibits superior performance compared to other algorithms	Path planning for UCAVs
Xu et al. (2016) [138]	Propose hierarchical WDO to solve the bi-level programming problem	Introduce a hierarchical algorithm, which consisted of two WDOs and figure out the optimal solution by invoking each other	The effectiveness of the proposed algorithm for solving bilevel programming problems is demonstrated through experimental results	Bi-level programming problems
Xia et al.(2016) [92]	Propose a modified WDO to detect weak maneuvering targets in radar systems	MWDO adjusts optimization coefficients using Levy and uniform distributions	It demonstrates superior performance over previous methods, such as the PSO, especially in noisy environments	Target detection
Boulesnane et al. (2017) [140]	WD2O is proposed as a solution for real problems in dynamic environments	Introduce the wind driven dynamic optimization algorithm, which is an enhanced MR-WDO model	Compare with MR-MWDO, WD2O shows better performance and achieves the best performance in high-dimensional problems	Dynamic environment optimization
Pandey et al. (2017) [46]	To solve the problem of navigation and collision avoidance of autonomous mobile robots	Introduce a fuzzy WDO hybrid controller	Experimental results show that the fuzzy WDO has better performance	Path planning of mobile robot
Xu et al. (2017) [139]	Propose HWDO to solve the bi-level programming problem	Introduce a hierarchical algorithm, which consisted of two WDOs and figure out the optimal solution by invoking each other	The performance of the proposed bi-level programming model combined with the HWDO is commendable	Bi-level programming problems
Zhou et al. (2017) [75]	To address the 0-1 knapsack problem	Introduce a complex-valued encoding method and a greedy strategy to WDO	It demonstrates that CWDO outperforms other algorithms in terms of performance, stability, and robustness	0-1 backpack problem
Ghosh et al. (2018) [141]	To optimize the scheduling of jobs in the computing grid system	Use WDO to optimize scheduling jobs in a computational grid system	Compared with GA and PSO, WDO shows better performance	Computational grid system control
Kaushal et al. (2018) [142]	To design the optimal portfolio	Use WDO to design the optimal portfolio	Compare with the results of GA, WDO outperforms GA in portfolio optimization	Portfolio optimization
Bayraktar et al. (2019) [96]	Apply AWDO into Digit classification	Apply AWDO into the training of feedforward artificial neural networks (NN)	The first successful application of AWDO to numerical classification	Digit classification
Gao et al. (2020) [82]	To solve the 3D position information of UAV without GPS	Use a single chain encoding Chan-QWDO	Compared with other algorithms, Chan-QWDO has stable performance, fast convergence speed and high positioning accuracy	3D location information of UAV
Bej et al. (2020) [143]	To minimize the traveling path length of a FWGR	Use WDO to search a minimal or near-minimal steering angle for the FWGR	Use WDO covers a shorter path length for the FWGR	Route planning
Singh et al. (2021) [85]	To solve reliability problems in workflow scheduling under budget constraints	Use HWDO for Scheduling Scientific Workflow Applications on Cloud Systems	HWDO outperforms other algorithms in scheduling reliability by 9%-17%	Workflow scheduling in cloud systems
Athira et al. (2022) [88]	To enhance the cloud data's security	In LF-WDO, use the levy flight distribution in place of the randomness to acquire effective DP	The LF-WDO is above 5% faster than the existent techniques. The security of the file data experienced a rapid enhancement	Cloud computing data security
Abd El- Mageed et al. (2022) [100]	To reduce the computational cost and improve the final classification accuracy for a given data set	Introduce a combination of crossover technique and SA within WDO framework	The performance and effectiveness of the method significantly improved	Supervision classification

techniques, and used WDO for function optimization, this method can effectively improve resource utilization.

Boulesnane and Meshoul [137] proposed a novel strategy for collision avoidance in dynamic environments using an improved WDO. They introduced the concept of multiple regions and a new collision avoidance technique. The performance of the algorithm was evaluated using the Moving Peak Benchmark, and the results showed superior performance compared to other algorithms in terms of collision avoidance.

Zhou et al. [72] introduced a new optimization algorithm called quantum WDO (QWDO) for solving the path planning problem of unmanned combat air vehicles (UCAVs). The algorithm incorporates quantum rotation gate and quantum non-gate strategies to enable individual variation within the population. Comparative analysis with other algorithms demonstrates that QWDO outperforms them in terms of performance, making it a promising approach for UCAV path planning.

To solve the bi-level programming problem, Xu and Teng [138], [139] introduced a hierarchical algorithm, which consisted of two WDOs and figure out the optimal solution by invoking each other. Experimental results show that the proposed algorithm is effective for solving bi-level programming problems.

Xia et al. [92] introduced a fast algorithm based on the Generalized Radon-Fourier Transform (GRFT) for detecting weak maneuvering targets in radar systems. The main contributions include the development of a modified WDO (MWDO) approach, which incorporates blind speed side lobe (BSSL) learning to improve detection performance while maintaining computational efficiency. The MWDO adjusts optimization coefficients using Levy and uniform distributions, demonstrating superior performance over previous methods, such as the PSO, especially in noisy environments. The effectiveness of the proposed algorithm is validated through numerical experiments, showing better detection capabilities with comparable computational costs.

To address the real problems in a dynamic environment, Boulesnane and Meshoul [140] introduced the wind driven dynamic optimization (WDO), which is an enhanced multi region modified WDO(MR-MWDO) model, compare with MR-MWDO, WD2O shows better performance and achieves the best performance in high-dimensional problems.

Pandey and Parhi [46] presented a hybrid Fuzzy-WDO for autonomous mobile robot navigation and collision avoidance in unknown static and dynamic environments. The novel approach integrates WDO to optimize the input/output membership function parameters of the fuzzy controller. This integration results in enhanced navigation performance, demonstrated through computer simulations and real-time experiments using the Khepera-III mobile robot. The algorithm showcases significant improvements in path planning and control, providing a promising solution for complex navigational challenges in robotics.

To solve the 0-1 knapsack problem, Zhou et al. [75] introduced a complex-valued encoding method and a greedy strategy to WDO, and the experimental results show that CWDO has better performance, stability, and robustness compared to other algorithms.

To optimize the scheduling of jobs in the computing grid system, Ghosh and Das [141] used WDO to optimize scheduling jobs in a computational grid system, and when compared with GA and PSO, WDO shows better performance.

To design the optimal portfolio, Kaushal and Singh [142] used WDO to design the optimal portfolio, compare with the results of GA, WDO outperforms GA in portfolio optimization.

In [96], the innovative Adaptive WDO (AWDO), a nature-inspired metaheuristic approach, is applied to train feedforward artificial neural networks, highlighting its potential in deep learning research. An examination using the MNIST dataset for digit classification demonstrates AWDO's unique performance, a derivative-free method, in contrast to the traditional gradient descent approach. The study provides insights into AWDO's future integration with deep neural networks, setting a foundation for subsequent explorations in this emerging field.

Gao et al. [82] proposed a single chain encoding quantum WDO combined with Chan algorithm (Chan-QWDO) to address the challenge of determining the 3D position information of unmanned aerial vehicles (UAVs) in the absence of GPS. Through comparative analysis with other algorithms, it was observed that Chan-QWDO exhibited stable performance, rapid convergence, and high accuracy in UAV positioning, making it a reliable solution for this location problem.

Bej et al. [143] focused on optimizing the navigation of a four-wheeled ground robot (FWGR)using WDO. The algorithm is designed to minimize the travel path length of the robot in various environmental conditions. WDO's efficacy is demonstrated by comparing it with PSO and GA, showing its superiority in achieving shorter path lengths and efficient navigation in complex scenarios.

Singh et al. [85] presented a hybrid WDO(HWDO) for scheduling scientific workflow applications on cloud systems. The main contribution of this paper is to address the reliability issue in workflow scheduling under budget constraint, which is a challenging problem in cloud environment. The objective of the proposed algorithm is to generate reliable workflow schedule by minimizing the failure factor and the execution time, while satisfying the user-defined budget limit. The results show that the proposed algorithm outperforms BGA, BPSO, BAT by achieving 9%–17% higher reliability. Meanwhile the HWDO demonstrated a notable ability to generate reliable schedules with the shortest possible makespan while adhering to budget constraints, outperforming the BGA, BPSO, BAT in this regard.

Athira and Sasikala [88] introduced a security framework for data deduplication and data portability in distributed cloud environments. It emphasizes enhancing data security by splitting files into blocks, selecting suitable cloud servers using a Hybrid Forest Genetic Algorithm, and applying the Whirlpool algorithm for data hashing and deduplication. The Levy Flight-WDO (LF-WDO) is employed for data portability, aiming to improve cloud data security. The

TABLE 15. Literature review of WDO application in medicine.

Authors/Year/Refs.	Object	Mechanism	Results	Application
Kotte et al. (2018) [144]	AWDO technique is employed to achieve optimal multilevel thresholding selection	Use the CMAES strategy to automatically tune c, g, α and RT parameters to find the optimal multilevel thresholding	It has a better segmentation effect and is significantly better than other algorithms	Image segmentation
Madipalli et al.(2018) [95]	Use AWDO for image segmentation	Use the CMAES strategy to automatically tune c, g, α and RT	Improve performance	Image segmentation
Nagaraj et al. (2018) [45]	To overcome the limitations of manual segmentation and eliminate speckle noise in carotid ultrasound images	Use a WDO for the segmentation of IMC based on automated ROI extraction and Otsu's thresholding technique	This method shows better performance and robustness	Image segmentation
Madipalli et al.(2018) [95]	To segmentate IMC in ultrasound images of CCA	Use AWDO to segmentate IMC automatically	Improve performance	Image segmentation
K. Wang et al.(2020) [98]	To mitigate the impact of noise on the segmentation results of ultrasonic images	Combine adaptive WDO with improved Otsu method to estimate IMT in a seamless manner	The absolute error of this method is only 10.1 $\pm$ 9.6 (mean $\pm$ std in m). Furthermore, this method has a correlation coefficient as high as 0.9922, and a bias as low as 0.0007	Image measurement
Laishram et al.(2021) [145]	To detect and diagnose mammographic masses automatically	Combine WDO with Otsu's multilevel thresholding and identify the potential candidates of mass lesion	Reduce false alarms and increased accuracy	Breast cancer detection
Anupama et al. (2022) [146]	To improve the effectiveness of medical images signcryption technology	Use a new WDO based medical image encryption (WDOA-MIE) technique	It has better security with increased PSNR of 60.7036dB	Medical image security and privacy

TABLE 16. Literature review of purely improved WDO.

Authors/Year/Refs.	Object	Mechanism	Results
Segundo et al. (2014) [102]	To overcome WDO early convergence problem	The value of c, g, α and RT are dynamically adjusted based on the number of iterations	The convergence speed of WDO is accelerated
Bao et al.(2015) [57]	To overcome WDO early convergence problem	Hybrid DE to maintain population diversity	Improve convergence speed, accuracy, and robustness of WDO
Boulesnane et al. (2015) [52]	To reduce the tuning parameters and overcome the drawback of early convergence	A pressure-based term is introduced to replace the rank-based term, automatically and adaptively set the value of the gravitational term	Improve accuracy and robustness of WDO
Z. Bayraktar et al. (2016) [91]	To address the challenges posed by multi-objective optimization problems	To select the values of c, g, α and RT adaptively using CMAES and introduce Pareto dominance into adaptive WDO	Improve performance

approach has improved performance and security compared to existing methods, with the use of advanced hashing and optimization algorithms.

To minimize cmputational costs and enhance the classification accuracy of a given dataset, Abd El-Mageed et al. [100] integrated a crossover technique and the simulated annealing algorithm into WDO framework. This incorporation resulted in notable improvements in the performance and effectiveness of the method. Table 14 shows the literature review of WDO application in computer science.

E. MEDICINE

In the research of the medical field, WDO has been applied in different work, mainly in image processing, Kotte et al. [144] used an adaptive approach to improve WDO and used this Adaptive WDO (AWDO) for optimal multilevel thresholding selection for brain MRI image segmentation, the optimal multilevel threshold is determined by maximizing the variance (Otsu method), which is Otsu-AWDO, it exhibits a superior segmentation effect and outperforms other algorithms significantly.

Similarly, Madipalli et al. [95] introduced a full-automatic segmentation method for intima media complex(IMC), they used adaptive WDO technology and CMAES, so people do not need to manually select parameters, based on the correlation coefficient and IMT $\pm$ std, this method is superior to other methods.

Nagaraj et al. [45] used a WDO for the segmentation of IMC based on automated region-of-interest (ROI) extraction

TABLE 17. The main application areas of WDO and its variants.

Domains	References
Engineering	Bayraktar et al. (2010) [56] Bayraktar et al. (2011) [107] Bayraktar et al. (2013) [55] Bhandari et al. (2014) [108] Mahto et al.(2015) [109] Mahto et al.(2015) [110]Zhang et al.(2015) [103] Mahto et al.(2016) [73] Mahto et al.(2016) [74] Yahia et al. (2017) [76] Sinha et al. (2017) [78] Dwivedi et al. (2017) [111] Nagar et al. (2018) [94] JEVTIĆ et al. (2018) [112] Sankar et al. (2018) [113] Sankar et al. (2018) [114] Mahto et al. (2019) [115] Sawant et al. (2019) [80] Sinha et al. (2019) [81] Liu et al. (2019) [116] Kangrang et al. (2019) [117] Moayedi et al. (2020) [118] Sawant et al. (2021) [83] Xu et al. (2021) [119] Abdelmadjid et al. (2021) [120] Ramli et al. (2022) [49] Mezhoud et al. (2022) [121] Li et al(2023) [122] He et al.(2023) [50]
Manufacturing	Ayala (2016) [123] Di Barba (2016) [124] Ho et al. (2017) [125] Ho et al. (2017) [126] Ranjan et al. (2018) [127] Ranjan et al.(2018) [104] Alhelou et al.(2018) [128] Ranjan et al. (2019) [105] Yang et al. (2019) [42] Ranjan et al. (2022) [106]
Energy scheduling	Naseem et al.(2017) [129] Javaid et al. (2017) [77] Alhelou et al. (2018) [128] Mathew et al. (2018) [130] T. N. Qureshi et al.(2018) [79] Shaheen et al.(2018) [93] Injeti et al.(2018) [131] Ermis et al. (2019) [132]Abdalla et al. (2019) [58] I. A. Ibrahim et al. (2020) [97]Ibrahim et al. (2020) [53] Mathew et al. (2020) [99] Y. Wang et al. (2020) [84]Ibrahim et al. (2021) [133] H. P. Liu et al. (2021) [43] Liu et al. (2021) [44] Makhadmeh et al. (2021) [134] Senthilkumara et al. (2021) [135] Ibrahim et al. (2022) [86] Mathew et al. (2022) [101]
Computer science	Sun et al. (2013) [136] Boulesnane et al. (2014) [137] Zhou et al. (2015) [72] Xu et al. (2016) [138] Xia et al. (2016) [92] Boulesnane et al. (2017) [140] Pandey et al. (2017) [46] Xu et al. (2017) [139] Zhou et al. (2017) [75] Ghosh et al. (2018) [141] Kaushal et al. (2018) [142] Bayraktar et al. (2019) [96] Gao et al. (2020) [82] Bej et al. (2020) [143] Singh et al. (2021) [85] Athira et al. (2022) [88] Abd El- Mageed et al. (2022) [100]
Medicine	Kotte et al.(2018) [144] Madipalli et al.(2018) [95] Nagaraj et al. (2018) [45] Madipalli et al.(2018) [95] Wang et al. (2020) [98] Laishram et al. (2021) [145] Anupama et al. (2022) [146]
Purely improved WDO	Segundo et al. (2014) [102] Bao et al.(2015) [57] Boulesnane et al.(2015) [52] Z. Bayraktar et al. (2016) [91]

and Otsu's thresholding technique. This method shows better performance and robustness.

Madipalli et al. [95] introduced a fully automated technique for the segmentation of the IMC in ultrasound images of the CCA, leveraging the AWDO. The efficacy of the proposed methodology is assessed using a dataset comprising 60 ultrasound images and is benchmarked against contemporary state-of-the-art techniques. The empirical outcomes underscore the superiority of the proposed method, demonstrating enhanced performance metrics when juxtaposed with existing methodologies.

To enhance the robustness of ultrasound image segmentation results and mitigate the impact of noise, Wang et al. [98] proposed an improved approach. They employed a fully automatic algorithm for estimating Intima-Media Thickness (IMT) using an enhanced Otsu method combined with adaptive wind-driven optimization. The experimental results demonstrated the effectiveness of this method, with an absolute error of only 10.1 ± 9.6 m (mean ± standard deviation). Moreover, the method achieved a high correlation coefficient of 0.9922 and a minimal bias of 0.0007. These findings indicate that the proposed method exhibits strong robustness and provides accurate IMT estimates.

Laishram and Rabidas [145] discussed an advanced computer-aided detection/diagnosis (CAD) system for identifying and diagnosing mammographic masses. The system

TABLE 18. WDO variants for different application areas.

Sub Areas	WDO variants used and References
Path planning for UCAVs	Quantum WDO [72]
Array antenna synthesis	Hybridized WDO with IWO [73], hybridized WDO with IWO [81]
Interference of linear sparse array	Hybridized WDO with IWO [74]
0-1 backpack problem	Binary WDO with complex-valued encoding, greedy strategy [75]
Antenna array system	Hybridized WDO with GSA, IWO [76]
Optimization technique for DSM in smart grid	Hybridized WDO with GA [77], hybridized WDO with HSA, EDE [79]
Adaptive filtering	Hybridized WDO with GA [78]
Hyperspectral band selection	Hybridized WDO with PSO [80]
3D location information of UAV	Hybridized WDO with Quantum computation, Chan algorithm [82]
Hyperspectral band selection	Hybridized WDO with CS, Chaotic map [83]
Optimization of DC distribution network	Hybridized WDO with GA [84]
Workflow scheduling in cloud systems	Hybridized WDO [85]
PV cells	Hybridized WDO with FO [86], adaptive WDO [53], [97], [99], [101]
Cloud computing data security	Hybridized WDO with Levy Flight [88]
Hyperspectral band selection	Adaptive WDO [98]
PV power generation	Adaptive WDO with new parameters [43]
Supervision classification	Improved binary adaptive WDO [100]
Beamforming of opportunistic array radar	Binary multi-objective WDO [103]
Electromagnetic device optimization	Binary WDO [104]–[106]
Electromagnetism optimization problem	Improved WDO [55], adaptive WDO [94]
Target detection	Modified WDO [92]
Power loss minimization in power systems	Modified WDO [93]
Image segmentation	Adaptive WDO [95]
Digit classification	Adaptive WDO [96]

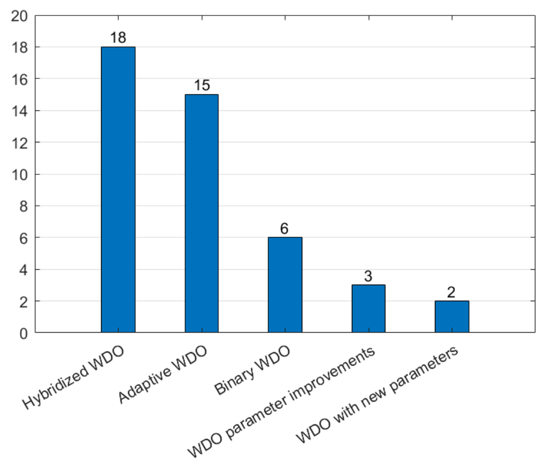

FIGURE 6. Improvements of WDO.

incorporates innovative techniques like multilevel image thresholding, WDO, and texture-based multi-gradient local quinary pattern (M-GQP) feature extraction. The methodology is rigorously tested on benchmark databases, exhibiting promising results and indicating a significant advancement over existing state-of-the-art methods.

TABLE 19. Improved algorithms by using two strategies.

Variants	References
Hybridized WDO and WDO with new parameters	[52]
Hybridized WDO and Binary WDO	[75]
Adaptive WDO and WDO with new parameters	[43]
Adaptive WDO and Binary WDO	[100]

To enhance the effectiveness of medical image signcryption technology, Anupama et al. [146] introduced a novel WDO based medical image encryption (WDOA-MIE) technique, this technique utilizes the principles of WDO to achieve improved security in medical image encryption. The experimental results demonstrated the superiority of WDOA-MIE, with a significant increase in the peak signal-to-noise ratio (PSNR) reaching 60.7036dB. For a comprehensive overview of WDO applications in the field of medicine, please refer to Table 15.

F. THEORETICAL APPLICATIONS

The literature reviewed in this paper indicates that approximately 9% of the papers solely focus on improving WDO

TABLE 20. Different WDO improvement strategies utilized in practical applications.

Applications	WDO parameter improvements	Hybridized WDO	Adaptive WDO	WDO with new parameters	Binary WDO
Engineering	[55]	[73], [74], [76], [78], [80], [83]	[94]	None	[103]
Manufacturing	None	None	None	None	[104]–[106]
Energy scheduling	None	[77], [79], [84], [86]	[43], [53], [93], [97], [99], [101]	[43]	None
Computer science	None	[72], [75], [82], [85], [88]	[96], [100]	None	[75], [100]
Medicine	None	None	[95], [98]	None	None
Purely improved WDO	[91]	[57]	[52], [91]	[52]	None

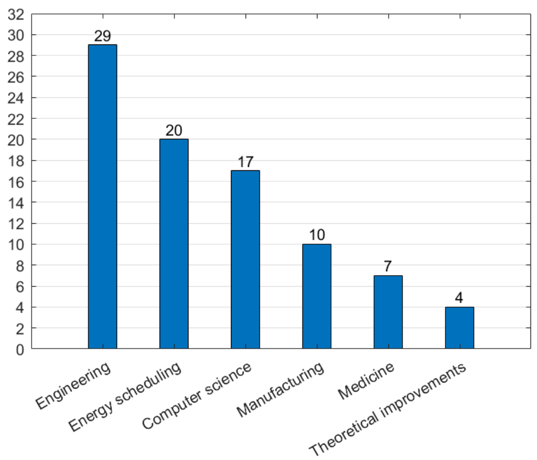

FIGURE 7. Major application categories in WDO.

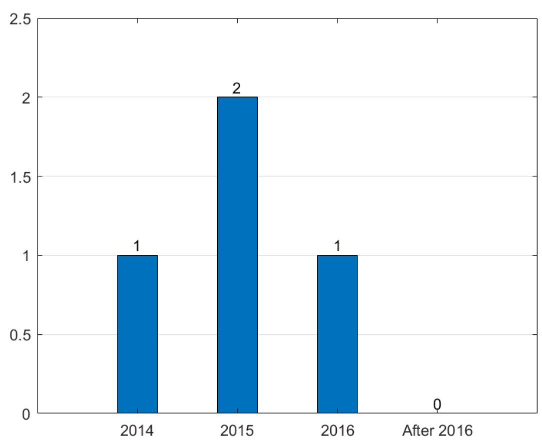

FIGURE 8. Number of theoretical application publications over the years.

without applying it to any practical scenarios. These papers propose enhanced variants of WDO for theoretical purposes only.

From the literatures [52], [57], [91], and [102], improvements to the application of WDO theory have revolved around adaptively setting parameters to overcome the disadvantage of WDO requiring the manual setting of the values of c, g, α and RT.

Segundo et al. [102] utilized Levy flights automatically adjust c, g, α and RT parameter values, which Improved the convergence speed of WDO.

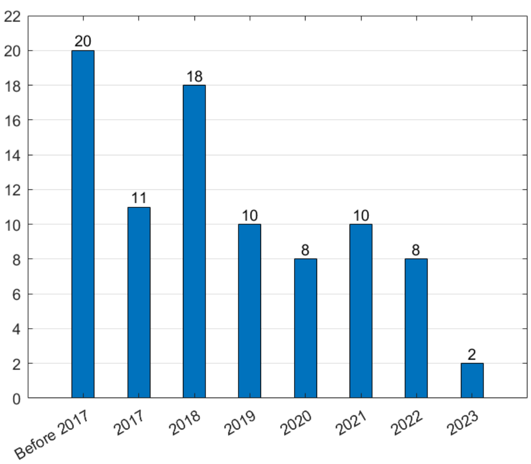

FIGURE 9. Number of real-world application publications over the years.

There is abundant literature evidence showcasing the utilization of various approaches to enhance the performance of WDO. One such approach involves parameter tuning and hybridization with other metaheuristics like DE [57]. These techniques have been empirically proven to enhance the convergence speed, accuracy, and robustness of WDO.

Boulesnane and Meshoul [52] introduced a novel modification to the original WDO model by introducing a pressure-based term to replace the rank-based term. This modification resulted in improved performance of WDO. The introduction of the pressure-based term allows for more efficient exploration of the search space, leading to enhanced optimization outcomes.

To handle multi-objective optimization problems, Bayraktar and Komurcu [91] introduced Pareto dominance into adaptive WDO. This incorporation of Pareto dominance enables the algorithm to effectively explore and optimize multiple conflicting objectives simultaneously.

The analyzed literature presents a diverse range of approaches aimed at enhancing the theoretical applications of WDO. These include mixing WDO with other algorithms, introducing new parameters, setting adaptive values, and combining two improvement strategies, however, no binary improvements or parametric improvements have been used in the application of WDO theory, as shown in Table 16.

G. SUMMARY OF APPLICATIONS OF WDO AND ITS VARIANTS

In this section, we categorized the applications of WDO into several domains, including engineering, manufacturing, energy scheduling, computer science, and medicine. The improved WDO shows better performance than the basic WDO and other algorithms such as GA, PSO, and DE in the above application areas. Table 17 provides a comprehensive summary of the practical applications of WDO in real-world scenarios, as well as the theoretical enhancements proposed by researchers. Table 18 comprehensively summarizes the principal applications of WDO, delineating the specific variant of WDO employed and citing key publications for each application domain. A critical observation from Table 18 is that distinct WDO variants are associated with different application areas, this implies that each PSO variant is uniquely tailored to efficiently solve particular problem sets, indicating a specialized focus in their design and application.

VI. DISCUSSION

In this section, WDO improvements, application areas of improved WDO, and WDO-related publications will be summarized, which will answer RQ8.

According to this recent literature review, the integration of WDO with other optimization techniques, such as metaheuristics, has shown significant advancements. Additionally, the application of adaptive techniques, along with parameter enhancements and the introduction of new parameters, has further enhanced the performance of WDO. Moreover, the utilization of binary algorithms has been illustrated to be effective, WDO is enhanced by applying different strategies as depicted in Figure 6.

Table 19 presents a summary of recent research on improving WDO. Notably, several studies have explored the use of multiple techniques to enhance WDO's performance, such as combining it with other optimization mechanisms [43], introducing adaptive algorithms, introducing new parameters [52], introducing adaptive parameters [53], and utilizing binary encoding [100]. For example, one study utilized a combination of binary encoding and adaptive algorithms, while another incorporated a mix of different optimization mechanisms and adaptive parameters. These multi-method approaches have shown promise in improving WDO's effectiveness in solving complex problems.

Through various studies, it has become evident that WDO's limitations can be effectively addressed through parameter improvements, the incorporation of other algorithms or mechanisms, and the use of adaptive algorithms. For instance, the use of adaptive algorithms eliminates the need for manual setting of WDO parameters, addressing one of its drawbacks. To avoid premature convergence and local optima problems, a combination of other algorithms and mechanisms can be employed. Improved parameters aid in selecting optimal parameters, thereby enhancing performance.

Table 20 presents various WDO improvement strategies applied in practical applications and theoretical research. It is observed that the engineering field and theoretical research adopt multiple improvement strategies to optimize WDO. On the other hand, improved WDO based on binary methods are mostly used in engineering [103], and manufacturing [105], [106]. The improved WDO based on the introduction of new parameters are commonly used in energy scheduling [43] and theoretical research [52]. The introduction of new parameters is typically used in combination with other improvement strategies.

Over the past few years, the utilization of different variants of WDO has experienced a significant rise. These variants have found applications in various fields, with engineering emerging as the leading area of implementation. Energy scheduling and computer science also demonstrate notable usage, as depicted in Figure 7. These observations indicate the broad applicability and potential of WDO and its variants in addressing diverse real-world problems.

Until 2016, several theoretical improvements had been made to WDO, albeit with limited progress. Notably, there have been no further theoretical applications of WDO since 2016. Figure 8 illustrates the trend of theoretical application publications over the years. WDO variants have been applied in practical settings prior to 2017, and the volume of practical applications has remained relatively consistent since then. Figure 9 depicts the progression of real-world application publications over the years.

VII. CONCLUSION

This comprehensive and systematic analysis of nearly 100 high-quality literature pieces presents the development trajectory of WDO, including its variants with improved parameters, mixed with other mechanisms, introducing new parameter variants, introducing adaptive algorithm variants, and introducing binary mechanism variants. Additionally, practical applications and theoretical research are analyzed from various perspectives. Existing literature demonstrates that the improvement of WDO primarily revolves around two key approaches: amalgamating it with other metaheuristic algorithms and enhancing its parameters. Some WDO variants employ both techniques to enhance the algorithm's performance.

The review of this paper indicates an increasing application of WDO in various real-world domains, prominently including engineering, manufacturing, energy scheduling, computer science, and medicine. Theoretical research applications have revealed that the basic WDO's inherent shortcomings necessitate modification of parameters or integration with other metaheuristic algorithms. This integration is crucial for enhancing the algorithm's performance. This article provides a comprehensive overview of WDO and its application fields, guiding researchers in applying WDO to optimization problems. However, researchers should be cognizant of WDO's advantages and limitations. The algorithm's ease of integration with other metaheuristic algorithms is evident from the multitude of hybrid optimization methods. More critically, WDO's sensitivity to algorithm parameters and premature to converge to local optimum are notable drawbacks. These limitations can be mitigated to some extent through hybridization with other metaheuristic algorithms. Therefore, it is imperative for researchers to judiciously leverage WDO's strengths and weaknesses. By drawing insights from various fields, a balanced approach can be adopted for potential enhancements. Through rigorous theoretical research, new WDO variants can be proposed for application in engineering, which currently dominates the real-world application of WDO.

To answer question RQ9, the following suggestions offer potential avenues for future research to researchers interested in WDO and its diverse applications: 1. Standard WDO and its recent variants can be synergistically combined with high-performance metaheuristics like Dung beetle optimizer(DBO) [147],One-to-One-Based Optimizer (OOBO) [148], Gold rush optimizer (GRO) [149], Snake Optimizer (SO) [150],Artificial gorilla troops optimizer (GTO) [151], and Whale Optimization Algorithm (WOA) [152] for improved optimization capabilities. 2. Future research could focus on the discrete WDO. By employing various discretization strategies, we can adapt WDO for solving problems that are characterized by discrete-valued design variables. Some of the binary WDO variants given in Section IV and Section V are used for solving engineering, manufacturing, and the electromagnetic domain problem, which can be considered for more applications, among which the hardware and software partitioning problem is an application area worth considering. 3. The performance of WDO variants on high-dimensional problems has not been well studied and new WDO variants can be investigated on high-dimensional problems. 4. There are several WDO variants that solve the multi-objective problem in Section IV, and the development of new WDO variants capable of solving the multi-objective problem is also a research direction worth considering. 5. It is likely to take the new WDO variant and apply it to a wider range of real-world optimization problems such as the field of industrial control, medical image analysis, disease diagnosis and prediction, treatment optimization and planning, and healthcare resource allocation.

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