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A survey of Beluga whale optimization and its variants: Statistical analysis, advances, and structural reviewing

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ABSTRACT

Optimization, as a fundamental pillar in engineering, computer science, economics, and many other fields, plays a decisive role in improving the performance of systems and achieving desired goals. Optimization problems involve many variables, various constraints, and nonlinear objective functions. Among the challenges of complex optimization problems is the extensive search space with local optima that prevents reaching the global optimal solution. Therefore, intelligent and collective methods are needed to solve problems, such as searching for large problem spaces and identifying near-optimal solutions. Metaheuristic algorithms are a successful method for solving complex optimization problems. Usually, metaheuristic algorithms, inspired by natural and social phenomena, try to find optimal or near-optimal solutions by using random searches and intelligent explorations in the problem space. Beluga Whale Optimization (BWO) is one of the metaheuristic algorithms for solving optimization problems that has attracted the attention of researchers in recent years. The BWO algorithm tries to optimize the search space and achieve optimal solutions by simulating the collective behavior of whales. A study and review of published articles on the BWO algorithm show that this algorithm has been used in various fields, including optimization of mathematical functions, engineering problems, and even problems related to artificial intelligence. In this article, the BWO algorithm is classified according to four categories (combination, improvement, variants, and optimization). An analysis of 151 papers shows that the BWO algorithm has the highest percentage (49%) in the improvement field. The combination, variants, and optimization fields comprise 12%, 7%, and 32%, respectively.

1. Introduction

The complexity of optimization issues has increased with the expansion of technical needs. These problems often include many goals, multi-objectives, or enormous scales. Deterministic techniques and meta-heuristic algorithms are frequently used to address optimization issues. Based on mathematical theories, deterministic techniques have been established. Some examples of these approaches are Newton's

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method, integer programming, and gradient descent [1]. These approaches are appropriate for addressing optimization problems with a distinct optimum solution and a solution that can be separated from the objective function. Deterministic methods, on the other hand, are often sensitive to the starting vector and can only arrive at a more precise ideal location if they begin with a solid first solution. Because of this, these methodologies suffer a great lot of difficulty when it comes to dealing with complex technical issues [2]. Metaheuristic algorithms, on the other hand, are dependent not only on the issue's convexity and concavity but also not sensitive to the chosen starting values [3]. Meta-heuristic algorithms such as genetic algorithms, ant colony optimization, and evolutionary algorithms are more suitable for problems with complex and large search spaces. These algorithms can approach global optimal points using random and hybrid search techniques and avoid getting stuck in local optima. Meta-heuristic algorithms are usually inspired by natural phenomena such as biological evolution, animal behavior, and physical processes [4,5].

One of the main challenges in deterministic methods is that they need to choose an appropriate initial vector, which can lead to getting stuck in local optima. Furthermore, these methods are unsuitable for problems with multiple objective functions or large search spaces. On the other hand, meta-heuristic algorithms do not need to choose the initial vector accurately due to stochastic processes and can move efficiently in the vast search space [6]. Metaheuristic algorithms also face challenges. They may require more computing time and may not reach the accuracy of deterministic methods [7]. Nevertheless, combining these two methods can lead to more efficient and optimal solutions. For example, using meta-heuristic algorithms to find suitable starting points and then using deterministic methods for more precise optimization can be an efficient approach.

In metaheuristic algorithms, two critical concepts of exploitation and exploration play a fundamental role in search. Exploitation means improving the convergence accuracy, which is done by increasing the search accuracy in a limited and specified space. This process is an attempt to find the best and most optimal solutions in an optimal part of the search space [8,9]. Exploitation deals with a detailed and thorough search in specific points of the problem space and tries to achieve better results. This feature increases the convergence accuracy; the algorithm is continuously directed towards more optimal solutions. In contrast, exploration is another aspect of the optimization process that aims to increase diversity in the evolutionary population and search the problem space more broadly. This feature prevents the search agents from getting stuck in a specific section and looking for new and diverse solutions in a larger space [10]. The exploration is designed in such a way that it prevents the search agents from falling into the trap of local optima. The critical point in metaheuristic algorithms is to create a proper balance between exploitation and exploration. If overexploited, the algorithm may get stuck at a local optimum point and fail to achieve better solutions in the global space. On the other hand, if too much exploration is done, instead of reaching an accurate and optimal solution, the agents will only discover various solutions [11].

Hybrid methods are used to achieve the right balance between exploitation and exploration, and they effectively cover both phases. For example, the Genetic Algorithm (GA) can balance exploitation and exploration simultaneously by using selection, crossover, and mutation operators. Exploitation in GA is done by selecting elite people and combining them, and it is capable of exploration by applying random mutations. The crossover operator helps to integrate the genes of two or more superior solutions to generate new solutions. This process can preserve genetic diversity and help search more precisely in areas close to current optima. In the particle swarm optimization (PSO) [12] algorithm, each particle updates its new position according to its position and the position of the best other particles. This approach makes the algorithm exploit, explore, and adequately balance these two phases. One of the advanced approaches in optimization is the combination of meta-heuristic methods. For example, combining GA and PSO can create algorithms with more extraordinary optimization ability. PSO algorithm can be used for extensive search and discovery of new regions, while the genetic algorithm can be used for more precise search and exploitation from high-quality areas.

Over the past few decades, many meta-heuristic algorithms have been developed inspired by various natural phenomena. These algorithms can generally be classified into four main categories: (1) algorithms based on evolution, (2) algorithms based on collective intelligence, (3) algorithms based on social and human behavior, and (4) physical or chemical algorithms. Each of these categories has specific features and applications that are used in solving complex optimization problems in different fields [13]. Evolutionary algorithms are inspired by biological and natural processes such as natural selection and inheritance. A clear example of these algorithms is the genetic algorithm based on Darwin's theory of evolution. The second category of algorithms is based on collective intelligence. The collective behavior of living organisms such as ants, bees, and birds inspire these algorithms. Algorithms based on social and human behavior form the third category of these algorithms. These algorithms are inspired by the social behavior of humans and their interactions. The fourth category includes physical or chemical algorithms inspired by physical and chemical processes. An example of this category is the simulated annealing algorithm, which is based on the material cooling process in physics. One of the salient features of these algorithms is their simplicity and high adaptability, which makes it possible to use them in optimization problems of different natures. Table (1) shows an overview of standard metaheuristic algorithms.

Metaheuristic algorithms have features such as simplicity and ease of implementation, independent of gradient information, flexibility against local optima, and applicability in different fields. These algorithms' simplicity and ease of implementation mean they do not require complex settings and heavy calculations and can be easily implemented in other systems. Being independent of the gradient information means that these algorithms do not need the information of the derivatives of the objective function and can be used in optimization problems whose derivatives are difficult to calculate. Flexibility against local optima means that these algorithms can avoid getting trapped in local optima and move towards global optima [59,60]. Finally, the applicability in different fields means that these algorithms can be applied to complex optimization problems and structures and provide desirable results.

The BWO [61] is a crowd-based metaheuristic algorithm developed in 2022 inspired by the behavior of the beluga whale. This algorithm consists of three main steps: swimming, hunting, and releasing the beluga whale into the sea. BWO is very useful and efficient for solving real-world problems due to its high optimization accuracy and fast convergence speed. The advantages of the BWO include the following: 1) The BWO is simple to implement due to derivative-free optimization techniques. 2) The BWO algorithm has an excellent global convergence with a suitable ability to balance the exploration and exploitation phases. 3) The BWO performs better than 12 other meta-heuristic algorithms on single-objective, multi-objective, and combined functions. Using BWO as an effective optimization method can bring significant benefits. The ability of this algorithm to find optimal solutions with high speed and appropriate accuracy has made it a powerful tool for optimization in various problems. The main contributions of this paper are as follows:

- Comprehensive Review of BWO Algorithm: This is a comprehensive review of the BWO algorithm with critical features. Hybridization techniques, parameter optimization, and adaptive mechanisms have been analyzed to increase the BWO algorithm's robustness in solving complex optimization problems.
- Analysis of BWO Hybrid Algorithms: This paper thoroughly analyzes various hybrid algorithms. The combination of BWO with other meta-heuristic algorithms has been investigated to solve complex optimization problems.

Table 1
An overview of standard metaheuristic algorithms.

Refs	Algorithm	Category	Year
[14]	Simulated Annealing (SA)	physical-based	1983
[12]	Particle swarm optimization (PSO)	swarm-based	1995
[15]	Firefly Algorithm (FA)	swarm-based	2009
[16]	Gravitational Search Algorithm (GSA)	physical-based	2009
[17]	Charged System Search (CSS)	physical-based	2010
[18]	bat algorithm (BA)	Nature-based	2012
[19]	Grey Wolf Optimizer (GWO)	Nature-based	2014
[20]	Moth-Flame Optimization (MFO)	Nature-based	2015
[21]	Whale Optimization Algorithm (WOA)	Nature-based	2016
[22]	Sine Cosine Algorithm (SCA)	physical-based	2016
[23]	Multi-Verse Optimizer (MVO)	physical-based	2016
[24]	Grasshopper Optimization Algorithm (GOA)	Nature-based	2017
[25]	Farmland Fertility (FF)	Nature-based	2018
[26]	biology migration algorithm (BMA)	evolutionary-based	2018
[27]	Henry gas solubility optimization (HGSO)	physical-based	2019
[28]	Transient Search Optimization (TSO)	physical-based	2020
[29]	Equilibrium Optimizer (EO)	physical-based	2020
[30]	Rain optimization algorithm (ROA)	Nature-based	2020
[31]	coronavirus herd immunity optimizer (CHIO)	Human-based	2020
[32]	Gaining Sharing Knowledge-based Algorithm (GSK)	Human-based	2020
[33]	Black Widow Optimization (BWO)	Nature-based	2020
[34]	Predator–prey optimization (PPO)	Nature-based	2021
[35]	African Vultures Optimization Algorithm (AVOA)	Nature-based	2021
[36]	Jellyfish Search (JS)	Nature-based	2021
[37]	Arithmetic Optimization Algorithm (AOA)	physical-based	2021
[38]	Capuchin Search Algorithm (CapSA)	Nature-based	2021
[39]	Aquila Optimizer (AO)	Nature-based	2021
[40]	heat transfer relation-based optimization algorithm (HTOA)	physical-based	2021
[41]	Mountain Gazelle Optimizer (MGO)	Nature-based	2022
[42]	White Shark Optimizer (WSO)	Nature-based	2022
[43]	Honey Badger Algorithm (HBA)	Nature-based	2022
[44]	Dwarf Mongoose Optimization (DMO)	Nature-based	2022
[45]	Snake Optimizer (SO)	Nature-based	2022
[46]	Dandelion Optimizer (DO)	Nature-based	2022
[47]	Ali Baba and the forty thieves (AFT)	Human-based	2022
[48]	Tyrannosaurus (T-Rex) optimization algorithm (TROA)	Nature-based	2023
[49]	Greylag Goose Optimization (GGO)	Nature-based	2024
[50]	Puma optimizer (PO)	Nature-based	2024
[51]	Greater Cane Rat Algorithm (GCRA)	Nature-based	2024
[52]	Artificial Circulatory System Algorithm (ACSA)	Human-based	2024
[53]	elk herd optimizer (EHO)	Nature-based	2024
[54]	Groupers and moray eels (GME)	Nature-based	2025
[55]	supercell thunderstorm algorithm (STA)	Nature-based	2025
[56]	Artificial Lemming Algorithm (ALA)	Nature-based	2025
[57]	Dream Optimization Algorithm (DOA)	Human-based	2025
[58]	Coyote and Badger Optimization (CBO)	Nature-based	2025

- Binary and multi-objective BWO: Two binary and multi-objective versions of the BWO algorithm have been investigated.
- Applications of the BWO algorithm in different domains: The BWO algorithm has investigated various optimization problems.
- Strengths and Weaknesses of the BWO Algorithm: Strengths like exploration capabilities and convergence speed and weaknesses like getting stuck in local optima are critically analyzed.
- Future Research for BWO Algorithm: This study suggested future research directions for BWO.

The structure of this paper is as follows: In Section 2, the advancements of BWO and its publication percentage in different fields are reviewed. In Section 3, BWO and its mathematical model are defined. In Section 4, all the versions and modifications of BWO are reviewed. BWO methods are classified into the following four categories: hybridization, improved, BWO variants and optimization problems. In Section 5, the applications of the BWO algorithm in key fields are reviewed. Section 6 includes the capabilities, advantages and disadvantages of the BWO algorithm. In Section 7, the final summary and future works are discussed.

2. The growth of BWO

Metaheuristic algorithms such as the BWO algorithm have increased significantly in the industrial, engineering, and medical fields. These algorithms can improve complex processes in industry and engineering, such as scheduling, supply chain management, and optimization of tool design, and reduce operating costs. In the medical field, metaheuristic algorithms have gained special importance in various sectors, such as disease diagnosis and medical imaging, due to their high accuracy. For example, in cancer diagnosis, metaheuristic algorithms help improve the accuracy of machine learning algorithms and discover hidden patterns in complex medical data. Another reason for the increase in the use of these algorithms is their high convergence speed and remarkable accuracy compared to traditional optimization methods. These algorithms are easily adjusted for new problems and changing conditions, which makes them a flexible tool for solving various challenges. Table (2) analyzes the most important papers published in 2025 using the BWO algorithm. The publication of scientific papers shows that the BWO algorithm has been used in various fields in 2025. For example, it has been used in engineering optimization and complex systems. The growing trend of research shows that the BWO algorithm has found a special place among metaheuristic algorithms due to its simplicity of implementation, high speed, and appropriate efficiency in multi-objective optimization problems, and it is expected to be considered in newer fields in the coming years.

Fig. (1) shows the most important keywords for extracting BWO papers. These words play a decisive role in analyzing and reviewing this field. Keywords such as machine learning, deep learning, data mining, and cloud computing indicate that BWO is widely used in artificial intelligence and data science. The presence of words such as global optimization, multi-objective optimization, and Constrained optimization indicates that BWO is used in complex optimization problems. Words such as Energy utilization, energy consumption, and energy management systems indicate that this algorithm is used in managing and optimizing energy consumption. Using keywords such as convolutional neural network, artificial neural network, long short-term memory, and adaptive boosting indicates that BWO plays an important role in improving the performance of the machine and deep learning models. Words such as engineering problems and Economics indicate that BWO is also used to solve optimization problems in industrial and economic fields.

Fig. (2) shows the distribution of papers related to the BWO algorithm based on different fields. The largest number of articles is related to engineering (139 papers) and computer science (102 papers). This shows that BWO has a wide application due to its powerful features in solving complex optimization problems, in the design of engineering systems, optimization of industrial processes, and in the development of computational algorithms. Mathematics is in third place with 66 papers. This shows the importance of BWO in developing mathematical models, multi-objective optimization, and solving complex mathematical problems. The energy field with 36 papers shows that the BWO algorithm has been used in optimizing energy consumption, managing energy resources, and improving the efficiency of energy systems.

In Fig. (3), the percentage of countries with the highest number of published articles in the field of BWO algorithm is plotted. According to the data presented, China has the highest number of published articles, with a significant share of 59%. Then, India is in second place with 21%, which is a significant difference from China. Next, Saudi Arabia and Egypt have the next positions with a share of 8% each. Finally, Malaysia has the lowest number of papers among these five countries, with a share of 4%. This distribution indicates the high concentration of research related to the BWO algorithm in Asian countries, especially China and India.

Table 2
Most important papers published in 2025 using the BWO.

Title	Authors	Journal	Publisher	Country	Year
Multi-objective feature selection algorithm using Beluga Whale Optimization [62]	Kiana Kouhpah Esfahani, Behnam Mohammad Hasani Zade, Najme Mansouri	Chemometrics and Intelligent Laboratory Systems	ScienceDirect	Iran	2025
An improved beluga whale optimization using ring topology for solving multi-objective task scheduling in cloud [63]	Behnam Mohammad Hasani Zade, Najme Mansouri, Mohammad Masoud Javidi	Computers & Industrial Engineering	ScienceDirect	Iran	2025
Study of the three-dimensional distribution of chloride in coral aggregate concrete: A CNN-BiGRU-attention data-intelligence model driven by beluga whale optimization algorithm [64]	Daming Luo, Tianze Wang, Jie Han, Ditao Niu	Construction and Building Materials	ScienceDirect	China	2025
Capacity configuration optimization of regenerative braking energy utilization system for electrified railways based on power sharing and energy storage [65]	Fangyuan Zhou, Zhaohui Tang, Da Tan, Yongfang Xie	Electric Power Systems Research	ScienceDirect	China	2025
Intelligent detection framework for IoT-botnet detection: DBN-RNN with improved feature set [66]	Sandip Y. Bobade, Ravindra S Apare, Ravindra H. Borhade, Parikshit N. Mahalle	J. Info. Secur. Appl.	ScienceDirect	India	2025
DeepBrainTumorNet: An effective framework of heuristic-aided brain Tumour detection and classification system using residual Attention-Multiscale Dilated inception network [67]	A. Vinisha, Ravi Boda	Biomedical Signal Processing and Control	ScienceDirect	India	2025
BWO—CAformer: An improved Informer model for AQI prediction in Beijing and Wuhan [68]	Xu Dong, Deyi Li, Wenbo Wang, Yang Shen	Process Safety and Environmental Protection	ScienceDirect	China	2025
NHBBWO: A novel hybrid butterfly-beluga whale optimization algorithm with a dynamic strategy for WSN coverage optimization [69]	Xinyi Chen, Mengjian Zhang, Ming Yang & Deguang Wang	Peer-to-Peer Networking and Applications	Springer	China	2025
Improved multi-strategy beluga whale optimization algorithm: a case study for multiple engineering optimization problems [70]	Huanhuan Zou & Kai Wang	Cluster Computing	Springer	China	2025
IBWC: a user-centric approach to multi-objective cloud task scheduling using improved beluga whale optimization [71]	Ravi Kumar & Manu Vardhan	Knowledge and Information Systems	Springer	India	2025
Efficient Resource Allocation Algorithm for Maximizing Operator Profit in 5 G Edge Computing Network [72]	Jing Liu, Yuting Huang, Chunhua Deng, Longxin Zhang, Cen Chen & Keqin Li	Journal of Grid Computing	Springer	China, USA	2025
Efficient framework for Blackspot analysis and re-route selection using RBLMCN and GPWBWO [73]	Nishant Singh & Sunil Kumar Katiyar	Earth Science Informatics	Springer	India	2025
Double fuzzy clustering-driven context neural network for intrusion detection in cloud computing [74]	S. Anu Velavan & C. Sureshkumar	Wireless Networks	Springer	India	2025
A Triaxial Magnetometer Calibration Method with Improved Beluga Whale Optimization Algorithm [75]	Zhuoxuan Li, Yuguo Li, Ming Luo, Chenxu Dong, Xuezhen Ding	IEEE Sensors Journal	IEEE	China	2025
A Intelligent Fault Diagnosis Method Based on Optimized Parallel Convolutional Neural Network [76]	Chunhui Li, Youfu Tang, Na Lei, Xu Wang	IEEE Sensors Journal	IEEE	China	2025
An Improved Bio-Inspired Material Generation Algorithm for Engineering Optimization Problems Including PV Source Penetration in Distribution Systems [77]	Mona Gafar, Shahenda Sarhan, Ahmed R. Ginidi andAbdullah M. Shaheen	Appl. Sci.	MDPI	Saudi Arabia and Egypt	2025

Fig. (4) shows the percentage of papers published by BWO in different publications. BWO papers have been published in various scientific databases. 35% of papers are published in ScienceDirect, the largest share among sources. 29% of the documents were published by Springer, which shows the high credibility of Springer in providing scientific papers in various fields, including metaheuristic algorithms. 18% of the documents have been published in IEEE, considered one of the leading bases in technology, engineering, and meta-heuristic algorithms. 7% of papers are published in MDPI. 4% of the documents were published in Wiley and 4% in other databases. 3% of the articles are published in *Tandonline*, This database has fewer articles than other sources. ScienceDirect and Springer are the best databases for searching for authoritative and comprehensive sources about the BWO algorithm. Due to the high volume of published papers, these databases cover various topics related to BWO.

Fig. (5) shows the number of BWO papers published per year. The number of BWO papers published in 2023 was equal to 53. In 2023, the evolution and production of BWO papers will increase. Papers published in 2023 broadly belong to engineering and scientific applications. In 2024, there was a very significant growth, with the number of papers reaching 105, almost double that of 2023. Although only two months have passed since 2025, the number of papers has reached 15. If this trend continues, the number of papers in 2025 will likely be higher than in 2024.

Fig. (6) shows the process of extracting articles related to the BWO algorithm. The diagram shows the stages of finding and extracting papers about the BWO algorithm.

3. Beluga whale optimization

The BWO [61] (derived from the natural behaviour of white whales) consists of two basic steps: exploration and exploitation. The exploration phase is designed so that whales are randomly selected for a broader search in the problem space. This step aims to find better solutions in the search space and allows the BWO algorithm to avoid getting stuck in local optima. In contrast, the exploitation phase is activated when whales seek to improve results by changing their position around optimal points. At this stage, the BWO focuses on a more detailed search in a narrower space to identify the best available solutions. One of the exciting concepts in BWO is the concept of falling whales, which acts as a random factor. This concept refers to the random changes in the whales' position and helps introduce new solutions in the problem space. These random changes increase the diversity and efficiency of the search in the problem space. In other words, the whale crash concept helps improve the search space exploration and avoids getting stuck in local optima.

White whales in the problem space are considered search agents, and each whale represents a candidate solution that is updated during iterations. A position matrix is defined to manage the whales' position in the search space. This matrix represents the current state of the whales and the position changes stored over time. In this matrix, each row represents a whale, and each column represents the specific features of a solution. Using the solution matrix, the BWO algorithm can monitor the position of the whales and identify the best solutions based on the evaluations. This method allows the whales to optimize their fitness continuously. Eq. (1) defines the matrix of search agent positions.

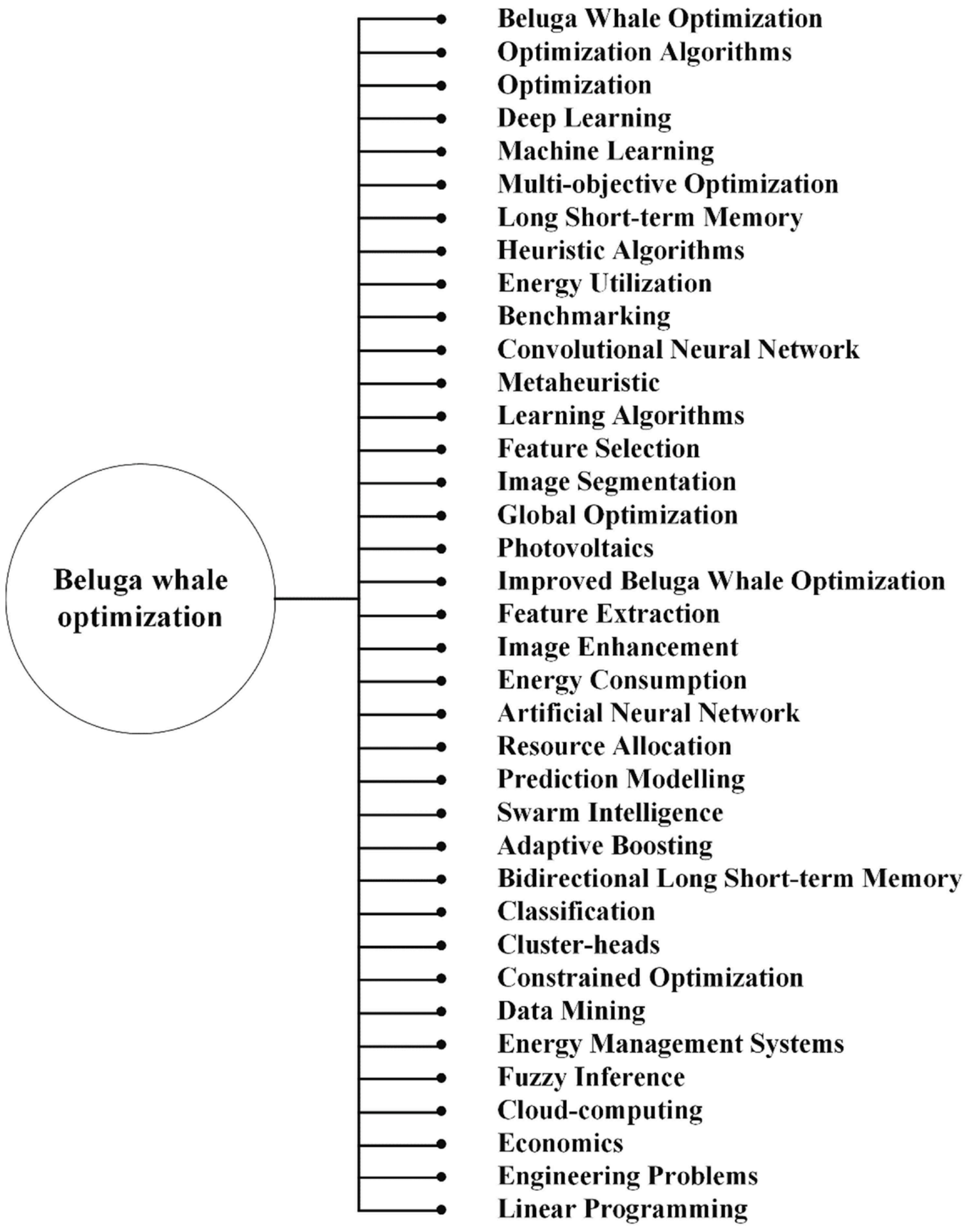

Fig. 1. The most important keywords used in extracting BWO papers (source: https://www.scopus.com).

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d} \end{bmatrix} \tag{1}$$

Key parameters include n (number of whale populations) and d (dimensions of variables). n represents the number of whales in the population, each known as a potential solution in the search space. d represents the number of variables to be optimized. Each whale is defined by a set of variables in the search space. Storing fitness values for all whales is essential because these values are used in whales' updating and selection processes for later exploration and exploitation stages. Based on these values, the algorithm decides which whales to keep as top solutions and which whales should be updated or changed. The fitness values are defined according to Eq. (2).

$$F_X = \begin{bmatrix} f\left(x_{1,1}, x_{1,2}, \ldots, x_{1,d}\right) \\ f\left(x_{2,1}, x_{2,2}, \ldots, x_{2,d}\right) \\ \vdots \\ f\left(x_{n,1}, x_{n,2}, \ldots, x_{n,d}\right) \end{bmatrix} \tag{2}$$

In the BWO, the balance factor (Bf) transitions from the exploration phase to the exploitation phase. The balance factor acts as a critical parameter and adjusts how much the algorithm focuses on exploring the search space or exploiting promising areas. In the early stages, the algorithm focuses primarily on exploration, as the main goal is to find promising regions in the search space. As the algorithm progresses and the final stages approach, Bf focuses more on exploiting the optimal areas.

$$B_f = B_0(1 - T / 2T_{max}) \tag{3}$$

The balance factor (B_f) is set according to the number of iterations of the algorithm (T) and the maximum number of iterations (T_{max}). B0 is a random number between 0 and 1 that changes in each iteration and is crucial in determining the algorithm's behavior (exploration or exploitation). If $B_f > 0.5$, then the algorithm is in the exploration phase. On the contrary, if $B_f \leq 0.5$, the algorithm enters the exploitation phase. As the number of repetitions (T) increases and T_{max} is approached, the amplitude of Bf fluctuations decreases. At the beginning of the algorithm, the fluctuation of Bf is in the interval (0, 1), which means a high probability

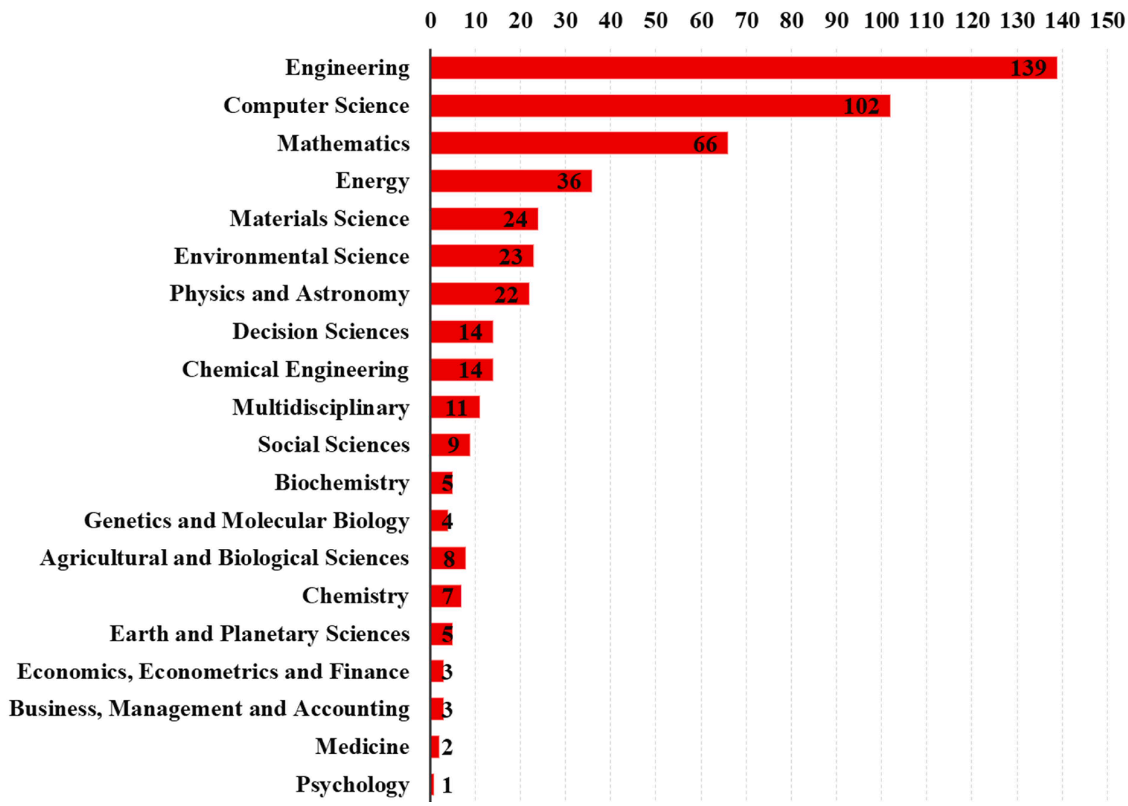

Fig. 2. Distribution of papers related to the BWO algorithm based on different fields (source: https://www.scopus.com).

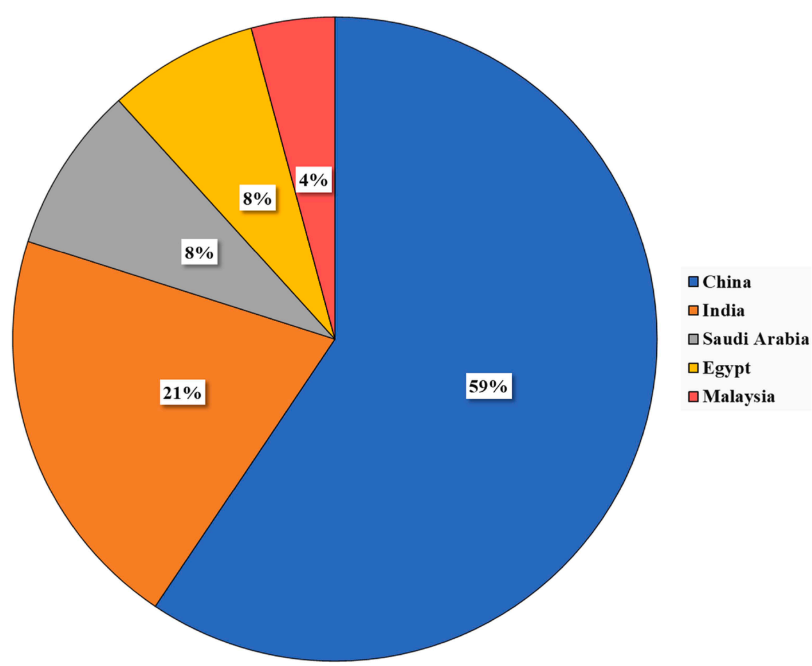

Fig. 3. Percentage of countries with the highest number of published articles on the BWO (source: https://www.scopus.com).

of both exploration and exploitation phases. However, with increasing repetitions, this range gradually decreases to (0, 0.5). The decrease in the range of fluctuations indicates that the probability of the algorithm being in the exploitation phase increases. This gradual change is a smart way to transition from exploration to exploitation.

3.1. Exploration phase

In the BWO, the exploration phase is designed based on the swimming behavior of beluga whales. Swimming behavior includes pair swimming, where two beluga whales swim close together in synchronized or mirrored movements. Paired swimming behavior is used as a template to update the position of search agents (beluga whales) in the

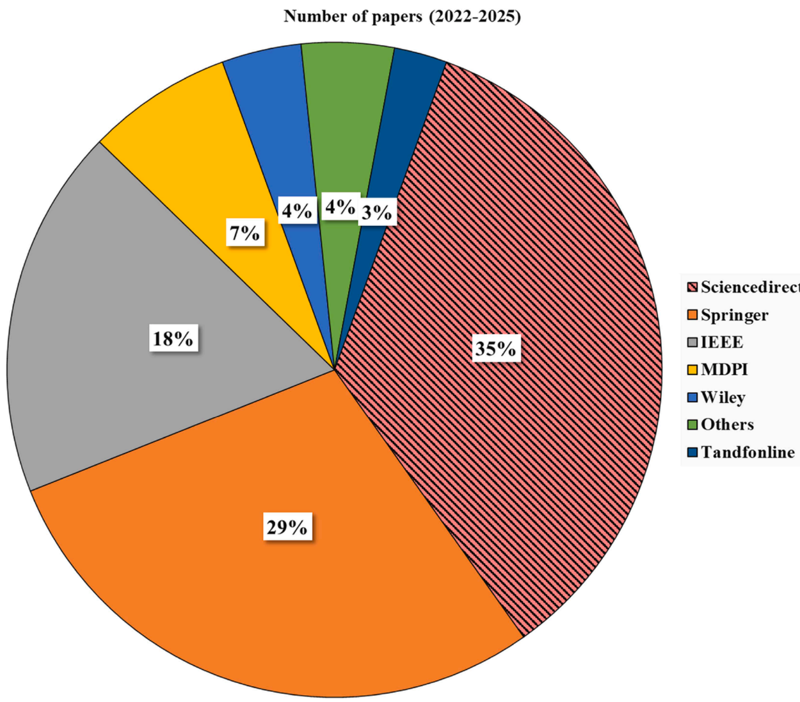

Fig. 4. Percentage of papers published with BWO in different publications.

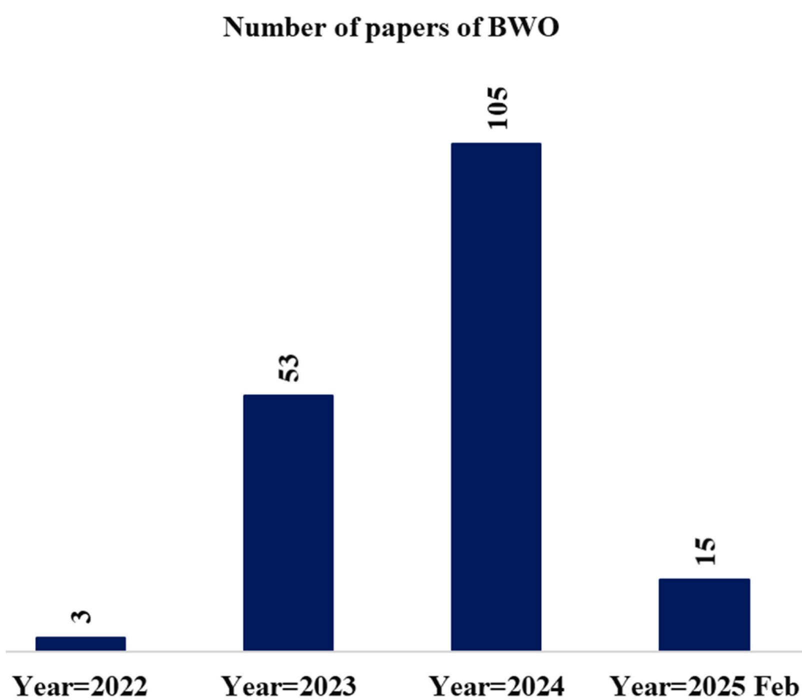

Fig. 5. Number of BWO papers published per year.

exploration phase. The position of the agents is determined based on the paired swimming pattern of the whales. That is, the new locations of the search are updated in sync with each other and with the influence of the previous positions. This behavior makes the agents (whales) move in the search space coordinated and follow each other, which helps to explore the search space more effectively. Beluga whales' position updates usually include a combination of current positions and similar behaviors that help the whales find optimal areas in the search space. The exploration phase is defined by Eq. (4).

$$\begin{cases} X_{i,j}^{T+1} = X_{i,p_j}^{T} + \left(X_{r,p_1}^{T} - X_{i,p_j}^{T}\right)(1+r_1)\sin(2\pi r_2), & j = \textbf{even} \\ X_{i,j}^{T+1} = X_{i,p_j}^{T} + \left(X_{r,p_1}^{T} - X_{i,p_j}^{T}\right)(1+r_1)\cos(2\pi r_2), & j = \textbf{odd} \end{cases} \tag{4}$$

In the BWO, the position update in the exploration phase is based on a stochastic model of whales' swimming behavior and social interaction. There are several parameters in this phase, each of which has a specific role in determining the new position of the whales. T represents the current iteration number of the algorithm. The new position of beluga

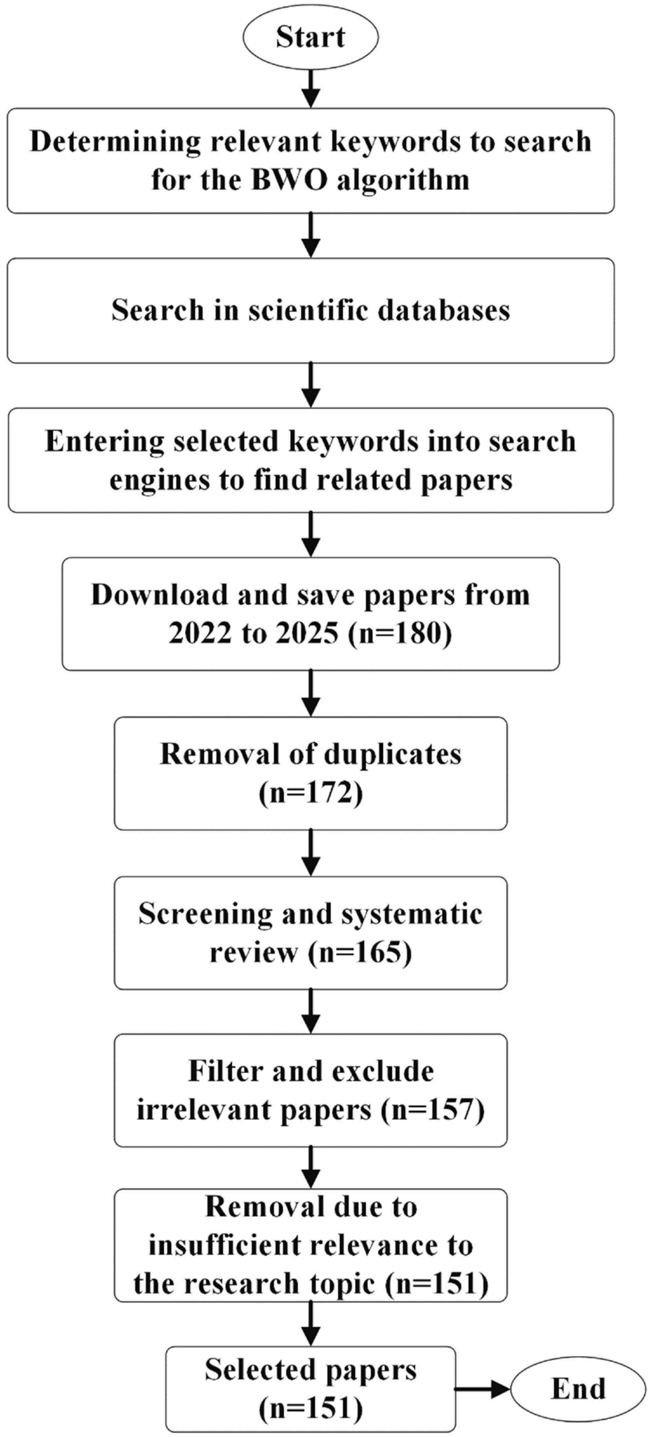

Fig. 6. The Procedure for extracting papers belongs to the BWO algorithm.

whale *i* is in dimension j ($X_{i,j}^{T+1}$). A random number chosen from different dimensions (p_j). The current position of beluga whale *i* is in dimension $p_j(X_{i,p_j}^T)$. The current position of beluga whale r (a randomly selected whale) is in dimension p_1 (X_{r,p_1}^T). Random numbers between (0, 1) add a random factor to the algorithm and improve the exploration process (r_1 and r_2). The functions $\sin(2\pi r_2)$ and $\cos(2\pi r_2)$ are defined as the mirror behavior of the fins of whales, which indicates the simultaneous or mirror behavior of whales while swimming. In updating the position, the algorithm decides whether the behavior of the whales is synchronous or mirror based on the even or odd. In synchronous mode, whales move with similar and coordinated behavior, while in mirror mode, whales move in different directions but act symmetrically. Two random numbers, r_1, and r_2, are used as random operators to make the exploration process dynamic and unpredictable. Combining these mechanisms helps beluga whales explore the search space and find better solutions.

3.2. Exploitation phase

In the exploitation phase, the hunting behavior of beluga whales inspires the search and optimization process. Hunting for prey by beluga whales is based on cooperation, and they coordinate their movements according to the position of other whales nearby. This feature leads to the sharing of information between whales. That is, each whale is aware of the position of the best whale (the best candidate) and the position of other whales. The Levy Flight (LF) strategy is defined as improving convergence and increasing efficiency in the exploitation phase. LF strategy helps whales explore small parts of the search space simultaneously, avoiding getting stuck in local optima. By defining long and random steps, LF enables the BWO algorithm to overcome the limitations of regional optimization and explore more distant and less explored spaces. By combining the LF strategy, the exploitation phase leads to a more effective and faster search for optimal spaces. Exploitation phase is defined by Eq. (5).

$$X_i^{T+1} = r_3 X_{best}^T - r_4 X_i^T + C_1 \cdot L_F \cdot \left(X_r^T - X_i^T\right) \tag{5}$$

Where T is the current iteration, X_i^T and X_r^T are current positions for the i^{th} agent and a random agent, X_i^{T+1} is the location of the new location of the i^{th} agent, X_{best}^T is the best location among agents, r_3 and r_4 are a random number between (0, 1)., $C_1 = 2 \times r_4(1 - T/T_{max})$ is the random jump strength that measures the intensity of LF. According to the random parameter and its gradual reduction with increasing repetitions, it controls the effect of LF in different stages. This parameter (C_1) determines the power of random jumping of whales and decreases with increasing the number of repetitions (T). As the number of iterations gets closer to T_{max} (the maximum number of iterations), the value of C_1 also decreases, and whales' behavior is more directed towards exploiting areas close to the best solutions. The LF function is calculated as Eq. (6).

$$L_F = 0.05 \times \frac{u \times \sigma}{|v|^{1/\beta}} \tag{6}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma((1+\beta)/2) \times \beta \times 2^{(\beta-1)/2}}\right)^{1/\beta} \tag{7}$$

Where u and v are random values that follow a normal distribution, and β is the default constant equal to 1.5.

3.3. Whale fall

In the BWO, the whale fall phenomenon is simulated as a dynamic state for the natural behavior of whales in the face of threats and its effects on the whale population. In the real world, beluga whales face threats like polar bears, killer whales, and humans during migration and feeding. Most beluga whales escape these threats with intelligence and social interactions, but a few cannot survive and fall into the deep sea. A whale crash means the death of a whale whose dead body sinks to the bottom of the ocean and provides many food sources for creatures in the deep sea. The whale crash phenomenon is considered a mechanism to simulate small changes in the population and maintain the dynamics in each iteration. Each iteration, one or more beluga whales from the population will fall. As a random factor, this phenomenon leads to small fluctuations in agents' behavior. Making small random changes enables the discovery of new areas in the search space and prevents the algorithm from getting stuck in local optimal points. The mathematical model is expressed as Eq. (8).

$$X_i^{T+1} = r_5 X_i^T - r_6 X_r^T + r_7 X_{\text{step}} \quad (8)$$

Where r5, r6, and r7 are random numbers between (0, 1). X_{step} is the step size of a whale fall. This parameter updates the position of the dead whale randomly. The whale fall step size acts as an adjustment mechanism in the whale fall phase, preventing the algorithm from falling into local optimal points and increasing the search's dynamic and randomness. X_{step} is defined by Eq. (9).

$$X_{\text{step}} = (u_b - l_b)\exp(-C_2 T / T_{max}) \quad (9)$$

The C2 ($C2 = 2W_f \times n$) factor determines how fast the algorithm moves through the search space. Changes in this factor have a direct impact on how agents search. Increasing this factor may cause more significant jumps in the search process, while decreasing it means a more accurate and localized search. *ub* and *lb* represent the upper and lower bounds of the problem variables, respectively. The upper and lower bounds determine that the values of the variables should not be outside a particular range. These boundaries are the constraints applied to the problem. T_{max} parameter is used as a criterion to stop the algorithm. In this model, the probability of whale fall (W_f) is calculated as a linear function based on Eq. (10).

$$W_f = 0.1 - 0.05T / T_{max} \quad (10)$$

The probability of a whale falling gradually decreases from 0.1 in the initial iteration to 0.05 in the final iteration. In the early stages of optimization, when whales (or solutions) explore the problem search space, they are more prone to encountering challenges or suboptimal paths. Exploration is initially costly but becomes more focused as the goal approaches, eventually leading to more efficient convergence toward the optimal solution. The pseudo-code of the BWO is reported in Algorithm 1.

Fig. (7) shows the flowchart of the BWO algorithm.

3.4. Computational complexity

The algorithm (BWO) consists of the following parts: the initialization stage, the evaluation of the fitting function, and the update of the whales' position. In the initialization step, the number of whales is defined by n, and the initial position of each whale in the search space is randomly determined. The time required for this allocation grows linearly with the number of whales. In other words, the more whales there are, the more time it will take to complete this step. By increasing the number of whales or the complexity of the fitting function, the execution time of the BWO algorithm increases significantly. In the exploration and exploitation phase, the computational complexity is defined as $O(n \times T_{max})$, where T_{max} represents the maximum number of iterations. This relationship indicates that with the number of whales or iterations, the time required to execute the BWO algorithm increases linearly. Therefore, the fitness of each whale in different iterations must be calculated and updated. The computational complexity of the whale fall phase is influenced by two factors: the whale fall probability (W_f) and the balance factor (B_f). The complexity of this step is roughly defined as $O(0.1 \times n \times T_{max})$. A coefficient of 0.1 indicates a significant reduction in operations compared to the exploration and exploitation stages. The whale fall stage occurs in certain conditions with a certain probability and does not include all whales. In general, the computational complexity of the BWO algorithm is approximately $O(n \times (1 + 1.1 \times T_{max}))$. As the number of whales and iterations increases, the algorithm's execution time increases linearly, but the main effect occurs in the exploration and exploitation phases.

4. Methods of BWO

Fig. (8) shows the classification of BWO methods. The classification includes four main categories: hybrid, improved, variants of BWO, and optimization problems. These categories include different algorithms for strengthening and developing the BWO algorithm. Combining BWO with other algorithms allows its weaknesses to be compensated by the

Algorithm 1
pseudocode of the BWO algorithm [61].

Input: Optimization settings (maximum iteration, population size)
Output: The optimal solution
Establish the population and assess fitness levels, obtain the optimal solution (P*)
While $T \le T_{max}$ **Do**
Determine the probability of whale fall W_f using Eq. (10) and the balancing factor B_f using Eq. (3).
For each particle (X_i) **Do**
If $B_f(i) > 0.5$
// In the exploration stage
Produce $p_j (j = 1, 2, \ldots, d)$ randomly from dimension
Select a particle X_r randomly
Update the new location of *i th* particle using Eq. (4)
Else If $B_f(i) \le 0.5$
// In the exploitation stage
Revise the random jump strength C1 and compute the Lévy Flight function
Renew the new location of *i th* beluga whale using Eq. (6)
End If
Review the limitations of new positions and assess their fitness values
Examine the limits of new placements and evaluate their corresponding fitness scores.
End For
For each particle (Xi) **Do**
//The whale fall stage
If $B_f(i) \le W_f$
Update the step factor C_2
Compute the step size X_{step}
Renew the new location of *i th* beluga whale using Eq. (8)
Assess the limitations of the new location and determine the fitness value
End If
End For
Discover the current best solution P*
$T = T + 1$
End While
Provide the optimal solution

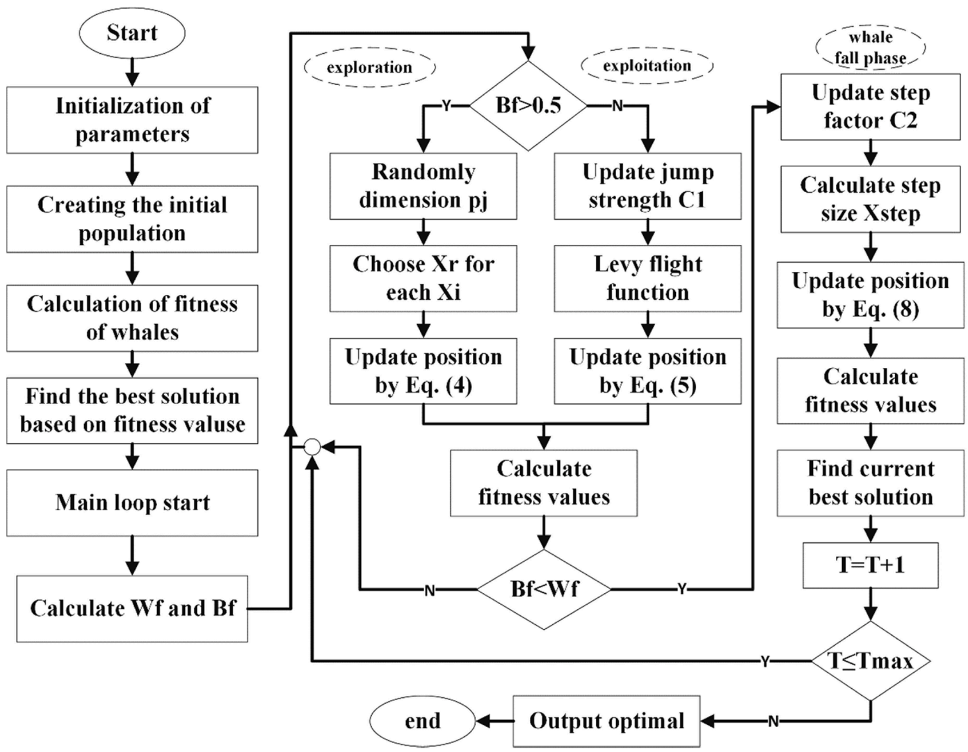

Fig. 7. Flowchart of the proposed BWO [61].

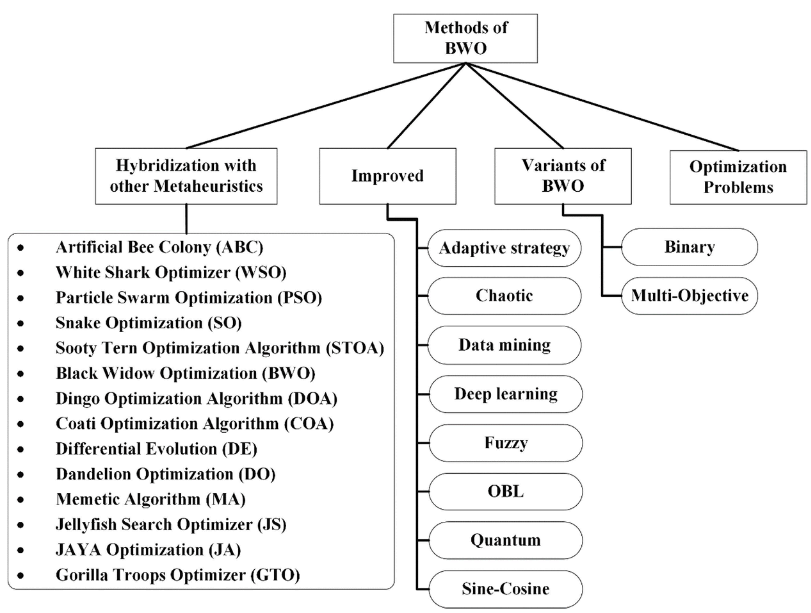

Fig. 8. Classification of BWO methods.

strengths of the other algorithms. This combination can increase the diversity of the population and avoid getting stuck in local optima. In improved versions, changes in the structure of the BWO algorithm led to increased efficiency. These improvements can include changes in movement rules and exploration and exploitation strategies.

4.1. Hybridization with other metaheuristics

An improved method inspired by the BWO is proposed for the capacity allocation process of a microgrid system, which includes wind, solar, and storage [78]. The improvement of BWO is achieved by combining opposition-based learning (OBL), artificial bee colony algorithm (ABC), and dynamic opposition approach. This combination increases population diversity and convergence accuracy in the optimization process. After finding the best choice in the Pareto front, the technique (TOPSIS) is used to select the most favorable solutions. Optimization in microgrid systems includes multiple energy sources (wind, solar, and storage), so balancing different criteria, such as cost, sustainability, and efficiency, is important. OBL and ABC approaches have been used to overcome the problems of BWO. OBL helps improve the algorithm's ability to search the problem space optimally. This process helps to increase population diversity and avoid getting stuck in local optima. ABC algorithm helps to improve the local and global search process and increases the ability of BWO in multi-objective optimization. Using real load data and meteorological information has shown that this method can be suitable for capacity allocation in microgrid systems connected to the grid.

On a worldwide scale, brain tumors rank high among the worst diseases. The prognosis and likelihood of recovery are improved when the patient is diagnosed promptly. It takes much work to separate brain tumors from other abnormalities in MRI images and diagnose cancer. Many approaches have been used to predict and classify the tumor. A few of the challenges they encounter include the requirement for specialist help, the lengthened processing time required, and choosing the best feature extractor. To address these concerns, a Deep Convolutional Neural Network (DCNN) based on a White Shark-assisted BWO and an improved U-Net are introduced to segment and classify brain tumors into four distinct stages [79]. This study uses an upgraded U-Net image segmentation model. The first stage of MF-based preprocessing of the input picture is included. Statistical traits like I-GBP and MTH are obtained in the third stage, feature extraction. After training on WSBWO, the DCNN classification method is used to categorize brain tumors.

A new method gaining momentum in the energy industry is managing real-time energy in microgrids connected to the general grid. It makes it easier for microgrids to communicate with a larger electrical grid, which helps improve efficiency, strengthen energy resilience, and reduce costs and emissions to a greater extent. Additionally, it enables grid-connected microgrids to flexibly adjust to changing circumstances, which paves the way for improved energy infrastructure and higher levels of energy insurance. For microgrids, locating an efficient and accurate strategy for managing energy in real-time is necessary. A modified metaheuristic known as the Boosted BWO (BBWO) for real-time energy management to enhance battery control in a community microgrid (CM) is proposed [80]This study delivers compelling results by leveraging the PSO algorithm and the advantages of the BWO approach. Regarding real-time energy management, the regularized BBWO algorithm, with a cost function tailored to society's needs, emerges as a practical and effective solution.

A hybrid optimization technique known as Snake Optimization Updated BWO (SOUBWO) [81] Our approach, which uses a hybrid optimization technique known as Snake Optimization Updated BWO (SOUBWO), comprehensively addresses the issue of routing in the IoT. This method considers energy, latency, distance, and trust restrictions. Moreover, it covers a wide range of procedures involved in waste management, including pre-processing, feature extraction, segmentation, and classification. With optimal routing, the garbage images collected by IoT devices are efficiently sent from the source node (SN) to the destination node (DN). The Wiener filtering technique is used to pre-process the sent rubbish images, and the suggested BIRCH-ADM approach is used to segment the pre-processed images. Statistical features, a feature based on the proposed Local Gabor XOR Pattern (LGXP), and multi-text on the histogram are subsequently extracted. By combining conventional deep *maxout*With bidirectional Long-Short-Term Memory (Bi-LSTM) networks, a hybrid classification model successfully identifies the extracted features. Performance and statistical analyses are among the several assessments that back up the effectiveness of the proposed strategy. Also, the calculated figure of 0.123 for energy consumption shows that the proposed method is very energy efficient. Multiple tests have shown that this hybrid classification model effectively sorts trash.

An innovative optimization technique that integrates LSSVR with the Sooty Tern Optimization Algorithm (STOA) and the BWO Algorithm (BWOA) to efficiently predict shear strength and permeability, two crucial soil properties, for the design and construction of various civil engineering structures [82]. One major challenge to getting reliable parameter predictions is the lack of available experimental data on soil quality. This challenge has been addressed using the strengths of two nature-based algorithms: BWOA, which mimics the hunting behaviour of beluga whales, and STOA, based on the foraging approach of sooty terns. The hybrid approach outperforms individual algorithms' performance by using each's unique characteristics to increase prediction accuracy. The suggested model was trained and evaluated using a comprehensive soil properties dataset. It was compared to more conventional optimization methods to assess how well the hybrid technique worked. According to the results, soil property predictions are much improved by the combined BWOA-STOA optimization strategy. This allows for more reliable and efficient design and construction methods in civil engineering projects.

The constant and increasing fluctuations and dynamic changes in renewable electricity generation systems such as wind and solar power plants lead to disturbance in the reliability and stability of the network. The instability of renewable resources leads to extreme frequency fluctuations due to changes in demand. Wind energy, in particular, causes grid instability due to its inherent unpredictability and reduced system inertia. An optimal control method based on flatness-based Active Disturbance Rejection Control (FADRC)and an improved version of the BWO (EBWO) is designed to deal with dynamic challenges [83]. In this approach, the BWO methodology has been improved using the Particle Swarm Optimization (PSO) algorithm in the whale fall phase. Several scenarios have been tested to validate the hybrid model. The simulation results show that the active control of flat-based turbulence compensation has a significant advantage over other methods in terms of stability and flexibility against load changes and parameter uncertainties. Overall, this solution proves the ability to improve the stability of power systems connected to renewable energy by effectively controlling complex dynamics and instabilities.

The Internet of Vehicles (IoV) facilitates vehicle data interchange for collaborative evaluation, improving the driving experience and service quality. A deep learning approach for energy-efficient routing and secure data transfer has been presented. This study employs the Bidirectional Long Short-Term Memory-Modified Attention Layer (Bi-LSTM-MAL) methodology for the energy prediction of each node in the preliminary phase. This study offers the Combined Beluga with Black Widow Optimization (CBBWO) method for optimum cluster head selection, considering several constraints such as energy, risk, distance, and delay [84]. This guarantees accurate routing, ideally achieved by considering restrictions such as trust, mobility, and network quality. This study addresses safe data transmission using a security standard, Fusion Key induced in Elliptic Curve Cryptography (FK-ECC), which facilitates the secure data transfer between the source and destination. Ultimately, the study assesses its efficacy in inefficient routing and secure data transfer compared to traditional approaches. The CBBWO has documented the reduced cost value.

An improved Dingo Algorithm and Enhanced BWO (IDBBWO) method is proposed to identify the appropriate cluster head and implement optimal routing [85]. The purpose of this method is to reduce energy consumption and increase network life. In this model, the improved Dingo Algorithm (IDOA) is responsible for selecting the cluster head (CH) and optimal routing, which are done using fit criteria. Also, the Boosted BWO (BBWO) has been used to determine the best locations for the well node. The simulation results of the proposed IDBBWOA method showed that this method has been significantly effective in improving the average throughput, keeping active nodes and preserving the remaining energy. The average throughput has increased by 18.92%, and maintaining the number of active nodes equals 34.28%. The results show the high efficiency of the IDBBWO method in managing energy consumption and increasing network durability in wireless systems.

The rapid progress of technology affects our lives daily. Nonetheless, the area coverage challenge presented by sensor nodes in wireless sensor networks remains a complex topic despite the development of area coverage augmentation models. A practical area coverage maximization strategy using an improved optimization model, Coati Modernized BWO

(CMBWO), is suggested [86]. The whole procedure of the area coverage maximizing technique consists of two crucial steps: Sensor node coverage model and area coverage optimization. The first phase involves establishing a 2D Wireless Sensor Network (WSN) monitoring region, whereby target monitoring sites are designated to address the coverage problem. The distance between the sensor node and the goal monitoring point is computed using weighted Manhattan distance evaluation rather than traditional Euclidean distance assessment. This enhancement is implemented to ascertain the exact location of the target monitoring point relative to the sensor node's position. The subsequent phase in area coverage optimization is executed using the CMBWO algorithm to maximize area coverage in WSN. This hybridization is achievable with the modernization of the BWO algorithm via COA. This effective hybridization resulted in optimizing area coverage for sensor nodes in WSN.

During fast epidemics, a two-stage metaheuristic algorithm is proposed to optimize the distribution of medical supplies in constrained community logistics networks, focusing on efficient waste collection. To plan the cooperative distribution of many UAVs in a three-dimensional environment, the multi-strategy guided adaptive differential evolution (MSGA-DE) is introduced in the first step of the solution technique [87]. To solve the vehicle-UAV scheduling and distribution dilemma, an upgraded BWO employing hybrid neighborhood search (HNS-IBWO) is included in the second phase. The results show effectiveness, especially in global search capability, convergence, and multi-objective search. To evaluate the HNS-IBWO algorithm's ability to solve problems and its competitiveness compared to similar algorithms, comparative simulation tests were conducted using well-known algorithms, including PSO, GWO, DE, and BOA. Compared to PSO, GWO, DE, and BOA, HNS-IBWO exhibits improvements in mean values, optimal values, and standard deviations for every test function.

To address the deficiencies in transformer failure detection, a fusion algorithm (BWODO) that integrates the BWO and Dandelion algorithms (DO) is presented in conjunction with variational mode decomposition (VMD) and long short-term memory neural networks (LSTM) [88]. Initially, fault classification and feature extraction are performed using dissolved gas analysis (DGA) data in oil. The chaotic mapping opposition learning method, mixed reverse learning strategy, and Beluga whale predation strategy enhance the DO to augment its optimization speed and solution correctness. The enhanced method is used to optimize the parameters of the VMDLSTM model, hence augmenting the accuracy of transformer failure detection. The test findings indicate that the BWODO-VMD-LSTM model achieves an accuracy of 97.4%, surpassing the PSO-VMD-LSTM and DO-VMD-LSTM models by 4.2% and 5.9%, respectively, demonstrating that the suggested technique significantly enhances the accuracy of transformer failure detection.

Sentiment analysis is one of the main topics of interest to academics in the field of social networks. Twitter has evolved into a prominent social media platform and is a focal point of considerable interest for academics in sentiment analysis. An optimization-based ensemble classifier, the beluga dodger, is presented to identify and classify feelings in social media to address existing challenges. The ensemble classifier is integrated with the beluga dodger (BD) optimization to formulate the classifier [89]. The hybrid ensemble classifier, which integrates convolutional neural networks (CNNs) with bidirectional short-term memory classifiers, demonstrates enhanced efficiency. The suggested BD optimization began by integrating shark hunting traits with whale optimization to enhance classification effectiveness and expedite emotion prediction. Compared to all other models, the BD-optimized deep ensemble classifier attained an accuracy of 97.61%, sensitivity of 96.20%, and specificity of 98.61%.

As data dimensionality increases, feature selection has garnered considerable attention recently. Feature selection is a challenging endeavor because of the extensive search space included. Due to its global search capability, Swarm intelligence has been effectively used to tackle feature selection issues. BWO is a swarm intelligence technique seldom used for feature selection owing to its constrained exploration capability towards the conclusion of repeats. A novel approach termed Memetic BWO (MBWO) is introduced for FS [90]Incorporating local perturbation and altering search operators may enhance MBWO's performance in feature selection. Comparative experiments indicate that the improvements have substantially improved the MBWO algorithm's efficiency relative to other algorithms.

Clustering is an efficient method for enhancing energy efficiency by reducing or managing energy consumption across sensor nodes (SNs). In previous cluster-based designs, the nodes closest to the cluster's center are often chosen to function as Cluster Heads (CH). Moreover, Member Nodes (MNs) exhibit inconsistent energy consumption since direct data transmission is mainly used for intra-cluster routing during communication between MNs and the CH. Consequently, nodes situated further from the CH use more energy to transmit their data packets than those nearer the CH. The disproportionate energy depletion of MNs results in coverage gaps and reduces coverage duration. The duration during which the initial MN is exhausted is called coverage time, leading to partial coverage of the sensing region. This study provides a novel energy-efficient clustering framework. The model includes stages like Optimal Clustering, Routing, and Data Aggregation. The Optimal Clustering phase introduces the novel Jelly Customized BWO algorithm (JC-BWOA) [91] to execute the clustering process, taking into account Delay, Energy, Trust, and both intra- and Inter-Cluster distances. The JC-BWOA algorithm achieves optimal routing, taking into account network quality and distance.

BWO algorithm faces challenges such as imbalance between exploration and exploitation, and reduced convergence accuracy in complex and high-dimensional problems. To solve these problems, a hybrid version called BWO with jellyfish search optimizer (HBWO-JS) is designed [92]. The hybrid model uses vertical integration operator and Gaussian transformation approach to solve optimization problems. The combination of BWO with JS algorithm results in stopping at local solutions and improving the accuracy in the exploitation stage. This algorithm uses multi-stage exploration and cooperative exploitation to solve complex problems. The vertical integration operator solves the imbalance problem between exploration and exploitation. Based on the Gaussian variation approach, the surrounding environments of the agents are searched and the search process is extended and the problem of premature stopping is solved. The effectiveness of the HBWO-JS method is done through a comprehensive comparison with the original BWO and eight other algorithms on the CEC2019 and CEC2020 test sets. The findings show that HBWO-JS has achieved highly competitive power in complex problems and practical optimization.

One of the issues that arises with facility location is the positioning of electric vehicle charging stations. In addition, the positioning of electric vehicle charging stations creates challenges for electric distribution networks, system losses, and the total number of convergences across the traffic network associated with voltage variations. In the distributed model, two fundamental problems addressed are the enhancement of voltage profiles and the avoidance of losses. Shunt capacitors are often used to implement the distributed model to compensate for reactive power. A novel charging model for electric vehicles is developed using hybrid optimization techniques to solve the issue. The reduction of greenhouse gas emissions may be accomplished by the use of a hybrid approach known as BWO-Jaya Optimization (BWJO) [93], which encompasses both BWO and JA. The built model has shown higher performance than conventional electric vehicle charging schemes.

A crucial task for correctly analyzing the performance of photovoltaic (PV) systems in power systems is modeling the photovoltaic (PV) generating unit. It is the assignment of the optimal parameters of the photovoltaic equivalent circuit that is the focus of the modeling of the photovoltaic system. Determining these quantities is a problematic optimization issue mainly because of the fluctuation in solar irradiation and the temperature of the surrounding environment. To determine the parameters of the PV cell or panel that are optimal, a novel hybrid multi-population gorilla troops optimizer and BWO (HMGTO-BWO) model is used [94]. A strategy considering many populations is used to provide variation and prevent the typical GTO from becoming stagnant. The capabilities of the BWO, which are based on coordinated motion and Lévy flying, are used for exploration and utilization. Based on statistical analysis and convergence characteristics, the HGTO-BWO is analyzed using both standard and CEC-2019 benchmark functions. The results are then compared to seven other optimization strategies. During the parameter estimation process for PV modules, the data revealed that the suggested HGTO-BWO was both practical and superior.

Fig. (9) shows the advantages of combining the BWO algorithm with other algorithms

4.2. Improved

The improved section includes various methods to improve the performance of the BWO algorithm. These methods include new and advanced techniques such as adaptive, chaotic, data mining, deep learning, fuzzy, OBL, quantum, and Sine-Cosine. Each of these methods, by using specific features and capabilities, increases the efficiency of the BWO algorithm in dealing with complex problems.

4.2.1. Adaptive

Adaptive methods are a set of algorithms and strategies that automatically adjust parameters or strategies during the optimization process. These methods improve the performance of the BWO algorithm by dynamically and intelligently changing the parameters or procedures. Adaptive methods are usually used to optimize complex, dynamic, and high-dimensional problems. In dynamic optimization problems where the environment or the objective function changes over time, adaptive methods seek to change strategies to adapt to the new environment. One of the significant challenges in optimizing the balance between exploration (global search) and exploitation (local search) is. Adaptive methods can manage this balance by changing search strategies over time. Table (3) reviews the advantages and limitations of adaptive BWO based on 2024 papers.

Table (4) reviews the advantages and limitations of adaptive BWO based on 2023 papers.

4.2.2. Chaotic

A suggested IBWO employs several ways to tackle optimum chiller loading (OCL) issues [114]. IBWO integrates circular chaotic mapping, the effective search operator from the sparrow search algorithm, and the Cauchy mutation method to improve global optimization efficacy, convergence, and resilience. The augmented algorithm performance was corroborated by testing with six benchmark functions in MATLAB, illustrating its boosted efficacy. Furthermore, IBWO optimizes power consumption and load distribution in two representative chiller systems. Compared to the traditional technique and other meta-heuristic algorithms, the findings show that IBWO offers an energy-saving solution characterized by superior resilience, reduced power consumption, and enhanced total refrigeration efficiency within a limited number of iterations.

To improve the accuracy of energy consumption predictions, it is proposed that an IBWO be used to increase extended short-term memory networks (LSTM) [115]. An innovative strategy for dynamic alteration of the step factor, combined with techniques such as nonlinear decrement, is devised to boost BWO. This is done to enhance the effectiveness of BWO in both global search and local exploitation. An upgraded BWO method will be used to optimize two, three, and four hyper-parameters of LSTM, respectively, to explore the accuracy of the hyper-parameters of LSTM in forecasting energy consumption. This research intends to

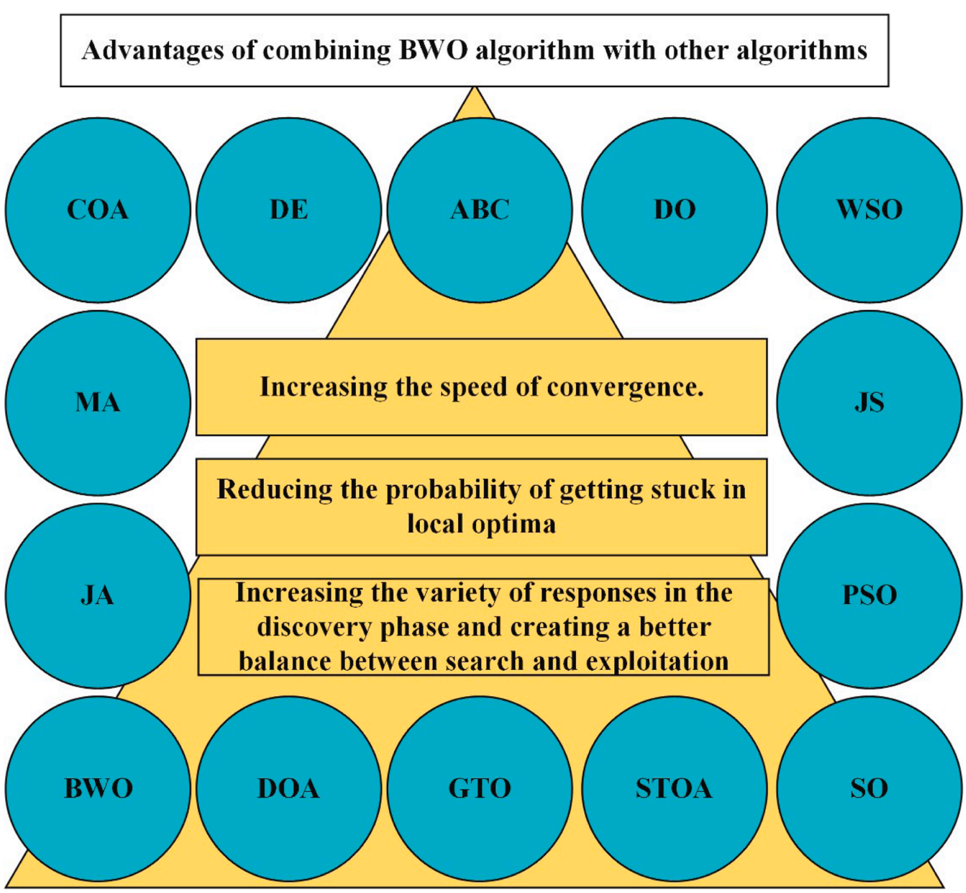

Fig. 9. The advantages of combining the BWO algorithm with other algorithms.

Table 3
A review of advantages and limitations of adaptive BWO based on 2024 papers.

refs	model	application	strategy	Advantages	limitations
[95]	Adaptive BWO (ABWO)	Stochastic Optimal Reactive Power Dispatch (SORPD) with PV units	Fitness-Distance Balance Selection (FDBS)	Improved system performance, optimal reactive power control, efficient renewable integration	Increase the number of repetitions
[96]	Enhanced BWO (EBWO)	Feature extraction and classification of underwater acoustic signals (UAS)	Time-Shift Multiscale Fuzzy Dispersion Entropy	High recognition accuracy (98.43%); effective noise reduction; accurate feature extraction; universal application for different UAS types	Complexity in decomposition and computational cost
[97]	Improved BWO (IBWO)	Distribution network operation optimization for photovoltaic	non-linearly inertia weight	Improved network resilience and cost efficiency	Increasing computational complexity
[98]	IBWO	Resource allocation optimization in multiple-input multiple-output (MIMO)	deferential evolution (DE)	improved search capabilities for exploration and exploitation	Increase the number of repetitions
[99]	Self-Improved BWO (SI-BWO)	Intrusion Detection System (IDS) for Wireless Sensor Networks (WSN)	modified logistic map	Improved attack detection accuracy; optimized feature selection and training; effective handling of class imbalance	Computational overhead from hybrid model training; dependency on the proper tuning of SI-BWO and CNN-DBN
[100]	Optimal BWO (OBWO)	Measuring and evaluating the geometric parameters	Optimum weighting of update steps	low measurement errors	Complexity in measuring intricate geometries
[101]	Leader BWO (LBWO)	optimizing energy	Leader-based mutation-selection	lower PAR; effective handling of intermittent renewable energy sources	Increase the number of repetitions
[102]	IBWO	Frequency control in islanded hybrid microgrids with renewable energy sources	Sobol sequence; Stochastic universal sampling	improved search capabilities for exploration and exploitation	Complexity in tuning and implementation
[103]	Enhanced BWO Algorithm (EBWOA)	Engineering optimization problems	Two-step approach with a dynamic update factor for convergence acceleration and Cauchy mutation operator for diversity and avoiding local optima	Improved convergence speed; superior solution quality, better avoidance of local optima; effective in real-world and benchmark problems	Complexity in parameter tuning; potential computational overhead due to mutation and diversity mechanisms
[104]	Adaptive Spiral Elitist BWO (ASEBWO)	Short-term hydrothermal scheduling (STHS) optimization	Adaptive parameter strategy (cosine function); spiral search, elitist strategy; feasibility-based selection comparison; heuristic approach for constraint handling	Improved exploration-exploitation balance; narrowed search space; superior convergence accuracy; effective constraint handling	Potential complexity in tuning adaptive parameters

investigate the accuracy of these hyper-parameters. Through the use of the IBWO proposed in this paper, experiments have shown that adjusting the four hyperparameters of the LSTM may potentially reduce the mean absolute error (MAE) of the pre-improvement model from 830.71 KW to 128.28 KW.

A solution technique is provided using an IBWO [116] for distributed generation (DG). The Tent map produces a chaotic sequence characterized by superior dispersion and unpredictability. In contrast, the *Sobol*The sequence generates a reasonably uniform point set in space. By integrating the benefits of the two initialization techniques, the initial position distribution of the beluga whale population may achieve more uniformity within the constraint range and include a broader geographical range. The suggested initialization technique may enhance the algorithm's exploration efficacy. A superior-performing IBWO algorithm is presented. IBWO has superior convergence speed and enhanced problem-solving capability. The proposed method efficiently addresses the DG planning issue compared to other superior intelligent algorithms.

The Extreme Learning Machine (ELM) served as the foundational model, while the Enhanced and Improved BWO (EIBWO) was introduced to optimize ELM's internal parameters [117]. This work presented a chaotic mapping approach, a sine dynamic adaptive factor, and a disturbance strategy for BWO, resulting in the proposal of EIBWO, which exhibits excellent convergence accuracy and robust optimization capability. Standard testing functions confirmed that EIBWO outperformed comparison algorithms. Secondly, EIBWO was used to optimize the internal parameters of ELM and to develop a photovoltaic power forecast model using the enhanced BWO algorithm combined with an extreme learning machine (EIBWO-ELM). The measured data of the photovoltaic output were used for validation, and the findings indicate that the photovoltaic power prediction results of EIBWO-ELM were more precise, irrespective of cloudiness or sunshine. The R2 of EIBWO-ELM surpassed 0.99, underscoring its proficient capacity to adjust to photovoltaic power output. The predictive accuracy of EIBWO-ELM surpasses that of comparator models. EIBWO-ELM significantly enhances photovoltaic power production's prediction reliability and economic advantages compared to current models.

To overcome the inherent limitations of the classic BWO (MHIBWO) [118]. This study proposes a multi-strategy hybrid upgrade that may be applied to the method. *MTent*, a step size adjustment mechanism and a crisscross method are all components included in this innovative improvement process. Subsequently, a bi-layer iterative model is built, wherein annual net income and grid-connected compatibility are specified as optimization objectives for the outer and inner layers, respectively, employing MHIBWO and CPLEX for resolution. The model generates a capacity scheme that perfectly balances economic performance and stability using a layered repetition of the two levels. Through the simulation, it was made abundantly evident that MHIBWO and the model that was offered both have their benefits. The fuzzy C-means algorithm (FCMA) tests the approach's effectiveness in practice by identifying and consolidating typical days. This provides an enhanced solution for optimizing microgrid topologies. Furthermore, the technique is evaluated using actual data from the Elia power plant.

BWO is a competitive approach that adeptly tackles both unimodal and multimodal obstacles, demonstrating benefits and possibilities in the resolution of complicated optimization problems faced in real-world scenarios [119]. The original BWO algorithm is only applicable to continuous single-objective optimization problems. It faces difficulties achieving a uniformly distributed population through random initialization, maintaining a balance between exploration and exploitation

Table 4
A review of advantages and limitations of adaptive BWO based on 2023 papers.

refs	model	application	strategy	Advantages	limitations
[105]	Improved BWO (IBWO)	Preventive maintenance (PM) strategy optimization for subway train bogie components	Optimization using IBWO and Lévy flight PSO	Improved early convergence	Potential computational complexity in integrating multiple optimization methods
[106]	Modified BWO (MBWO)	Solving optimization problems, including engineering design tasks (e.g., welded beams, pressure vessels, refrigeration systems)	Elite evolution technique; randomization control parameter; transition factor between exploration and exploitation; Gaussian local mutation (GM)	Enhanced exploration and exploitation balance; improved prevention of local optima stagnation; superior performance in both constrained and unconstrained problems	Increasing time complexity
[107]	MBWO	Solving benchmark and practical engineering optimization problems	Group aggregation strategy for local search and faster convergence; migration strategy for escaping local optima	Enhanced optimization performance; better convergence speed; improved ability to avoid local optima; strong optimization capabilities for real-world applications	Potential for increased computational complexity due to multiple strategies
[108]	Kalman Filter-based BWO (KBWO)	Complex optimization problems	Logistic growth model for balance factor update; Kalman Filter for enhanced state updating and local search	Improved convergence; better balance between global and local search; enhanced stability; and more reliable approach to global optima	Increasing the complexity of the algorithm
[109]	Fitness-Distance Balance BWO (FDBBWO)	Solving high-dimensional optimization problems (CEC2020 benchmark functions)	Fitness-distance balance (FDB) selection method	Improved early convergence; reduced likelihood of getting stuck in local optima	Increasing time complexity; performance dependent on problem dimensionality and structure
[110]	IBWO	Addressing simulation optimization challenges with stochastic constraints	Three-level approach with polynomial chaos expansion (emulator); improved BWO for candidate selection (diversification)	Efficient search in large spaces; reduced computation time, real-time applicability; improved robustness and performance compared to other heuristics	Potential complexity in implementation and dependence on the problem structure and quality of the emulator
[111]	Adaptive BWO (ABWO)	fractional-order proportional-integral-derivative (FOPID) controller	Factor for adaptive weighting; method for random spare	Improved frequency stability; reduced tie-line power fluctuations; and enhanced overall system reliability	Increasing time complexity
[112]	IBWO	Micrograids with hydrogen storage	Adaptive weight factor	Faster convergence	Low efficiency in large-scale operation
[113]	IBWO	Optimal capacitor placement in radial distribution systems	Adaptive weight factor	Faster convergence; higher solution quality; effective voltage profile enhancement; reduced power losses	may be affected by system complexity and constraints.

phases, and lacking global exploration in later iterations. These challenges are a result of the algorithm's limitations. Due to these factors, problems arise associated with inadequate population variety, vulnerability to local optimum environments and decreased solution accuracy. As a result, BWO using binary and Pareto dominance relations is used to address the binary multi-objective optimization model. In addition, the tent map is used to determine the main location of the beluga whale population. Reinforcement learning is used to guide the decision process between exploration and exploitation. Additionally, a multifaceted swarm strategy is implemented to enable distinct populations to adopt various update strategies, ultimately resulting in improved search capabilities and the identification of the optimal.

A hybrid method, termed CBWO, employs a chaotic form of the existing optimization algorithm to augment its exploitation capability [120]. The performance of CBWO is first evaluated using 23 typical benchmark functions. Comparison research demonstrates the suggested algorithm's superiority to other existing algorithms. Simulation results were conducted on eleven traditional engineering topics. The results indicate that CBWO may be more successful in optimization due to its accelerated convergence rate and enhanced accuracy.

Fig. (10) shows the advantages of combining chaos with the BWO algorithm.

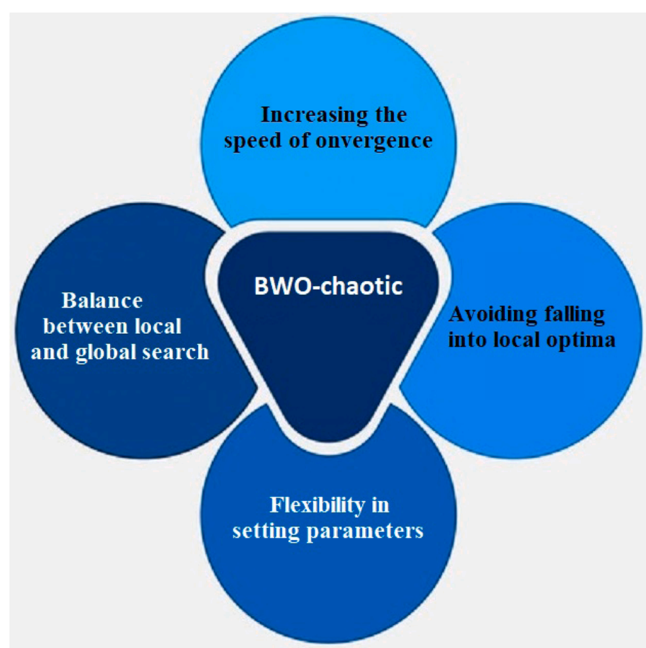

Fig. 10. The advantages of combining chaotic with the BWO algorithm.

4.2.3. Data mining

Combining meta-heuristic algorithms with data mining methods effectively improves machine learning models' efficiency and reduces parameter optimization problems. Combining the BWO algorithm with algorithms such as artificial neural network (ANN) and support vector machine (SVM) is used to improve performance and efficiency in various problems such as classification, regression, and prediction. ANN is one of the most widely used algorithms in machine learning, and it is used in many complex issues, such as data classification and prediction. However, proper adjustment of weights and training parameters such as learning rate, number of layers, and neurons is a fundamental challenge in ANN. BWO algorithm should be used as a meta-heuristic optimization method to adjust these parameters. Setting the kernel parameters and parameters C and γ play a vital role in the performance of SVM. BWO algorithm can be used to adjust SVM parameters optimally to increase the performance of SVM in classification. In addition to ANN and SVM, the BWO algorithm is combined with other data mining algorithms, such as Decision Trees and Random Forest algorithms. The main goal in these combinations is to improve the performance of machine learning algorithms by optimizing key parameters and increasing accuracy in complex data mining problems. Table (5) reviews the advantages and limitations of BWO with data mining.

4.2.4. Deep learning

Combining BWO with deep learning methods such as CNN, long-short-term memory neural networks (LSTM), and gated recurrent units (GRU) is one of the effective methods for solving complex problems such as image classification, time series analysis, and natural language processing. BWO algorithm helps to adjust various parameters of these networks, such as weights, learning rate, number of layers, and units. CNN is one of the best deep-learning architectures for image processing problems. One of the main challenges in using CNN is the optimal selection of the number of filters, size of filters, number of convolutional layers, and learning parameters (learning rate and weight loss rate). BWO algorithm is suitable for optimizing these parameters. LSTM neural networks are adequate for time series analysis and natural language processing. Setting parameters such as the number of LSTM memory units, the number of layers, and the learning rate is one of the key challenges in using LSTM. BWO algorithm is suitable for optimizing these parameters. GRU is a recurrent neural network used, like LSTM, to analyze sequential data. Maximizing the number of GRU units, the number of layers, and the learning rate are the main challenges of GRU. The BWO algorithm seeks to find the best value for the parameters of the GRU by adjusting the parameters at each step. Table (6) reviews the advantages and limitations of BWO with deep learning.

4.2.5. Fuzzy

BWO-fuzzy is used to adjust the gains of the virtual synchronous generator (VSG) controller to enhance control performance [144]An adaptive droop-based voltage control system is presented to regulate the reactive power reference for the photovoltaic (PV) plant. The droop controller's gain is adjusted to the photovoltaic system's fluctuating maximum reactive power capacity, guaranteeing the complete use of the PV system's surplus reactive power capacity. Simulation experiments substantiate the efficacy of the suggested frequency and voltage control techniques across several actual scenarios. The results indicate that the proposed control strategy may effectively use the capacity of photovoltaic plants to manage both frequency and voltage disturbances.

A new model for predicting the compressive strength of recycled aggregate concrete (RAC) is presented in the research that was conducted using the adaptive neuro-fuzzy inference system (ANFIS) [145]. Additionally, to improve the accuracy of the models, two meta-heuristic approaches, namely BWO and electrically charged particle optimization (ECPO), are used. The investigation produces three distinct models: ANEC, ANBW, and one ANFIS model. The ANBW model is superior to all others, as it has a fantastic RMSE value of 1.299 and R2 value of 0.993, which is incredibly low. The results of this study not only support the accuracy and dependability of the ANBW model but indicate the model's capacity to forecast result outcomes accurately. The enhancement of compressive strength in the construction sector is a prominent area where this technique shows tremendous potential.

Introducing a novel approach to promote efficient routing and increase connection stability, the Fuzzy BWO (FBWO) has been devised. [146]. Data packets are sent to their intended destination by several different channels identified by the BWO algorithm. These pathways are spread out throughout the network. Conversely, the proposed routes may be vulnerable to connectivity disruptions due to the total energy exhaustion inside the nodes during uninterrupted data transfer. Thus, the dependability of links is guaranteed by assessing the indicators of link stability, which include the probabilistic link reliability duration, the link expiry time, the remaining battery power, the link received signal strength and the link packet error rate. In addition, a fuzzy rule system is used to discover the optimal pathways inside the network. This is accomplished via the use of fuzzy rules. In addition to improving connection stability and signal strength, the FBWO approach that has

Table 5
A review of advantages and limitations on BWO with data mining.

refs	model	application	Data mining	Advantages	limitations
[121]	IBWO-BP model	Prediction of swelling and shrinkage ratio	Back Propagation-Artificial Neural Network	Improved generalization ability and prediction accuracy.	The complexity of integrating multiple optimization techniques.
[122]	Robust STL–BTSF and IBWO–LSSVR model	Optimization problems	IBWO to optimize hyperparameters of Least Squares Support Vector Regression (LSSVR)	Enhanced accuracy and speed of icing predictions; Effective for short-term data and limited samples.	It increased computational complexity due to multi-faceted optimization.
[123]	BWO-RF (BWO–Random Forest) model	Regional flood disaster risk assessment	BWO (BWO) to refine and optimize the Random Forest (RF)	Robust generalization capability and optimization efficacy; Effective in spatial and temporal flood risk assessment.	High computational demand for model training.
[124]	IBWO-LSSVM (Improved BWO–Least Squares Support Vector Machine)	Evaluation of the aging condition of composite insulators at the pixel level via hyperspectral imaging (HSI).	Improved BWO (IBWO) for tuning LSSVM hyperparameters	High accuracy (96.83%) in aging classification through k-fold cross-validation; Fast convergence and optimization accuracy of IBWO.	Specialized HSI equipment and pre-processing steps are required.
[125]	SG-LDA-BWO-ELM (Savitzky-Golay, Linear Discriminant Analysis, BWO–Extreme Learning Machine)	Rapid identification of coal mine water sources	Dimensionality reduction using Factor Analysis (FA) and Linear Discriminant Analysis (LDA).	Optimal convergence and minimal absolute error across models.	Need to set different parameters
[126]	BWO-XGBoost (BWO–Extreme Gradient Boosting) model	Identifying pulse signals	Hybrid of BWO with XGBoost	A high accuracy rate of 95.58%	Dependent on accurate feature extraction from pulse signals.
[127]	BWO-IVSO-SVM (BWO–Iterative Variable Subset Optimization–Support Vector Machine)	Material analysis	Support Vector Machine (SVM) model	Effective elimination of irrelevant variables; improving detection accuracy.	Relies on precise pre-processing and feature selection.
[128]	ELM-BWO (Extreme Learning Machine–BWO) model	Drought forecasting	BWO to optimize ELM parameters.	High correlation coefficients (up to 0.9944) and Wilmot index values (up to 0.9971).	Requires computational resources for model optimization and validation

Table 6
A review of the advantages and limitations of BWO with deep learning.

refs	model	application	Deep learning	Advantages	limitations
[129]	LFS-HDLBWO (Load Forecasting Scheme–Hybrid Deep Learning and BWO) model	Short-term load forecasting in Smart Grids (SG) for optimizing energy management	Convolutional bidirectional long short-term memory with autoencoder (CBLSTM-AE)	Effectively captures complex temporal dependencies in load data; Optimized hyperparameter selection enhances prediction performance.	Heavy computation due to deep learning and optimization processes.
[130]	BWO-SLEN (BWO–Slope Entropy) with 1D-CNN	Recognition of sea state signals (SSS) in complex marine environments.	Classification of underwater acoustic signals with one-dimensional convolutional neural network (1D-CNN).	Highest recognition accuracy for noise and sea state signals; Efficient for complex signal environments in marine applications.	Requires significant computational resources for optimization and CNN training.
[131]	BWO-BiLSTM (BWO–Bidirectional Long Short-Term Memory) model	Prediction of Remaining Useful Life (RUL) of lithium-ion batteries.	BWO optimizes BiLSTM network parameters for accurate RUL prediction.	High generalizability and robustness across different datasets.	Heavy computation due to deep learning and optimization processes.
[132]	BWO-BiLSTM-Attention (BWO–Bidirectional Long Short-Term Memory with Attention) model	Prediction of dissolved gas	BWO optimizes BiLSTM-Attention network hyperparameters	High prediction accuracy; Superior performance compared to five other models.	Heavy computation due to hyperparameter optimization and attention mechanisms.
[133]	BWO-GRU (BWO–Gated Recurrent Unit) model	Prediction of galvanometer scanner motion trajectories to enhance laser machining accuracy.	BWO algorithm optimizes GRU model parameters (neuron count, learning rate, batch size) to enhance predictive performance.	High prediction accuracy; Efficient runtime	Computational demands due to BWO optimization and GRU model complexity
[134]	FNB Optimization Method (Finite Element Method Surrogate with BWO)	Design and optimization	LSTM	Enhanced optimization efficiency and accuracy compared to traditional methods	Increasing time complexity
[135]	Chaogram-Based Deep Convolutional Neural Network with BWO	Speech Emotion Recognition (SER)	CNN	Reduction of Overfitting; High Classification Accuracy; Effective Feature Representation	Dataset Limitations
[136]	BWO for 6 G communications	Enhancing channel estimation and performance in 6 G communications	Deep Siamese Capsule Network	The advanced neural network model reduces computational complexity while maintaining high performance, facilitating real-time applications.	Complex Implementation
[137]	BWO Algorithm	Detecting glaucoma in retinal images	Features are trained on the DeepMaxout classifier	Accurate feature extraction with multiple feature sets.	High computational cost.
[138]	IBWO-TCN	Predicting gas outbursts in underground mines	IBWO optimizes the hyperparameters of the Temporal Convolutional Network	Improved prediction accuracy; Robust optimization of TCN hyperparameters; Effective for real-world gas outburst data.	Increasing time complexity
[139]	BWO-VMD-GRU Model	Predicting dissolved gas	Gated recurrent unit (GRU)	High prediction accuracy	High computational complexity
[140]	BWO-LSTM	Predicting mechanical properties	LSTM	High prediction accuracy: Fast and reliable predictions.	High computational cost.
[141]	CNN-BWO	Landslide susceptibility mapping	CNN	Better prediction accuracy than familiar CNN.	Model complexity increases with hybrid optimization.
[142]	BWO	Predicting heart disease to prevent heart attacks and strokes	Deep max out	High prediction accuracy; Efficient feature extraction.	Model complexity is due to hybrid architecture; it requires comprehensive data preprocessing.
[143]	IBWO	Semantic segmentation of aerial images	CNN	High segmentation accuracy; Efficient performance with a computation time of 113.0123 ss.	High computational cost

been presented provides optimal paths for packet broadcasting, which in turn enhances the performance of the network. Furthermore, the results of the experiments show that the FBWO model achieves a higher level of accuracy across all measures compared to other currently used methods.

4.2.6. OBL

OBL is an auxiliary method in meta-heuristic algorithms that helps the efficiency and speed of the BWO algorithm by generating and evaluating opposing points in the search space. In OBL, instead of evaluating only one point in the search space, its opposite point is also assessed to increase the probability of finding the optimal solution. In meta-heuristic algorithms, population diversity is an essential factor that makes the search space more efficiently explored and prevents getting stuck in local optima. In OBL, its opposite point is generated for each point in the search space (whale position). Instead of focusing on random positions, opposite points on the other side of the search space are evaluated. This mechanism increases the variety of solutions and improves search. The balance between exploration and exploitation is essential in BWO. OBL leads to a better and broader search space exploration by evaluating the opposite points. The probability of finding more optimal solutions increases when opposing points are evaluated. By examining both sides of a point (the current position and its opposite point), the BWO algorithm can make better decisions to exploit the best points. One of the essential goals of combining OBL with BWO is accelerating convergence. Evaluating counterpoints helps the BWO algorithm move more quickly to the best regions of the search space because both initial points and counterpoints are checked at each step. Table (7) reviews the advantages and limitations of BWO with OBL.

4.2.7. Quantum

The Quantum BWO (QBWO) method is introduced for a photovoltaic-wind system with integrated hydrogen storage [157]. QBWO mitigates some of BWO's constraints by integrating quantum theory concepts and tackling issues associated with limited population variety and local optimum stagnation. Simulations were performed for situations including wind turbine/fuel cell, photovoltaic/fuel cell, and photovoltaic/wind turbine/fuel cell systems. The findings demonstrate that the PV/WT/FC combo is the most economical solution for meeting

Table 7
A review of the advantages and limitations of BWO with OBL.

refs	model	application	Type of OBL	Advantages	limitations
[147]	IBWO	Optimizing capacity and location of distributed generation (DG)	Elite OBL (EOBL): Balance for population diversity and local/global search capability.	Reduces active power loss; improves voltage stability; minimizes investment and operating costs	Increasing time complexity
[148]	Modified BWO	Hybrid isolated power system with combined cycle gas turbine (CCGT)	Quasi-OBL (QOBL)	Convergence speed	potential challenges in real-time implementation and adaptability to dynamic conditions.
[149]	Hybrid BWO (HBWO)	They solve complex multidimensional optimization problems and enhance performance in engineering design and benchmark test functions.	Quasi-oppositional based learning (QOBL): An adaptive and spiral predation strategy for exploration and exploitation	Comparison of convergence speed and optimization efficacy relative to regular BWO and other methods.	The complexity of the hybrid approach may increase computational requirements.
[150]	Enhanced BWO (EBWO)	We optimize container migration between virtual machines (VMs) to improve energy consumption and load balancing in cloud computing environments.	OBL	Significantly reduces energy consumption during high resource utilization; efficient load balancing minimizes VM migration costs.	Performance may be affected by the specific cloud environment and resource availability.
[151]	Modified BWO	Optimizing UAV flight paths by minimizing total overhead costs	Combines random OBL, adaptive Gauss variational operator, and elitist group genetic strategy to enhance convergence and overcome local optima challenges.	Superior optimization performance on CEC2022 test functions	The algorithm's complexity may lead to an increase in the computational cost.
[152]	Opposition-BWO (OBWO)	Improving communication reliability in Flying Ad Hoc Networks (FANETs) with high-speed UAVs.	OBL enhances the search efficiency and diversity in the BWO algorithm.	Increasing packet delivery ratio; extending network lifetime; optimization of energy usage	Computational overhead for real-time updates in highly dynamic environments.
[153]	Enhanced BWO (EBWO)	Solving the Economic Load Dispatch (ELD)	Cyclone foraging motion to enhance exploitation and quasi-oppositional based learning (QOBL) to improve population diversity	Effective in high-dimensional and non-convex ELD problems, especially in large-scale systems	Computational complexity increases with larger systems.
[154]	Opposition-Based BWO with Dynamic Candidate Solution (OBWOD)	Solving single-objective bound-constraint optimization problems and classifying medical datasets	OBL will improve exploration in the search process, and the Dynamic Candidate Solution (DCS) mechanism will boost diversity and select optimal solutions.	Improve search efficiency; reduce the risk of local optima	Increasing complexity based on problem dimensions.
[155]	Opposition-Based BWO (OBWO)	Solving complex optimization problems; CEC_2013 benchmark functions.	OBL to enhance exploration and an adaptive strategy to balance exploration and exploitation.	The balance between exploration and exploitation; quicker and more accurate convergence.	It requires fine-tuning of adaptive parameters for different scenarios.
[156]	IBWO	Addressing global optimization and engineering challenges.	OBL	Enhancing balance between exploration and exploitation; improving global search capabilities; convergence speed; population diversity.	It requires fine-tuning of adaptive parameters for different scenarios.

local demands in a microgrid framework. This framework offers a systematic approach to developing energy systems, considering power-generating costs and improving reliability among uncertainties. QBWO surpasses the original BWO, PSO, and Crow Search Algorithm (CSA) by reducing design costs and enhancing dependability.

The quantum BWO (QBWO) method [158] is engineered to effectively and centrally arrange clusters, including cluster centroids, members, energy, priority, and validity duration. It may transmit the computational energy consumption initially associated with the node to the base station and coordinate operations for the succeeding switching and steady stages. Simulation trials demonstrate the advantages of QBWO. Compared to previous clustering approaches, QBWO achieves a more balanced network load and energy consumption, exhibiting superior energy efficiency and network longevity.

4.2.8. *Sine-Cosine*

TCBWO-DPR [159] is suggested for clustered wireless sensor networks. In the cluster head selection process, we propose a novel excitation function to assess and identify more appropriate candidate cluster heads by establishing the link between node energy and the spatial relationships across nodes. The BWO algorithm has been enhanced by integrating the cosine factor and t-distribution to augment its local and global search efficacy and boost its convergence rate and capacity. We use Prim's technique to create a spanning tree for the data transmission line and utilize DPR to ascertain the ideal route between cluster heads, guided by the correlation distances of the cluster heads. This efficiently reduces the data transmission distance and improves network stability. Simulation findings indicate that the enhanced BWO method may significantly extend the survival cycle and decrease the average energy consumption of the network.

For UAV route planning, a modified version of the BWO method is suggested [160]. The suggested approach uses the Sine-cosine algorithm to enhance the BWO exploration process. The Sine-cosine modified BWO (SBWO) is then used to design the UAV's flight route. The simulation's findings demonstrate SBWO's clear benefits in terms of convergence speed. Additionally, compared to other algorithms, SBWO may provide superior results in UAV 3D route planning, averaging a 5.6% shorter shortest path and a 40.3% shorter execution time. This further demonstrates the efficacy of SBWO.

4.3. *Variants of BWO*

Two common types of BWO algorithms are Binary BWO and Multi-objective BWO. Each is used for specific optimization problems.

4.3.1. *Binary*

To facilitate the process of jamming task allocations, a binary sparrow-hybridized BWO approach is provided [161]. Specifically, the approach combines the binary sparrow search algorithm (BSSA) with the binary BWO (BBWO), customized with multi-dimensional limits that span the time, frequency, and geographic domains. Formulating a fitness function that considers the radar coverage and the signal-to-jamming ratio acquired by each radar is needed to determine the optimal strategy for allocating jobs involving collaborative interference. The simulation results suggest that the proposed method's optimization speed and accuracy are significantly superior to those of BSSA and BBWO when the quantity of uncrewed aerial vehicles (UAVs) is seven and the number of radars is ten. As a consequence of this, the algorithm displays robust coverage and effectiveness in the field of jamming job assignments. An illustration of the advantages of using the BWO algorithm for feature selection is drawn in Fig. (11).

The Beluga Whale–Tasmanian Devil Optimization (BWTDO) [162] is presented for parameter optimization to develop a high-performance Intrusion Detection System (IDS) using a Fuzzy Classifier in a cloud environment. The hybrid Deep CNN-BWTDO algorithm was validated using a benchmark IDS dataset, and comparison findings for this algorithm with other recent hybrid methods have been published. The suggested method achieved a precision of 0.926, a recall of 0.924, an F1-score of 0.927, and an accuracy of 0.924.

4.3.2. Multi-Objective optimization

Multi-objective optimization (MOO) is an approach in which several conflicting or different objectives are optimized simultaneously [163]. The BWO algorithm in its MOO version has been used for various purposes, such as reducing costs, increasing productivity, and improving performance. BWO algorithm can establish an optimal balance between objectives due to its search power and high flexibility. In many real-world problems, multiple objectives must be optimized simultaneously. For example, economic costs, energy efficiency, and carbon emission reduction in energy networks should be optimized simultaneously. The multi-objective version of BWO (MOBWO) is a powerful tool for solving complex problems requiring simultaneous optimization of several criteria. Table (8) reviews the advantages and limitations of MOBWO.

The MOBWO algorithm has performed better in multi-objective optimization problems than other algorithms. It can better find optimal solutions in multi-objective problems by combining non-dominant search strategies. MOBWO has been faster in reaching optimal solutions than the NSGA-II and MOPSO algorithms. Compared with other algorithms, MOBWO has achieved better performance in fundamental issues such as energy consumption optimization, resource management, and smart grids. Fig. (12) shows the compared algorithms with the MOBWO algorithm.

4.4. Optimization problems

In this section, BWO algorithm articles are reviewed in the field of optimization problems. BWO algorithm has obtained optimal and efficient performance in various engineering problems that require solving complex and multidimensional optimization problems. This algorithm can design engineering structures to optimize weight, cost, and resistance parameters. It is also an effective algorithm in complex industrial processes such as production planning, energy consumption reduction, and cost optimization. Another application of BWO is in network routing optimization, which leads to improved network performance by minimizing delay and energy consumption in data transmission. Table (9) shows a general review of BWO in the optimization field in the 2024 papers.

Tables (10 and 11) shows a general review of BWO in the optimization field on the 2023 and 2022 papers.

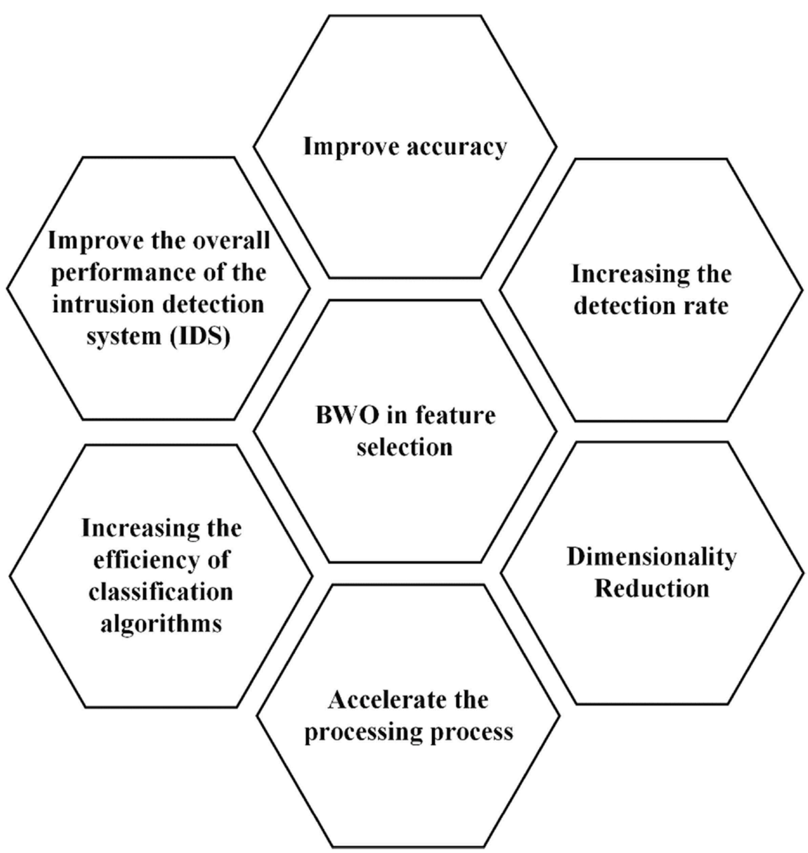

Fig. 11. The advantages of the BWO algorithm for feature selection.

Table 8
A review of the advantages and limitations of MOBWO.

refs	model	application	compared algorithms	Advantages	limitations
[164]	Non-Dominated Sorting BWO (NSBWO) algorithm	Optimizing multi-objective scheduling for a park-integrated energy system (PIES)	NSGA-II; MOPSO	Improved flexibility in scheduling, Faster convergence, and better search capabilities.	Complex optimization problems may require high computational power.
[165]	Multi-Objective BWO (MBWO)	Enhancing the classification of waste materials	SOA, GWO, EO, and WOA	High accuracy and efficiency in waste classification	Performance is reliant on the quality and diversity of the training dataset.
[166]	MBWO	Improving load forecasting accuracy in the electricity market	Multi-Objective Ant Lion Optimizer; Multi-Objective Dragonfly Algorithm; Multi-Objective Whale Optimization Algorithm	Adaptive model selection and multi-objective optimization enhance forecasting accuracy.	High complexity in model design and implementation.
[167]	Adaptive Mixed Inverse Learning Strategy Multi-Objective BWO (AMOBWO)	Optimizing household electricity consumption and reducing carbon emissions	NSGA-II; MOPSO; IMOWOA	The balance between exploration and exploitation; quicker and more accurate convergence.	It increased computational complexity due to multi-objective optimization and dynamic scheduling.
[168]	Multi-Objective Real-Time Scheduling Model using Non-Dominated Sorting BWO (NSBWO)	Optimizing real-time scheduling for grid-connected hydropower stations	NSGA-II and BWO	Enhancing navigability and grid load management simultaneously.	The high computational complexity for real-time scheduling across multiple objectives.
[169]	non-dominant sorting BWO algorithm (NSBWOA)	Enhancing the economic efficiency of shared energy storage systems	adaptive greedy search algorithm (AGSA)	The balance between exploration and exploitation	Increasing time complexity
[170]	improved multi-objective BWO (MOFO)	Enhancing PV utilization and supporting green	–	Provide robust planning through simulation on the IEEE33 node system.	Complexity in implementing bi-level planning and coordination between layers.

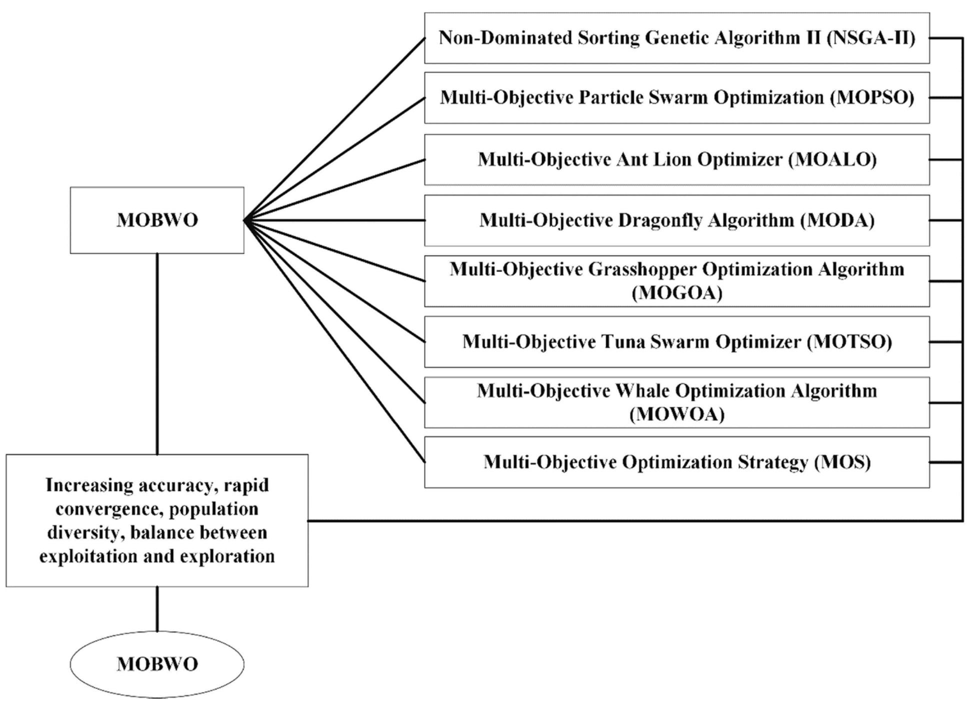

Fig. 12. The compared algorithms with the MOBWO algorithm.

5. Literature reviews

In this section, problems solved by metaheuristic algorithms are reviewed. Metaheuristic algorithms have been used in various fields, such as security, feature selection, image processing, and task scheduling in cloud computing and fog computing environments due to their high adaptability and ability to handle complex and multi-objective problems. In the field of information security, metaheuristic algorithms are used to identify complex patterns and optimize intrusion detection models, data encryption, and access management. In image processing, metaheuristic algorithms optimize tasks such as image segmentation, image quality enhancement, and pattern recognition.

Security: In cloud environments and big data systems, there is a huge volume of data and transactions, which makes monitoring and detecting cyber-attacks challenging [214]. Metaheuristic algorithms such as BWO and SOA algorithms are used to identify unusual patterns and cyber-attacks. These algorithms detect malicious patterns by intelligently searching the data space and help improve anomaly detection systems. Metaheuristic algorithms can increase the security of systems by optimizing resource allocation. For example, these algorithms can determine how security resources should be distributed between different users and services to achieve the highest level of security at the

Table 9
The general review of BWO in the field of optimization on the 2024 papers.

Refs	Application	Advantages	Weaknesses	Publisher
[171]	continuous optimization and engineering applications	Population diversity; Good balance between exploration and exploitation; Strong convergence ability	Struggle with highly complex optimization problems	ScienceDirect
[172]	uncrewed aerial vehicle (UAV)	Combination mutation, quadratic interpolation, and OBL strategies; Extensive validation on CEC2017 test suite	Algorithm complexity could increase computational cost	ScienceDirect
[173]	Internet of Things (IoT)	Cost-effective and sustainable solution for residential energy needs	Complexity in integrating IoT with existing energy systems: The initial cost of IoT implementation might be high	ScienceDirect
[174]	Energy-saving optimization	Fast convergence of the optimization process; Strong global search capability; Ability to avoid local optimization traps	High computational cost	ScienceDirect
[175]	Safety and reliability of metro train door systems		High computational complexity	springer
[176]	Energy management	reduce resource consumption in the microgrid system	Limited application to specific energy management systems and microgrid setups	ScienceDirect
[177]	communication networks	Fast convergence of the optimization process; Strong global search capability	High computational complexity	springer
[178]	Prediction of Average Daily Electricity Consumption	Reduce forecasting errors	Complexity in implementation; High computational overhead due to multiple hybridization strategies	springer
[179]	Energy-saving optimization	Increasing convergence speed and solutions quality.	The modeling and optimization process is complex	ScienceDirect
[180]	Breast Cancer Classification	Early detection of breast malignancy	Complexity in implementation: Requires substantial computational resources for training and tuning.	springer
[181]	Load frequency control (LFC)	Regulate frequency in electrical power systems.	Complexity in implementing; High computational cost for optimization processes.	IEEE
[182]	A novel prediction model for work roll wear	Fast convergence of the optimization process; Strong global search capability	Complexity in model architecture may lead to challenges in implementation and training.	springer
[183]	economic operation-based load dispatch (ELD) problem	Compared to existing algorithms, it achieves higher performance and efficiency in solving non-convex optimization problems.	High computational complexity	springer
[184]	Engineering problems	Increasing convergence speed and solutions quality.	Limited exploration of the algorithm's performance in dynamic environments or real-time applications.	springer
[185]	Engineering problems	Population diversity; Improved convergence	Complex Implementation	springer
[186]	optimal power flow solution	Population diversity: good balance between exploration and exploitation	Long processing times	ScienceDirect
[187]	solving engineering design optimization	High Population Diversity; Improved Convergence Speed; Effective Local and Global Search Balance	Complex Implementation: Overfitting	ScienceDirect
[188]	renewable energy sources	Convergence speed	Higher Implementation Costs	ScienceDirect
[189]	Data processing	Enhance Global Search Ability; Balance Exploration and Exploitation	Computational Overhead	springer
[190]	Engineering problems	Convergence speed	High Computational Cost	ScienceDirect
[191]	photovoltaic (PV)	Increasing convergence speed and solutions quality.	Dependence on Quality Data	ScienceDirect
[192]	Engineering problems	Effective for High-	Complexity of Implementation;	springer

(continued on next page)

Table 9 (*continued*)

Refs	Application	Advantages	Weaknesses	Publisher
		Dimensional Problems	Parameter Sensitivity:	

lowest cost. Data encryption is essential in big data and cloud computing to protect sensitive information. Metaheuristic algorithms are used to optimize encryption methods and generate security keys. For example, these algorithms can generate stronger encryption keys or improve encryption methods. Metaheuristic algorithms can increase the security of cloud networks by optimizing data transmission paths and identifying network weaknesses. For example, these algorithms can find more secure data transmission paths or predict possible network attacks.

Feature selection: as powerful optimization methods, Metaheuristic algorithms efficiently search the large and complex space of possible feature subsets to find the best combination of features. Using intelligent mechanisms (such as directed random search, ensemble learning, and inspiration from nature), these algorithms avoid falling into local optima and reach solutions close to the global optimum [215]. In feature selection, the main goal is to reduce the dimensionality of the data while maintaining or improving the model's accuracy. By evaluating different subsets of features based on criteria such as classification accuracy, prediction error, or other relevant criteria, metaheuristic algorithms help identify relevant features and eliminate redundant or irrelevant features. These methods are especially effective when dealing with high-dimensional data and complex problems, as they can also consider nonlinear and complex interactions between features. As a result, using meta-heuristic algorithms in feature selection leads to improved model performance, reduced training time, and increased interpretability of results.

Image Processing: Image partitioning is one of the most important steps in image processing and analysis, which aims to divide an image into similar regions or areas based on specific characteristics such as colour, texture, pixel intensity, or other features [216]. This process is very important in various applications such as face recognition, medical imaging, robotics, and intelligent systems. In image partitioning using metaheuristic algorithms, the objective function is important. For example, metaheuristic algorithms can find the best thresholds to divide pixels into different classes in the thresholding method. Using metaheuristic methods is an effective way to find the best thresholds. These methods can provide more accurate results even in images with noise or large light intensity variations.

Data Replication: As a new computing model, Cloud computing provides access to computing resources and data storage virtually and on-demand [217]. With the increase in data volume and complexity of applications in cloud environments, managing and optimizing the data replication process is of particular importance. Metaheuristic algorithms, as intelligent optimization methods, effectively improve the performance and efficiency of data replication systems in cloud environments. Data replication refers to creating and maintaining multiple copies of data in different locations. In cloud computing, data replication is performed to increase availability, improve performance, and increase resilience to errors and outages. However, data replication can increase storage costs and the complexity of data management. Data replication management has significant costs due to storing and transferring data. Metaheuristic algorithms can determine the most optimal number and location for duplicate data to reduce storage and network costs.

IoT Applications: Image segmentation divides an image into meaningful regions or objects. This is done using various techniques, such as multi-level thresholding [216]. Traditional methods, such as MLT, have difficulty determining the optimal number of thresholds and their values. These methods often use fixed values for thresholds, which makes them inapplicable to different images. MLT only considers the brightness of pixels and does not consider information about the texture and neighbourhood of pixels. This can lead to incorrect segmentation and jagged boundaries in the image. As the number of thresholds increases, the computational complexity of MLT increases significantly. This can make image processing slow and inefficient. Metaheuristic algorithms are used to automatically and optimally select thresholds. Using metaheuristic algorithms, the image is divided into smaller,

Table 10
The general review of BWO in the field of optimization on the 2023 and 2022 papers.

Refs	Application	Advantages	Weaknesses	Publisher
[193]	energy consumption in intelligent building	Good balance between exploration and exploitation	Complexity of Implementation	ScienceDirect
[194]	manage energy consumption	Population diversity; Improved convergence	Failure to address all potential challenges in energy management for diverse residential environments	springer
[195]	renewable energy system	Convergence speed	Comparative Focus on Cost	ScienceDirect
[196]	Disease diagnosis	The algorithm effectively minimizes patient waiting times.	Sensitive to parameter initialization	IEEE
[197]	Wind-Integrated Distribution Network	The approach demonstrates improved convergence characteristics in optimization.	The algorithm may require significant computational resources	MDPI
[198]	Energy management	I am handling the non-linear relationships between economy, energy, and environment (3E) systems.	Complexity of Model Structure	ScienceDirect
[199]	Dynamic Resource Allocation	Adaptive resource allocation based on user mobility and needs	Increases the complexity of the system and makes implementation challenging.	MDPI
[200]	engineering optimization	No Gradient Requirement; Avoid Local Optima; Applicability to Complex Problems	Less efficient in large-scale optimization problems with vast search spaces.	ScienceDirect
[201]	Cloud computing	Suitable for scalable cloud environments due to its efficient processes.	Complexity of Implementation	springer
[202]	engineering optimization	Balanced Exploration and Exploitation; Applicability in Engineering	Computational solid resources are needed for large-scale problems.	ScienceDirect
[203]	optimal power flow (OPF) issue	Enhanced population diversity; Faster and more effective convergence (tested on 23 benchmark functions); Reduction in overall power cost	Additional costs increase complexity in the goal function	Wiley

Table 11
The general review of BWO in the field of optimization on the 2023 and 2022 papers (continue).

Refs	Application	Advantages	Weaknesses	Publisher
[204]	Energy management	Reduction in cost and energy consumption	Dependence on advanced computational resources for optimization	springer
[205]	engineering optimization	Minimizes the sum of square errors in the solution; Considers nonlinear lateral flow for more realistic modeling	Complexity of Implementation	springer
[206]	Energy management	Extensive statistical validation (Friedman rank, ANOVA, Wilcoxon, Kruskal Wallis tests)	Lack of real-time implementation and testing in practical microgrid systems	ScienceDirect
[207]	engineering design optimization	Enhancing balance between exploration and exploitation; Avoiding local optima more effectively; Successfully handling six well-known engineering design problems; Achieving global optimal solutions more efficiently;	Implementation and setup may be complex	springer
[208]	Vehicular ad hoc network (VANET)	Achieves stable cluster construction in VANET; Prevents premature convergence; improves network stability; Optimizes clusters based on energy; communication range.	Configuration and parameter tuning can be complex	Wiley
[209]	Energy management	Simulation results in MATLAB/ SIMULINK verify the effectiveness of the proposed strategy	Real-time implementation in large-scale power grids may be complex	IEEE
[210]	Energy management	Optimize initial parameters and forgetting factor using BWO; Demonstrates strong tracking capability and robustness under complex working conditions	Increase complexity with combined optimization algorithms; Accurate tuning of parameters for optimal performance in practical applications	springer
[211]	Uncrewed aerial vehicle (UAV)	Fast coverage search strategy for UAV swarm path planning; Reduces computational time and faster convergence	Extensive parameter tuning for different mission	IEEE
[212]	Distribution Networks	Population diversity; Improved convergence	complexity in algorithm implementation	springer
[213]	Economic Dispatch Model (EDM)	Effective reduction of fuel costs; Significant reduction of pollutant emissions	Sensitivity to algorithm parameter tuning	MDPI

discrete regions. This allows the algorithm to more effectively analyze the local features of the image and determine appropriate thresholds for each area.

Task Scheduling: In the dynamic world of cloud computing and fog computing, optimal allocation of resources to tasks plays a vital role in improving the performance and efficiency of cloud systems [218]. In cloud computing, where resources are provided to users virtually and on-demand, task scheduling can lead to reduced execution time, reduced costs, and improved quality of service. In fog computing, where data processing is performed at the network's edge and closer to the data generation sources, task scheduling can help reduce latency and improve system responsiveness. Metaheuristic algorithms such as AHA, genetic, PSO, and sine-cosine algorithms provide innovative solutions to improve the task scheduling process in cloud and fog environments. These algorithms can optimally allocate resources, determine the order of task execution, and balance the load in the system by analyzing the characteristics of tasks and resources. In general, using metaheuristic algorithms in task scheduling is an effective step towards the optimal utilization of computational resources and improving the performance of cloud and fog systems. Each solution is evaluated based on a fitness function. This function calculates criteria such as total completion time, energy consumption, processing cost, or load balancing. Solutions that perform better receive a higher score.

6. Discussion

Two essential elements in optimization and solving complex problems include a powerful discovery process and a robust global search capability, which are used in many fields, including engineering, computer science, and operations research. These features are essential in solving continuous and discrete problems [219]. A robust heuristic process can help find local and global optimism for constant issues. For example, in complex mathematical function optimization, techniques such as a genetic algorithm with integration and random mutations can explore different regions of the search space and find the best solutions. However, the robust exploration process has a heightened significance in discrete problems, such as the travelling salesperson problem or task scheduling. It can explore different possible paths and combinations to find the best solutions, making it a crucial component in solving these problems.

PSO stands out for its exceptional exploration capabilities. Leveraging the collective movement of the swarm enables whales to navigate diverse areas within the search space, thereby significantly increasing the chances of discovering optimal solutions. [83]. Moreover, the exploitation component of PSO, where particles are drawn towards the identified optimal sites, aids BWO in converging on advantageous regions. This feature involves the universal exchange of information among particles based on their optimal placements. By leveraging this information exchange, whales can communicate their ideal locations, influencing the movements of their peers and ultimately enhancing convergence.

LSTM network is one of the famous architectures in sequential data processing because it can handle long-term dependencies. The unique structure of LSTM includes special memory units that hold vital information and transfer it to subsequent processing steps. This capability allows the LSTM network to recognize patterns and relationships in input sequences successfully. LSTM networks are trained through the gradient descent algorithm, enabling the network to effectively identify patterns and connections in the input data. Wide applications of LSTM networks in fields such as natural language processing, speech recognition, and time series prediction indicate their high ability to handle variable-length sequences and learn long-term temporal dependencies. However, the optimal performance of these networks largely depends on the setting of various hyperparameters, such as the number of neurons, learning rate, and threshold. These hyperparameters play a vital role in network prediction accuracy, and their proper setting can significantly improve the results. Therefore, it seems necessary to use collective intelligence algorithms such as BWO to optimize these hyperparameters. By searching the parameter space and finding optimal combinations, these methods can improve the prediction accuracy of LSTM networks and exploit their full potential.

The BWO algorithm has been tested on 30 different functions in MATLAB 2018b.[2] Unimodal, multimodal, and composition functions based on different dimensions have been used. Unimodal functions demonstrate the algorithm's exploitation performance, while multimodal functions challenge the algorithm's exploration ability. Also, composition functions test the algorithm's ability to avoid local optimums. This comprehensive set of functions allows for a thorough and comprehensive examination of the BWO algorithm's performance. The BWO has been compared with different metaheuristic algorithms. These algorithms include PSO [12], Differential evolution (DE) [220], arithmetic optimization algorithm (AOA) [37], Big Bang–Big Crunch (BB–BC) [221], Biogeography-based optimization (BBO) [222], Cuckoo search algorithm (CSA) [223], gravitational search algorithm (GSA) [16], gray wolf optimization algorithm (GWO) [19], Harris hawk optimization algorithm (HHO) [63], Moth-flame optimization (MFO) [20], ray optimization (RO) [224], Salp swarm algorithm (SSA) [225], Seagull optimization algorithm (SOA) [226], Teaching-learning-based optimization (TLBO) [227], and whale optimization algorithm (WOA) [21]. These algorithms have been widely used in solving optimization problems. This comprehensive comparison allows for a detailed evaluation and comparison of the performance of the BWO algorithm with other well-known methods. The results show that the BWO algorithm has better performance.

The BWO algorithm consists of three main phases: exploration, exploitation, and whale fall. These phases allow the algorithm to balance global search (exploration) and local search (exploitation) well. The whale fall phase also helps the algorithm avoid getting trapped in local optima. In PSO, the balance between exploration and exploitation depends heavily on tuning parameters such as inertia weights and cognitive and social coefficients. If these parameters are not tuned properly, the algorithm may converge quickly to local optima. In the exploitation phase, BWO uses the Levy flight mechanism, which makes it move randomly and with large jumps in the search space. This feature increases the ability of the algorithm to escape from local optima and improve global convergence. The PSO algorithm does not use such a mechanism, and the movement of particles is more directed towards the best local and global positions, which may cause them to get trapped in local optima. The whale fall phase allows the BWO algorithm to move some particles in the search space randomly. This mechanism helps the algorithm escape from local optima and explore more search space. The PSO algorithm lacks such a mechanism; the particles move only based on the best local and global positions.

[2] https://ww2.mathworks.cn/matlabcentral/fileexchange/112830-beluga-whale-optimization-bwo

The combination of several strategies helps the BWO to perform better in the exploration stage and the exploitation stage. The speed of convergence and performance of BWO optimization in dealing with complex and multidimensional problems have shortcomings. As a result, the use of improved strategies such as pseudo-adversarial-based learning (QOBL) [149] Adaptive and spiral strategies are suitable for increasing the BWO's accuracy and exploration and exploitation phases. The adaptive method leads to individual optimal locations and resolves the local optimality entrapment. Helix movement using cosine maintains a balance between exploration and exploitation.

The use of the BWO algorithm in artificial neural networks (ANNs) has several reasons that help to improve the performance of ANNs [121]. ANNs are highly dependent on initial settings of parameters such as weights, biases, and learning rates. Properly selecting these parameters plays a crucial role in ANN's convergence and final accuracy. In standard methods such as gradient-based algorithms (error backpropagation), the adjustment of weights and biases are strongly dependent on the initial value, and it is possible to get trapped in local optima. The BWO reduces the convergence time of the ANN network by intelligently setting the parameters and choosing the best values in each step, guiding the network in finding the optimal parameters. Therefore, ANN achieves accurate predictions more quickly without the need for many changes in its structure. Finding the optimal value for the ANN parameters reduces the errors caused by the number of weights and biases and allows the network to perform at its best.

Fig. (13) shows the percentage of BWO methods based on four different areas. The improved area is higher than the other areas. The enhanced methods include high convergence speed, accuracy in searching for optimal solutions, and avoiding getting stuck in local optima. Improved methods using advanced strategies can prevent large fluctuations and maintain higher stability in the optimization path.

Fig. (14) shows the number of improved BWOs based on different methods. Compared to other models, the number of papers on adaptive strategy, deep learning, and OBL is higher. Adaptive strategies increase flexibility and efficiency by dynamically adjusting the parameters of the BWO algorithm during the optimization process. Deep learning also improves the ability of BWO to solve complex and multidimensional problems by using the capabilities of neural networks. On the other hand, OBL helps to improve the search process and increase the convergence speed by considering opposition solutions. These three methods are known as the most effective and widely used approaches to overcome the limitations of the BWO algorithm and, for this reason, have attracted more attention in scientific research.

Combining the BWO algorithm with the chaos technique has the following advantages and disadvantages: This combination improves the search process, enabling the BWO algorithm to explore the search space more effectively by creating variety in the search steps and avoiding getting stuck in local optima. In addition, the use of chaos functions leads to an increase in the convergence speed of the algorithm because these functions accelerate the search process by creating nonlinear and random changes in the algorithm parameters. Also, the chaos technique generates a more diverse initial population, allowing the algorithm to explore more areas of the search space in the early stages of the search and increasing the chance of finding optimal solutions. On the other hand, combining BWO with chaos also has disadvantages. The use of chaos functions requires precise parameter tuning, and if these parameters are not tuned correctly, the algorithm's performance may not improve or even worsen. Furthermore, the performance of combining BWO with chaos techniques is strongly dependent on the type of chaos function used, and choosing an inappropriate chaos function leads to undesirable results.

Combining the BWO with fuzzy techniques has significant advantages. One of the most important advantages is the increased flexibility of the algorithm in the face of uncertainty and imprecise data. Fuzzy logic techniques allow the BWO to work more effectively with ambiguous and uncertain data. In addition, fuzzy techniques help improve the

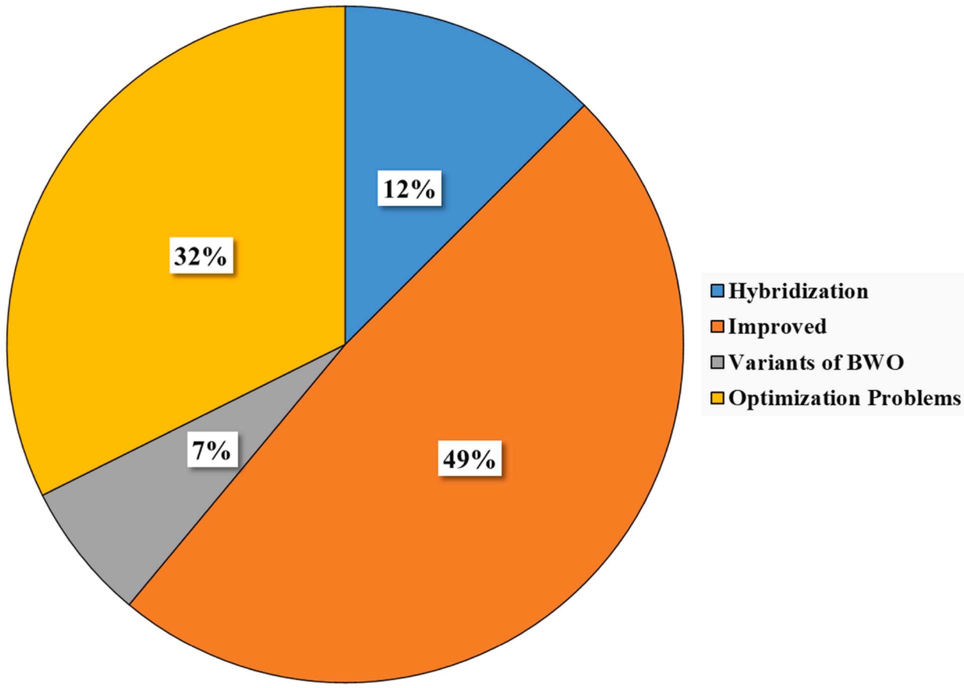

Fig. 13. Percentage of BWO methods based on four different areas.

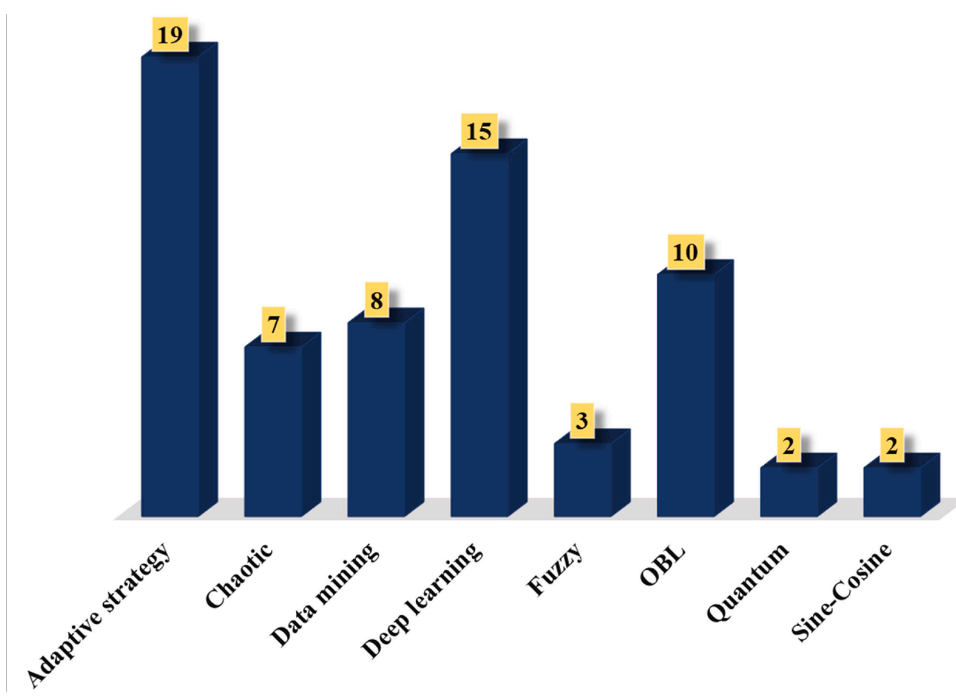

Fig. 14. The numbers of improved BWO based on different methods.

search and decision-making process of the algorithm. The algorithm can use fuzzy membership functions to make more optimal decisions at different search stages and avoid getting stuck in local optima. Also, combining BWO with fuzzy techniques helps improve the convergence speed of the algorithm because fuzzy logic accelerates the search process by dynamically adjusting the parameters. In contrast, combining BWO with fuzzy techniques is highly dependent on the type of implementation and parameter settings. If these parameters are not adjusted correctly, desirable results may not be achieved.

Table (12) shows the general advantages and disadvantages of the BWO algorithm.

7. Conclusion and future works

The BWO algorithm effectively solves optimization problems due to its strong search ability and intelligent exploration in large and complex spaces. A review of 151 papers related to BWO showed that most of the research was done in the field of improved models. These improved models, powered by advanced mechanisms, can increase the accuracy and speed of convergence in solving optimization problems and reduce

Table 12
Advantages and disadvantages of the BWO algorithm.

	Factors
Advantages	BWO algorithm can balance searching for new areas and exploitation. Applicable to various real-world engineering optimization tasks Scalability in solving big and sensitive problems The initial population is improved using chaos and OBL techniques. In many engineering problems, the BWO algorithm can quickly approach the optimal points, reducing computation time. Solving multi-objective problems with multiple functions The number of replications and the initial population are balanced. There is no risk of getting stuck in local optima using stochastic mechanisms and moving towards global optima. High performance in classification and clustering. The weighting factors lead to the improvement of the BWO algorithm. The BWO algorithm has a simple structure and easy implementation.
Disadvantages	In large-scale problems, the execution cost may increase. Limited exploration of the BWO in dynamic environments or real-time applications. For optimal performance, there is a need to fine-tune the parameters of the BWO algorithm.

the risk of getting stuck in local optima. With their extensive search capabilities, these models can quickly achieve optimal or near-optimal solutions, impressing the audience efficiently. The research results of this article showed that deep learning techniques such as LSTM, CNN, and GRU networks by BWO have achieved high efficiency in adjusting parameters and increasing the accuracy of prediction models. BWO algorithm has achieved the optimal value of parameters such as learning rate, number of nodes, and depth of layers by intelligently searching the parameter space. Using the BWO algorithm in combination with these networks leads to faster convergence and more accurate results in complex problems such as pattern recognition, natural language processing, and time series analysis.

Improved BWO models use advanced mechanisms such as adaptive search, exploration-exploitation balance, and dynamic parameter updating. Adaptive search allows the algorithm to dynamically adjust its behavior according to the problem conditions and feedback from the objective function evaluation. This mechanism makes the algorithm focus more on exploring the search space in the early stages of the search and gradually move towards exploiting promising regions in the later stages. The balance between exploration and exploitation is also one of the key factors in the performance of BWO, as it prevents the algorithm from getting stuck in local optima and increases the probability of finding global optima. In addition, dynamic parameter updating, such as the learning rate and search step size, allows the algorithm to adapt to changing problem conditions during optimization and maintain efficiency.

In complex problems such as neural network parameter optimization, BWO intelligently searches the parameter space to find optimal values such as learning rate, number of neurons per layer, and layer depth. These parameters play a key role in the performance of deep learning models, and their fine-tuning can significantly improve the accuracy and efficiency of the model. For example, in LSTM and CNN, optimal tuning of these parameters allows complex patterns to be identified more accurately and avoids problems such as overfitting or underfitting. The BWO algorithm increases the accuracy of predictive models and significantly reduces the convergence time. In neural networks, faster convergence means reduced training time and computational resource consumption, which is especially important for large-scale problems and large data. In general, using the BWO algorithm in combination with neural networks leads to improved model performance, especially in applications such as pattern recognition, natural language processing, and time series analysis.

High computational complexity is one of the main limitations of using hybrid algorithms for large-scale problems. Metaheuristic algorithms, including BWO, require repeated evaluation of the objective function, which is time-consuming and expensive for large-scale problems. This poses significant challenges, especially in environments with limited hardware resources or time constraints. For example, in optimization problems with hundreds or thousands of variables, evaluating the objective function may require complex and time-consuming calculations. Therefore, the main focus in combining metaheuristic algorithms should be reducing computational complexity. This can be done through parallelizing calculations, approximation methods to reduce the number of evaluations, or optimizing the code. Also, using technologies such as GPU or cloud computing can significantly increase the execution speed of the BWO algorithm. Also, using high-level programming languages such as Python or MATLAB with optimized libraries for matrix and vector operations significantly reduces execution time.

Future works in line with this paper include the following goals: 1) To increase the accuracy and speed of the BWO algorithm to find the global optimum, hybrid mechanisms help solve continuous optimization problems. 2) Applying the BWO algorithm to solve multi-objective optimization problems such as energy price prediction and optimal routing in IoT networks is an attractive research area for future work. For example, energy price forecasting involves reducing costs, increasing forecast accuracy, and optimizing energy consumption. In such cases, BWO simultaneously considers multiple objectives and finds optimal solutions using mechanisms such as multiple populations or Pareto Solutions. The BWO algorithm optimizes data transmission paths by considering criteria such as reducing latency, increasing network stability, and optimizing energy consumption. These applications are particularly critical in dynamic and resource-constrained environments, such as wireless sensor networks or distributed systems, and require algorithms with strong discovery and exploitation capabilities.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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