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A comprehensive survey of whale optimization algorithm: modifications and classification

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ABSTRACT

Whale optimization algorithm (WOA) is an emerging nature-inspired, swarm-intelligence based algorithm to solve optimization problems more efficiently. This algorithm is based on the bubble-net hunting strategy of the humpback whales. It has gained immense popularity among researchers, typically, due to its simple nature, fast convergence, and having minimum parameters. In the recent past, it has been widely adopted in various fields including data mining, machine learning, wireless sensor networks, cloud computing, civil engineering, and power systems due to its optimal performance. The WOA has given competitive results in comparison to the state-of-the-art optimization algorithms. In this study, we aim to present a comprehensive survey of WOA consisting of more than eighty existing variants of WOA. More specifically, we intend to put forward key aspects of WOA variants with reference to modifications and applications. Further, we classify the most dominant variants of WOA in distinct categories based on modification area such as equation modification, parameter tuning or the problem space for which an algorithm has been specifically altered. We believe that this study will be beneficial for the community working on optimization problems and it can serve as a basis for understanding the modification and improvement process of an optimization algorithm.

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1. INTRODUCTION

Nature-inspired optimization algorithms (NIOAs) have received a lot of attention from the researchers since the first proposal of genetic algorithm [1]. These algorithms are inspired from optimization processes that occur in nature and have been applied to solve various real world problems, for example, clustering in wireless sensor networks [2] , feature selection in machine learning [3], optimal power flow [4], resource allocation in cloud computing [5], data clustering in data mining [6], multilevel image segmentation [7]. Figure 1 provides a classification of the NIOAs based on the taxonomy provided in [8]–[10].

Different researchers have proposed various categories of nature-inspired optimization algorithm, for example, physics based, chemistry based, and biology based. Biology based NIOAs can be divided into two categories; evolutionary algorithms (EAs) and swarm-intelligence (SI) based algorithms. EAs are based on the Darwin's theory of natural evolution, and SI based algorithms are inspired by the natural grouping behaviour of animals or insects. Several such algorithms have received much attention from the researchers and are considered state-of-the-art including genetic algorithm [1], differential evolution [11], [12], simulated annealing [13], particle swarm optimization [14], ant and bee colony [15], [16], firefly algorithm [17], cuckoo search [18], and bat algorithm [19].

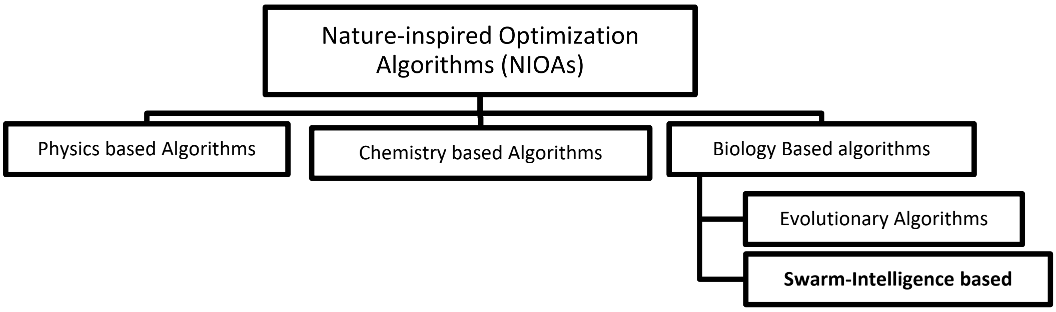

Figure 1. Classification of nature-inspired optimization algorithms [8]–[10]

These algorithms have shown dramatic results on the benchmark functions and have been widely evaluated on the real-world problems in engineering and computer science field where optimization is a requirement. This leads to more research in this area and a number of new techniques have been proposed by researchers which have received much attention including self-regulating particle swarm optimization [20], arithmetic optimization algorithm [21], whale optimization algorithm [22], chimp optimization algorithm [23], Quantum-based avian navigation optimizer algorithm [24], and starling murmuration optimizer [25]. This research is centered around whale optimization algorithm (WOA) and its variants because a recent study [26] evaluated the performance of seventeen well-known recent nature-inspired optimization algorithms where WOA showed remarkable performance on the majority of the benchmark functions.

Whale optimization algorithm [22] is an emerging swarm-intelligence (SI) based optimization algorithm that mimics the bubble-net feeding mechanism of hump-back whales. This research aims at providing a comprehensive survey of the available variants of WOA; more than eighty variants of WOA are available in the literature. Figure 2 shows a graph on the number of variants of WOA proposed each year. This is worth nothing that this count includes variations of WOA only, not all the papers related to WOA.

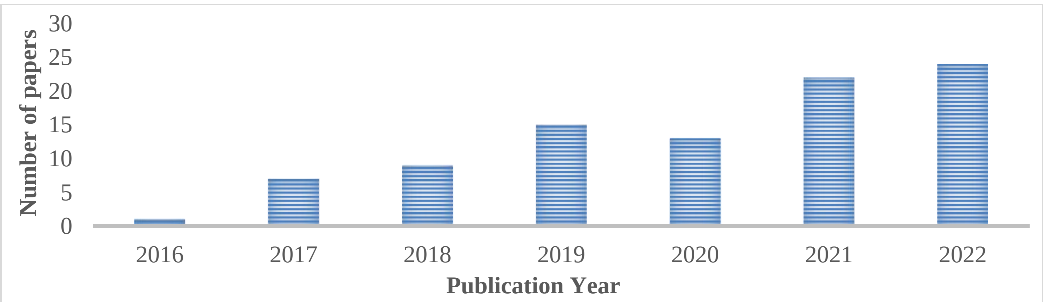

Figure 2. WOA variants proposed from 2016 to 2022

A small number of review articles are available in literature for the applications and modifications of WOA [27]–[29]. However, they [27]–[29] have covered literature up to 2020 and have focused on very few variants of WOA. In this study, we have tried to add all the variants that are available in the quality journals for WOA and have classified them according to the modification area. This study will provide a basis on how a variant of a NIOA can be designed and will also help early researchers to understand the modification process of a NIOA. Major contributions of this research can be summarized as:

- Holistic survey of WOA comprising around eighty variants is presented.
- A classification of WOA variants has been proposed and research in each category is separately discussed.
- Details of different approaches used in the modification process of WOA is presented.

The rest of the paper is organized as follows. Section 2 gives a brief overview of whale optimization algorithm along with mathematical model and limitations, section 3 gives a classification of WOA variants and modifications in various WOA variants are discussed category-wise. Section 4 discusses the outcomes of this study along with the conclusion and future work.

2. WHALE OPTIMIZATION ALGORITHM (WOA)

WOA is a recent SI based NIOA that is based on the bubble net feeding mechanism of humpback whales. Like all other NIOAs, it is divided into two phases: Exploration and exploitation, where exploration search globally for better solutions in a wider area and exploitation dives in-depth of a particular good solution. Whenever the prey is found, whales start sending bubbles towards the surface of the sea, called bubble net attacking method, and start moving in a shrinking spiral curve around the prey and slowly gets closer to the prey. In the algorithm it is referred to as shrinking encircling mechanism and spiral update position. The idea is to move around the prey in a nine shaped spiral and slowly getting close to it. The main advantage of the algorithm is the simplicity as it has only two internal adjustable parameters. In upcoming sub-sections, mathematical model and limitations of the algorithm are briefly discussed.

2.1. Mathematical model

Whales search for the prey in the whole sea however algorithm starts with the assumption that the current best solution is either the prey or nearby whale to the prey. All the whales update their position according to the best one as given:

$$\overrightarrow{D} = |\vec{C}.\overrightarrow{X^*}(t) - \vec{X}(t)| \tag{1}$$

$$\overrightarrow{X}(\mathrm{t}+1) = \overrightarrow{X^*}(t) - \overrightarrow{A}.\overrightarrow{D} \tag{2}$$

here X* is the best whale, X is the current whale and D is the distance. Vector A and C are represented by:

$$\overrightarrow{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{3}$$

$$\overrightarrow{C} = 2.\vec{r} \tag{4}$$

where a linearly decreases from 2 to 0 and r is a random vector whose values lie in the range [0, 1]. During exploitation, whales either follow shrinking mechanism or position updating in a spiral shape, which is called helix-shaped movement represented in (5).

$$\overrightarrow{X}(\mathrm{t}+1) = \overrightarrow{D'}.\mathrm{e}^{\mathrm{bl}}.\cos(2\pi l) + \overrightarrow{X^*}(t),$$
$$\overrightarrow{D'} = |\overrightarrow{X^*}(t) - \vec{X}(t)| \tag{5}$$

Where D’ is the distance between prey and whale, b is a constant for spiral and l is a random number in the range [-1, 1]. To promote search in a wider area (6) is used in the exploration phase.

$$\overrightarrow{X}(\mathrm{t}+1) = \overrightarrow{X_{rand}} - \overrightarrow{A}.\overrightarrow{D},$$
$$\overrightarrow{D} = |\vec{C}.\overrightarrow{X_{rand}} - \vec{X}| \tag{6}$$

There is a 50% chance to choose either shrinking mechanism or spiral equation for which a probability p is used to switch between both given in (7).

$$\overrightarrow{X}(\mathrm{t}+1) = \begin{cases} \overrightarrow{X^*}(t) - \overrightarrow{A}.\overrightarrow{D}, \text{if p} < 0.5 \\ \overrightarrow{D'}.\mathrm{e}^{\mathrm{bl}}.\cos(2\pi l) + \overrightarrow{X^*}(t), \text{if p} \geq 0.5 \end{cases} \tag{7}$$

Figure 3 shows the flow chart of the original WOA. For a detailed discussion of the mathematical model and algorithm, original WOA [22] can be consulted.

2.2. Scope and limitations of WOA

As already reported in WOA [22] that it is designed to work with single objective, continuous problems. Also, the formulation of WOA is kept simple to have only two internal adjustable parameters. Therefore, there is a room for creating a new variant of WOA with discrete or binary problem space or to solve multimodal problems. Other limitations have also been studied by various researchers where slow convergence speed and local optima stagnation have also been identified as the weakness of this algorithm [30].

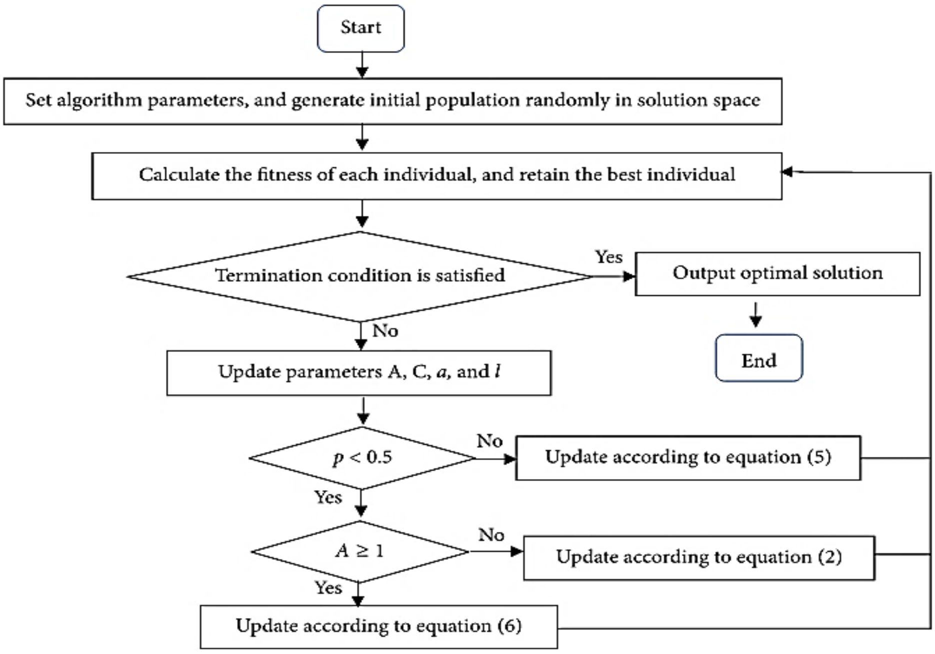

Figure 3. Flow chart of whale optimization algorithm

3. VARIANTS OF WOA

WOA mathematical representation includes equations for calculating distance of the whales with the prey and optimal position of the whale with some internal parameters, also it is designed to solve continuous optimization problems. Keeping this in consideration, various WOA variants have modified distance or position equations, tuned the internal parameters, introduced new mechanisms to generate initial parameters or changed problem space from continuous to discrete values or hybridizing WOA with other techniques to generate a better version of the basic algorithm. Various multi-objective variants have also been introduced to overcome the limitation of solving single objective problems.

After a careful study of the literature, a classification of WOA variants have been proposed in this study described below. Figure 4 depicts the number of variants of WOA studied for this research.

- Improved Learning strategy: Involves improvements in distance or position equations or improved steps of the original algorithm.
- Parameter Tuning: involves tuning existing internal parameters, adding new parameters or changing the way initial population is generated.
- Discrete Variants: Adding new equations to convert search space into discrete or binary values.
- Multi-objective Variants: Solving multiple objective problems.
- Hybrid Variants: Hybridizing with other techniques

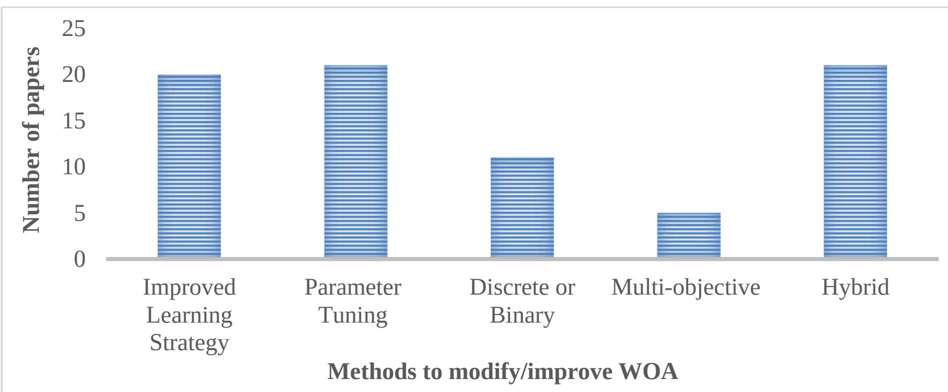

Figure 4. Number of papers studied under each category for WOA

3.1. Improved learning strategy

It has already been discussed in the previous section that an improved version of WOA may involve the modification of distance or position equations or some modifications in the steps of the WOA algorithm are achieved. In this section all such variants are discussed. Interestingly only one variant was published in 2016 [31] into which adaptive technique was used for finding optimal solution, considering only one internal parameter whose value was selected at random. Another simple approach was introduced in [32] where distance (D)'s calculation is modified for proper balance between diversification and intensification. In exploration, one component of each whale is changed with a random value with a probability *p*. Ruiye *et al*. [33] attempted to change both exploration and exploitation phases Initial Population is generated with Latin Hypercube sampling method, then fitness value is calculated and sorted, and best individual is selected as the best solution. New parameter *k* and *W* are also used to further update whales' position. Chen *et al*. [34] introduced two strategies: one is random spare and the other method is double adaptive weight, which is introduced to improve the exploration and exploitation.

WOA uses a simple approach as it has only two internal parameters therefore many modifications of WOA had kept this simplicity as an advantage and had made few modifications to the equations. Quantum rotation gate (QRG) operation is introduced and the position updating mechanism is modified, aiming to enhance population diversity and convergence accuracy [30]. Qiao *et al*. [35] try to improve the performance of whale optimization algorithm, adaptive search-surround mechanism is introduced for which probability is modified. Just one equation is added for the whale to jump out of the local optima. Hassouneh *et al*. [36] combined WOA with single point crossover method, five different selection methods are employed Tournament, Roulette wheel, Linear rank, Stochastic universal sampling, and random-based.

WOA works best with unimodal and low-dimensional problems however it converges towards the local optimum when tested with multimodal functions and slow convergence rate with high-dimensional problems. Therefore to overcome these weaknesses levy flight distribution is introduced in WOA in [37]–[42]. Levy flight is a random walk in which the step-lengths have a probability distribution that is heavy-tailed. Ling *et al.* [37] and Zhou *et al.* [38] Levy flight trajectory is used to update whale's position and a new equation is added after whale position is updated by original WOA.

Sun *et al.* [39] used quadratic crossover operator to create new solutions based on the best solution and two more solutions acting as partners. Levy flight is used to enhance exploration capability and cosine function is used to update the value of parameter a making it nonlinear. Levy flight is used to generate new agents corresponding to the current swarm in [40] then Chaotic local search is used to select the best agent or fittest agent. Three modified versions are proposed in [41]; for initialization purposes opposition-based learning technique is added. Secondly, the concept of exponentially decreasing exploratory operator a has been added. Then to improve exploration, the concept of re-initialization of worst particles is followed based on Lévy-distributed step size. Yen *et al.* [42] introduced levy flight strategy and a ranking based mutation operator for global optimization.

Few variations have been achieved by introducing natural laws or concepts in the original WOA algorithm such as in [43] to adjust the mutation space, wavelet mutation strategy is introduced, which enhances the ability of the algorithm to escape from local optimum. Long *et al.* [44] proposed a new refraction-learning strategy based on the principle of refraction of light. Original WOA uses a log spiral curve which has been replaced with equal pitch Archimedes spiral curve in [45] and Perceptual perturbation mechanism is used to improve global search. Another variant introduced in [46] is based on Lamarck's evolutionary theory that individuals with more development potential are selected to perform local enhanced search, in this Population is initialized based on good point set theory.

Chaotic maps are widely used in the optimization algorithms because of their randomness, ergodicity, and regularity. Yin *et al*. [47] used logistic chaotic map to select optimal features for brain tumour diagnosis. Jianhao *et al*. [48] generated initial population with tent chaotic map, then opposition-based learning strategy is used to consider opposite solutions and retaining well-diversified solutions.

3.2. Parameter tuning

This category includes all the available variants of WOA that have been achieved with tuning existing parameters, adding new parameters to the original algorithm, or changing the way how initial population is generated. There are only two internal parameters in WOA, A, and C, depending on a linearly decreasing parameter a and a random value r. A careful study of the variants showed that parameter a has been tuned by many researchers due to its linear nature and has been evaluated with a non-linear convergence nature. Few studies have added new parameters to the existing WOA algorithm, and many has tuned the initial population generation mechanism. In this section all such improved versions of WOA have been discussed. Table 1 summarizes the variants discussed in this section.

Table 1. Summary of parameters and operators in WOA variants

Reference	Parameter/operator Name	Description
[49]	linear convergence factor a	sine, cosine, tangent, log, and square functions used to update value of a in a non-linear fashion.
[50], [51]	adaptive inertia weights Parameter a	adaptive inertia weight is added to update whale position. Parameter a is changed into a nonlinear convergence factor.
[52]	Random walk W	equation is selected in exploitation phase
[53]	New parameter B	if B>=0 then a random search agent is selected and if B<0 then best search agent is selected.
[54]	DE's mutation operator search mode parameter	search mode is added to switch between exploration and exploitation phases.
[55]	Laplace's crossover operator	Two agents are selected, best one and a random then Laplace's crossover operator is applied to produce two new offspring.
[56]	Golden sine operator non-linear adaptive weight	Golden sine operator is incorporated along with non-linear adaptive weights.
[57]	probability (p) in original WOA	ten 1-D non-invertible chaotic maps are utilized to adjust probability p.
[58]	a, c, p, and l in original WOA.	Ten chaotic maps are used to update a, c, p, and l parameters.
[59]	probability (p) and C	C is updated with Levy distribution and logistic chaos map is used to update probability p.

When humpback whales identify prey then they can encircle them in a shrinking circle. It is achieved in the algorithm through internal parameter a which linearly decreases from 2 to 0 to mimic the encircling step. Several studies found out that instead of linear decrement in the value of a, a non-linear value adjustment of this parameter can improve the convergence speed and avoid the local optima stagnation problem. Zhong and Long [49] have proposed five non-linear strategies namely sine, cosine, tangent, log and square, to update the value of control parameter a and cosine method outperformed other four techniques and original WOA. Similarly [39], [50], [51] proposed nonlinear value adjustment of the same control parameter a. adaptive inertia weight is also added in [50] to update whales position.

Few variations of WOA involves adding new parameters or operators in the original WOA, as in [52] a random walk variable W is introduced and based on its value an equation is selected in exploitation phase. A new parameter B is added to switch between exploration and exploitation phases by Lu and Ma [53]. Bozorgi and Yazdani [54] has used DE's mutation operator to improve WOA exploration and exploitation, then a new parameter called search mode is added to switch between exploration and exploitation phases. After following original WOA procedure in [55], two agents are selected, best one and a random one then Laplace's crossover operator is applied to produce two new offspring. their fitness value is calculated against the worst solution of the current population. If offspring has better fitness, then it is replaced with the worst particle of the current population. golden sine operator has been incorporated in [56] with a nonlinear adaptive weight to give a proper balance between exploration and exploitation phases.

Chaos theory has been applied to various optimization algorithms due to its random nature and ergodicity. Kaur and Arora [57] adjusted probability (p) with chaotic number and ten chaotic maps are utilized to produce chaotic sets. Sayed *et al.* [58] have used ten chaotic maps to update a, c, p and l parameters in original WOA. Abdel-Basset [59] updated C parameter with Levy distribution and logistic chaos map is used to update probability p.

Initial population plays a very important role in finding out the optimal solution in any NIOA. The better the diversity of the initial population, the stronger the algorithm's global search ability. In almost all the NIOAs initial population is randomly generated. Many researchers have studied the effects of applying different mechanisms for generating initial population. Opposition based learning (OBL) was introduced by Tizhoosh [60] that for every point x there is an opposite x' that improves the convergence and helps in finding the better solution. Alamri *et al*. [61] has used OBL to find opposite solutions for an improvement of WOA and gave better results as compared to original WOA.

Abd Elaziz and Mirjalili [62] have used three methods to generate initial population, differential evolution (DE), chaotic map and opposition based learning. Logistic chaotic map is used in [47], [63], Bernoulli shift map in [64], and tent chaotic map in [65] is used to generate initial population value to maintain diversity of the population. Good point set method is used to generate initial population in [46], [66]. Randomization operation of the random Gaussian distribution is used to increase the diversity of the population in [67]. Jianhao *et al.* [48] combined chaotic map with opposition-based learning to generate initial population. All these methods to generate initial population are summarized in Table 2.

Table 2. Methods to generate initial population

Author and Reference	Methods to Generate Initial Population
Ruiye *et al.* [33]	Latin hyper cube sampling
Zhang and Liu [46]	Good point set method
Yin *et al.* [47]	Logistic chaotic map
Jianhao *et al.* [48]	Chaotic map/Opposition based learning
Alamri *et al.* [61]	Opposition based learning
Abd Elaziz and Mirjalili [62]	Differential evolution Chaotic map/Opposition based learning
Chen *et al.* [63]	Logistic chaotic map
Chen [64]	Bernoulli shift map
Fan *et al.* [65]	Tent chaotic map
Ning and Cao [66]	Good point set method
Jin *et al.* [67]	Random gaussian distribution

3.3. Discrete or binary variants

Since WOA was designed to solve continuous problems therefore it cannot be directly used to solve discrete or binary problems. Applications involving integer or binary values cannot directly use WOA, leading to the change in values used by the algorithm. Li *et al.* [68] have proposed a discrete version of WOA using a V-shaped function, which transfers a real vector to an integer vector. A similar approach is followed in [69] where knapsack problem is solved with a discrete version of WOA.

Feature selection is the process of finding the optimal subset of features to improve prediction accuracy or decrease the number of selected attributes without significantly decreasing prediction accuracy of the classifier [70]. Considering feature selection as an optimization problem, several swarm-intelligence based optimization algorithms have been employed to solve this problem. Xu *et al*. created binary variants of WOA and have applied that binary WOA to feature selection problems in different application areas [51], [71]–[77]. Table 3 summarizes all binary variants of WOA discussed in this section along with the application areas.

Table 3. WOA binary variants with applications

Author and Reference	Application Area
Xu *et al.* [51]	Feature selection for network intrusion detection
Abdel-Basset *et al.* [69]	single and multidimensional 0–1 knapsack problem
Eid *et al.* [71]	feature selection for ten UCI datasets
Hussein *et al.* [72]	Feature selection for twenty-four UCI datasets
Agrawal *et al.* [73]	Feature selection for fourteen UCI datasets
Hussein *et al.* [74], [76]	Feature selection for eleven UCI datasets
Eid [75]	Feature selection for nine UCI datasets
Nadimi-Shahraki *et al.* [77]	Feature selection for medical datasets and COVID-19
Hussein *et al.* [78]	Travelling salesman problem, engineering problems (Tension/compression string, welded beam, pressure vessel)

3.4. Multi-objective variants

Multi-objective optimization problems involve optimizing two or more objective functions to be minimized or maximized simultaneously, therefore algorithm must deal with a set of optimal solutions, called non-dominated solutions and there must be a proper balance in the optimal values of those solutions. In almost all the multi-objective versions of WOA discussed here, optimal solutions are stored in an external repository or archive, and it gets updated with better solutions as the algorithm progresses. WOA was tailored to solve bi-objective problems in [79], [80] and both two and three objective functions are solved in [81]–[83]. All these variants are discussed in detail in the following paragraph.

An archive repository and archive controller are added in [79] where archive controller is responsible to identify non-dominated solutions and archive repository is used to store best solutions. Ahmed *et al.* [80] considered two objectives, one is reducing energy consumption and other one is increasing lifetime of large scale wireless sensor networks (LSWSN). A fitness function is designed to achieve these objectives. The experimental results showed better performance with 26% reduction in the total power consumption. External archive updating and leader selection strategies are incorporated in [81]; optimal solutions are stored in an external archive in a descending sorting order and a leader of population is selected from good solutions along with crowding distance calculation which is used to increase the diversity of the solutions. Pareto archived evolutionary strategy (PAES), opposition based learning (OBL), and Nelder-Mead simplex methods are used in [82] to create a multi-objective version of WOA and once again distance control parameter a is converted to a nonlinear convergence factor with sine, cosine, and log functions. A pairwise competition mechanism is used in [83] instead of a global best solution and winner guides the population updating with best solution and differential evolution (DE) is integrated to diversify the population hence more feasible solutions are discovered. In this variant, instead of external archive, current population is used.

3.5. Hybrid variants

Hybridizing two or more optimization algorithms and combine salient features of the original algorithms to better improve the convergence speed and to overcome the local optima stagnation problem has attracted a lot of researchers. Hence several research publications have contributed towards hybridization and successfully improve the aforementioned areas. An in-depth discussion of hybrid variants is out of scope of this study therefore these are provided in tabular format in this section. In Table 4, hybrid modifications of WOA have been provided by outlining the name of the hybrid version, the other algorithm(s) with which a hybrid version is developed and publication year with reference.

Table 4. Hybrid versions of WOA

Hybridized with	Name	Year	Reference
Pattern Search	WOA-PS	2016	[84]
Simulated Annealing	WOA-SA	2017	[85]
Local Search Strategy	HWA	2018	[86]
Pearson’s correlation coefficient and distance	MPMDIWOA	2018	[87]
Differential Evolution	DE/WOA	2018	[88]
Pattern Search	hWOA-PS	2018	[89]
Modified Differential Evolution	MDE-WOA	2019	[90]
Differential Evolution	WOA-DE	2019	[91]
Simulated Annealing	HWS	2019	[92]
Ant-Bee Colony, Firefly Algorithm	WOA-AEFS	2019	[93]
Tabu Search	MOWOATS	2019	[94]
Neighbourhood rough set	BWOA-NRS	2020	[95]
Differential Evolution Genetic Algorithm	GWOA, WODEGA	2019, 2020	[96], [97]
Opposition learning, Grey Wolf Optimizer	HWGO, HWOAG	2019, 2021	[98], [99]
Flower pollination Algorithm	HWOAFPA	2021	[100]
seagull algorithm	WSOA	2021	[101]
Artificial Bee Colony	ACWOA	2022	[102]
Moth flame optimization	WMFO	2022	[103]

4. CONCLUSION

This study presents a review of more than eighty modifications of Whale Optimization Algorithm from 2016 till 2021, few modifications from the year 2022 are also included. An existing algorithm can be modified in several ways, this is the first attempt to give a classification on how to improve an existing optimization algorithm and according to these categories, variants of WOA have been discussed. We categorized the variants with respect to the equation modifications, parameter tuning, nature of values, number of objectives and hybridizations. To the best of our knowledge this is the first attempt to combine all the available modifications of Whale Optimization Algorithm in one place. Therefore, this study provides a strong ground for researchers and practitioners addressing complex optimization problems in various domain; specifically, to large community of academicians and practitioners willing to improve nature-inspired optimization algorithms. WOA was initially designed to address the complex engineering problems, however it was quickly adopted by the researchers in other fields due to its simple nature. More recently it is applied in the most popular field of AI, that is, deep learning. We believe that this algorithm will play an important role in the development of applications, where optimization is required such as intelligent transportation system, blockchain based systems and smart security. We intend to further extend this research by including the performance analysis of selected variants to provide a better comparison and analytical results.

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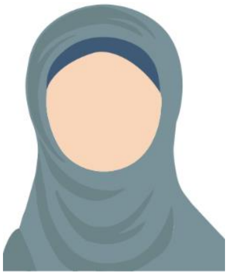

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