



Reactive Power Optimization Using New Enhanced Whale Optimization Algorithm

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ABSTRACT

The standard whale optimization algorithm (WOA) involves exploitation and exploration operations that are required to be balanced for improved performance. This paper suggests a new enhanced WOA to improve the convergence speed and enhance the global optimum by balancing exploitation and exploration processes. New stages have been suggested at the hunting stages of the WOA to increase the exploitation capability. The performance of the modified algorithm has been analyzed on few commonly used test functions and reactive power optimization (RPO) problem. The numerical studies have shown that the proposed WOA variant has outperformed other compared optimization algorithms in terms of global optimum and convergence speed.

KEYWORDS

Artificial Fish Swarm Algorithm, Benchmark Function, Fish Swarm, Metaheuristic Computing, Power System, Reactive Power Optimization, Swarm Intelligence, Whale Optimization Algorithm

INTRODUCTION

Engineering optimization comprises of complex types of algorithms with various application in the domain of power system networks. In the early 1950s, some scientific techniques or deterministic methods are applied like Linear Programming, Hill climbing, search techniques (gradient based), etc. for solving various engineering problems (Song et al., 2020). However, those deterministic techniques take rather long time to obtain a solution and failed to assure the optimum solution as well (Yang et al., 2016). Moreover, there is a higher chance for the optimization techniques to be trapped in a local minimum or maximum rather than achieving the optimal global solution (Kaluri & Pradeep, 2017). In the case of second generation of algorithms, most techniques are problem-specific and their mechanism mostly rely on the early assumption of the solution. Hence, these techniques such as Genetic Algorithm (GA) and Differential Evolution (DE) also require domain specific design of computational study (Bhattacharya, 2020; Kaluri & Pradeep, 2018).

The latest edition called third generation optimization techniques are known as improved heuristic techniques, evolutionary algorithms or meta-heuristic (Reddy et al., 2020). The key strength of meta-heuristic techniques is founded intensely on random initial solutions (Rahman & Mohamad-Saleh,

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2018). Two of such algorithms dedicated for underwater are the Artificial Fish Swarm Algorithm (AFSA) (Li, 2013) and Whale Optimization Algorithm (WOA) (Mirjalili & Lewis, 2016). The discussed optimization techniques are inspired by the performance of supportive like following other fishes to reach the food sources and shielding the swarm against pressures during the hunting of food (Mirjalili & Lewis, 2016). In order to study the interactions among fish swarm for hunting, in the year 2003, Artificial Fish Swarm Algorithm (AFSA) had been articulated mimicking the cooperative social hunting capability among the swarm of fishes (Yan et al., 2020). Meanwhile, AFSA passed through few alternations for the enhancement of overall performances of optimization techniques. Whale Optimization Algorithm (WOA) has been introduced a decade later using a distinct hunting performance of humpback whales in the early 2016. The performances of AFSA and WOA have been compared with few well developed and very prominent bio-inspired techniques like Particle Swarm Optimization (PSO), DE, etc.

However, lately WOA has established less accurate solution, biased reliability and higher computational complexity to obtain optimal solution (Gharehchopogh & Gholizadeh, 2019). To improve the overall performance of WOA, some research studies have been applied. However, the variants are either computationally complex or poor global and local search capabilities (Ray et al., 2020). The foundation of this study is to blend the exploitation capability of WOA with the exploration of AFSA to exploit both techniques' power. Authors further extends the previous study published in (Rahman et al., 2019) by applying the WOA variant into a power system optimization problems with related figures and Tables.

The rest of the paper is organized as follows: the following section, BACKGROUND discuss the general topics related to the work. The NEW ENHANCED WOA section explains about the proposed enhanced WOA, involving the modifications done onto it as well as presenting the performance results of the proposed enhanced WOA. The next section, APPLICATION IN RPO serves to demonstrate the practicality of the proposed enhanced WOA at solving a real-world problem. The CONCLUSION section is the final section with conclusive remarks and future recommendations.

BACKGROUND

Nature is God's creation and hence, its behaviour can certainly become a genuine source of motivation for solving complex real-world problems. In light of this motivation, developments in computing systems have adopted nature's behaviour into algorithms, and one of them being optimization algorithms. As already known, optimization has become progressively vital and widespread in various engineering applications that reliable and robust optimization method deems as a necessity demand (Belkadi & Daamouche, 2020). To this era, applying bio-inspired algorithms for solving optimization problems is becoming popular because bio-inspired computational intelligence technique has been able to find good solutions for a wide range of problems within a relatively shorter time (Mohamed et al., 2019; Belkadi & Daamouche, 2020).

Fish swarm is one among the frequently exploited underwater creature. The development of fish swarm optimization algorithm for complicated problem resolving has begun in the early 2000. AFSA is a fish-inspired swarm intelligent technique for numerical function optimization proposed by Li and Qian in the year of 2002 (Yang et al., 2016). However, AFSA has some drawbacks like premature convergence, trapping into the local optima and high computational time in (Rahman et al., 2019; Nasiri & Khiyabani, 2018). A decade later, Whale Optimization Algorithm (WOA) was first developed in 2016 by Mirjalili and Lewis. It is a swarm-based optimization technique mimicking the preying behaviour of a special species of Whales called humpback whales (Mirjalili & Lewis, 2016). Furthermore, the WOA is a recently established (year 2016) swarm intelligence-based method imitating the hunting performance of a distinct classes of Whales named as 'Humpback Whales' which are able to distinguish the position of target and catch prey in a circular style (Mirjalili & Lewis, 2016).

The standard WOA involves exploitation and exploration operations which require to be balanced for improved performance. The unique hunting behavior in WOA is its exploitation procedure, where

an agent (i.e., whale) adopts a circling technique to update its new position during an optimization process (Oliva & Hassanien, 2017), while its exploration procedure is similar to other bio-inspired algorithms. Although many WOA variants have been proposed for better optimization performance, they have not achieved optimal balance in their operations leading towards slow convergence speed and premature convergence. These drawbacks are obvious when solving power system optimization problems involving non-convex and non-linear fitness functions, particularly when considering modern day power system with complex inequality and equality constraints (Malik et al., 2019; Mohamed et al., 2018; Kumar et al., 2018). Hence, power optimization problem such as Reactive power optimization (RPO) is usually a good choice of application for assessing the practical performance of a newly proposed optimization algorithm.

RPO a constrained problem with large-scale combinatorial type and nonlinear pattern (Meng et al., 2016). It aids to decide the optimum set-up of the power grid to fulfill limited constraints such as the equipment operating limits, system security and equation of power flow (Touma, 2016). This optimization problem was first revealed by Carpentier in 1962 and it relates to security and economic dispatch of a power system (Li, 2013; Yan et al., 2020). As important as it is, many researchers, academics and scientists have gathered to develop various search strategies to optimize power system's operation and planning (Sulaiman et al., 2017). Attempts have been made to solve RPO problem using various classical methods such as linear programming, Newton method, and interior point based on stochastic and heuristics techniques (Rahman et al., 2015). Nonetheless, the methods have shown a number of inefficiency (Singh, 2018). Therefore, RPO becomes a suitable application to validate the robustness of a newly proposed swarm-intelligence algorithm. This paper presents the performance results of an enhanced WOA in terms of convergence rate and global optimum, and its practical performance is validated based on RPO application for Optimal Power Flow (OPF).

NEW ENHANCED WHALE OPTIMIZATION ALGORITHM (WOA)

Before explaining the implementation of the enhanced WOA, it is worth to briefly mention about the important Humpback Whale behavior and describe the original WOA operation. It has to be noted that the Humpback whales choose to prey krill school or tiny fishes near the marine surface. For that reason, whales swim around the prey using a shrinking circle and along a spiral-shaped path simultaneously to create distinctive bubbles along a circle or "9"-shaped path (Jin et al., 2021; Ding et al., 2020; Mirjalili and Lewis, 2016). To simulate this behaviour, the original WOA uses a probability of 50% to choose between the encircling mechanism and the spiral model, in order to update the position of whales during optimization.

As already mentioned, the original WOA is implemented based on the behaviour of Humpback Whales. When a Humpback whale identifies its prey, it signals the other whales to gather at the location and encircle the prey. Hence, the first phase in the implementation of WOA is encircling, which is an important mechanism in relation to the performance of WOA. Prior to encircling, with the aim of locating the optimum solution (the location with the most prey), a search space must be specified. As the optimum location of prey is unknown, the implementation of WOA assumes that a target prey is the best candidate of optimum solution, i.e., a location that is near to the optimum, at the particular time (Aljarah et al., 2016; Kaveh and Ghazaan, 2016). Once the best candidate of whale agent is defined (i.e., the whale nearest to the candidate solution), the next phase is the attempt of the other whale agents to update their positions towards the best whale agent. This updating behavior is shown in the form of the following equation (Mirjalili and Lewis, 2016):

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \bullet \vec{D} \quad (1)$$

where t indicates the current iteration, \vec{X} is the current position vector, \vec{X}^* is the position vector of the best-so-far candidate and \bullet is an element-by-element multiplication. It is worth mentioning here

that \vec{X}^* should be updated in each iteration if there is a better candidate solution compared to other previous ones, and hence is the best-so-far candidate solution. The vectors \vec{A} and \vec{D} are coefficient vectors calculated using (Mirjalili and Lewis, 2016):

$$\vec{A} = 2\vec{a} \bullet \vec{r} - \vec{a} \quad (2)$$

$$\vec{D} = \left| \vec{C} \bullet \vec{X}^*(t) - \vec{X}(t) \right| \quad (3)$$

where a is linearly decreasing from 2 to 0 over the course of iterations (in both exploration and exploitation phases), r is a random vector in range [0, 1] and \vec{C} is given by (Mirjalili and Lewis, 2016):

$$\vec{C} = 2 \bullet \vec{r} \quad (4)$$

Various positions around the best whale agent can be achieved with respect to the current position by adjusting the values in vectors \vec{A} and \vec{C} based on trial-and-error.

In this study, the modification done to the original WOA involves integrating the *step* equation from the hunting behavior of AFSA. Basically, in AFSA, *step* value is the distance between the current and updated fish positions. It is calculated using (Guo, 2017):

$$step = step_0 - q \times step_0 \times \frac{t_p}{m} \quad (5)$$

where $step_0$ is initial value of step length; q is change parameter of step length; t_p is the current generation number, m is the maximum generation. Hence, the value obtained from the *step* equation defines a fish's update location. As to enhance the original WOA, the *step* equation is integrated into the WOA's encircling stage to form a modified encircling mechanism. This modifies Equation (1) to become:

$$\vec{X}(t+1) = \vec{X}^*(t) + (2*rand - 1)*step \quad (6)$$

where *rand* is a randomly generated value and *step* is an equation as given in Equation (5). Theoretically, the modified encircling mechanism is expected to enhance the lack of exploration in WOA using the additional local search capability of AFSA's *step* equation. This adds-up to the global search ability towards improving WOA's exploration capability. The resultant AFSA-inspired WOA is referred to as AFS-WOA.

In line with this enhancement, an extensive trial and error method must be performed to investigate optimum probability values. These values are to be used in the condition for a decision on which of the two encircling mechanisms (modified or non-modified) to be used for updating a whale agent. The choice of whale updating equations is based on the probability, p value by considering the following conditions:

if ($p == 70\%$), execute Equation (1)

if ($p == 30\%$), execute Equation (6)

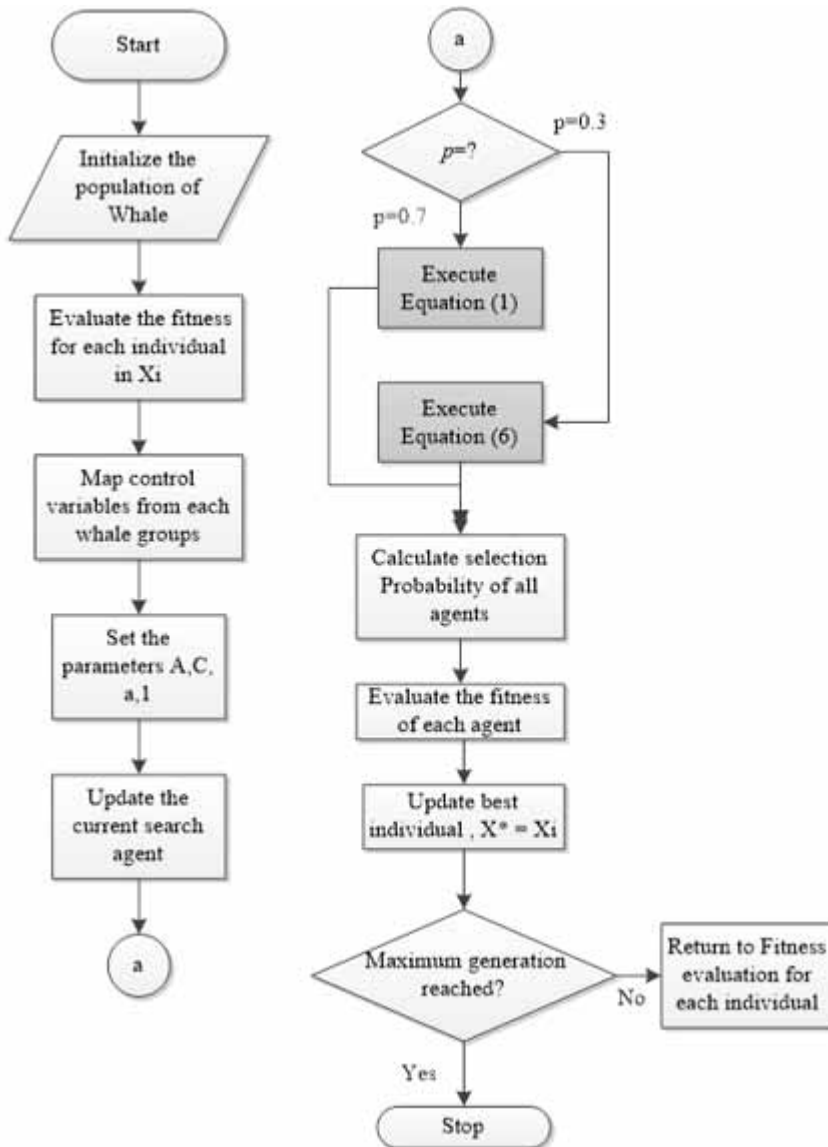
The optimum probability values selected in the proposed AFS-WOA has been determined based on trial-and-error simulation investigations. This stage of work is essential in order to obtain suitable probability values which ensures the global minimum achievement. For the purpose, probability values starting from 10%

to 100% with increments of 10% have been investigated using fifteen frequently used benchmark functions. The percentage of probability values which give the best (i.e., minimum) value of the benchmark function are chosen as the best pair of probability values for updating the whales' positions.

Figure 1 shows the flowchart of the proposed AFS-WOA variant, with the modified stages highlighted with darker color. Comprehensive explanations of AFSA and WOA techniques can be found in Neshat et al. (2014) and Mirjalili & Lewis (2016), correspondingly. As for the modified stages (see Figure 1), the probability values p determines which equation to be executed.

In order to assess the performance of proposed AFS-WOA, a total of 15 benchmark functions from CEC2005 (Mirjalili & Lewis, 2016; Neshat et al., 2014) have been used as test functions. The performance comparison is based on parameter values following the works of Gharehchopogh and Gholizadeh (2019) and Mirjalili and Lewis (2016), as listed in Table 1.

Figure 1. Flowchart of proposed Enhanced WOA



The numerical results of the proposed AFS-WOA in terms of fitness value have been compared with three other fish species to ensure fair comparison. The three underwater swarm intelligent algorithms used in the comparison are AFSA, WOA and Yellow Saddle Goatfish Algorithm (YSGA) (Zaldivar et al., 2018). The Yellow Saddle Goatfish is rather new and is one of the best swarm-intelligent optimization algorithm of fish species.

The simulation results of the proposed AFS-WOA in comparison to other fish species are shown in Table 2. The results are based on best fitness values. It can be clearly seen that AFS-WOA performs the best on most of the 15 test functions except Schwefel 22 and Infinity. This reveals that the modifications done on the encircling equation of WOA have successfully balanced out the exploration and exploitation capabilities in the proposed AFS-WOA. As for Griewank function, the results demonstrate that YSGA and WOA have also been able to obtain the same target optimum values as the proposed AFS-WOA.

Table 1. Parameter values used in the simulation

Parameter	Value
Population size	30
Maximum generation	200
Number of whale agents	30
Initial value of step length, $step_0$	0.4
$step$ length parameter change, q	0.9
Number of runs	30

Table 2. Average best fitness comparison of proposed AFS-WOA with other fish swarm algorithms considering 30 dimensions

Benchmark Function	Proposed AFS-WOA	WOA (Mirajalili & Lewis, 2016)	AFSA (Neshat et al., 2014)	YSGA (Zaldivar et al., 2018)
Sphere	0.00E+00	9.05E-02	3.17E-16	2.60E-188
Schwefel 2	0.00E+00	3.22E-24	4.71E-07	7.50E-174
Rotated Hyper-Ellipsoid	5.40E-188	4.16E-25	3.21E+02	7.00E-185
Sum Squares	0.00E+00	5.96E-36	5.88E-06	0.00E+00
Ackley	2.88E-16	2.32E-10	1.52E+01	2.44E-15
Rosenbrock	5.40E-184	2.92E-23	3.26E+02	7.50E-174
Griewank	0.00E+00	0.00E+00	3.40E-03	0.00E+00
Schwefel 22	3.24E-104	1.56E-14	1.93E+26	8.64E-106
Quartic	2.60E-01	2.78E-16	3.32E-08	3.33E-01
Rastrigin	0.00E+00	0.00E+00	1.08E+00	0.00E+00
Salomon	7.21E+00	1.02E+01	1.41E+01	8.74E+00
Infinity	1.20E-07	1.25E-07	1.14E+00	0.00E+00
Powell	1.78E+01	3.78E+01	6.75E+01	2.43E+01
Penalty I	1.08E+01	1.76E+03	6.85E+03	1.25E+01
Mishra1	-3.00E+01	-2.89E+01	-2.97E+01	-3.00E+01
Composite	2.01E+01	3.21E+02	2.91E+01	2.90E+01

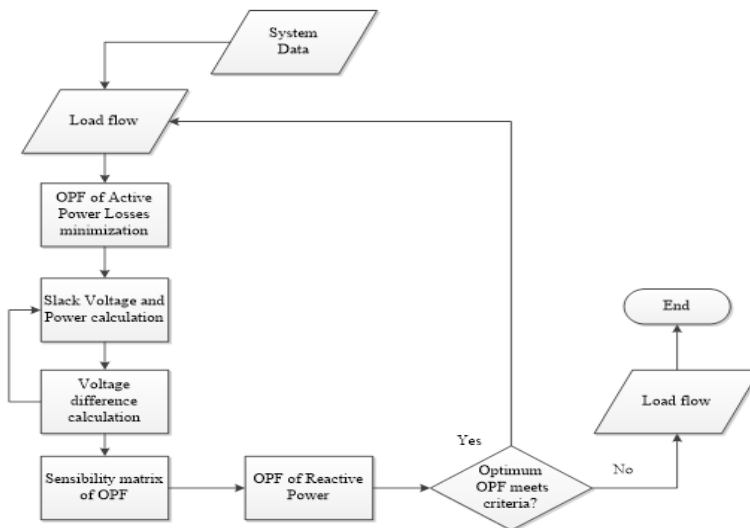
APPLICATION IN REACTIVE POWER OPTIMIZATION (RPO)

Reactive Power Optimization (RPO) has received growing attention from optimization researchers in the power sector due to its significance in modern power system. Its goal is to reduce real power losses of a power system while achieving enhancement in the bus voltage while maintaining the load demand and operational constraints (Muhammad et al., 2019). The Optimal Power Flow (OPF) involves reactive power optimization of power systems for the purpose of reducing overall power loss. Transformer taps, shunt capacitors and bus voltages control the reactive power distribution, besides, these affect to power quality, bus voltage profiles, network stability and power system losses (Mugemanyi et al., 2020). Optimization researchers have been suggesting various optimization algorithm in order to tackle the Reactive Power Optimization (RPO) (Neshat et al., 2014). However, most of the techniques are either computationally extensive or their optimal search operation become trapped in local minima. As a result, there is need to achieve optimization objective with good convergence rates. For that, an enhanced AFS-WOA as proposed in the previous section, has been applied to solve the RPO problem based on its objective function and its performance has been compared with the original WOA, PSO, AFSA and an enhanced Artificial Bee Colony algorithm known as EABC.

In this work, the optimal parameters for RPO simulations are set to be following the tested optimization algorithms to ensure fair results comparison. For WOA and PSO algorithm, the parameters are taken from Ben oualid Medani et al. (2018), for EABC, its parameter values area taken from the work of Sulaiman et al. (2015) and for AFSA, the parameter values are taken from Neshat et al. (2014).

Figure 2 shows the flow diagram of the proposed method. Initially, the data obtained from the *IEEE 30-bus IEEE 30-bus* system are loaded into the OPF model for optimization of active power loss. The mathematical formulation of active power loss used in the work is given as follows (Ben oualid Medani et al., 2018):

Figure 2. Flow diagram of RPO in OPF as adapted from Moreno et al. (2005)



$$P_{loss} = \sum_{k=1}^{NL} P_{loss,k} = \sum_{i=1}^N \sum_{j=1}^N g_{ij} [V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij}] \quad (7)$$

where P_{loss} is an active power loss, g_{ij} is the conductance between bus i and bus j , V_i is the voltage magnitude of bus i , V_j is the voltage magnitude of bus j , θ_{ij} is the angle difference of ij -th transmission line. The result of the active power optimization is loaded in the test system to optimize it in terms of reactive power. Then slack voltage, power and voltage difference are calculated and the process continues until optimization operation converges (Muhammad et al., 2019).

RPO optimization problem comprises various constraints as mentioned in Neshat et al. (2014). Thus, a penalty function has been added in the RPO algorithm in order to change the constrained problem into an unconstrained one by adding penalty terms. The sensibility matrix is the solution that represents the re-dispatching of reactive power with regard to the original ones. This matrix computation is the stage that follows and it relates to the reactive power. Finally, the criteria for optimal OPF is checked and the process repeats until best optimization is achieved.

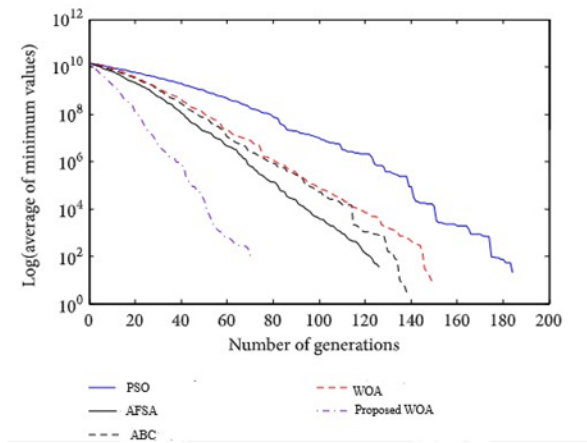
Table 3 shows the compared results. It is clearly depicted in Table 3, that the proposed AFS-WOA gives the least power loss in MW compared to other compared swarm intelligence techniques (i.e., PSO, EABC), AFSA and WOA. The power loss in MW is lowest among the compared algorithms.

A sample of convergence rate results taken from one of the simulations is depicted in Figure 3, to show the comparison amongst the compared swarm-optimization algorithms. Clearly, the results plotted

Table 3. Performance results of optimization algorithm at solving IEEE 30-bus power system

Optimization algorithm	Power Loss (MW)
PSO (Ben oualid Medani, et al., 2018)	4.6282
WOA (Ben oualid Medani et al., 2018)	2.255
EABC (Sulaiman et al., 2015)	1.5522
AFSA (Neshat et al., 2014)	3.4530
Proposed WOA (AFS-WOA)	1.4887

Figure 3. Comparison of convergence rate among various optimization techniques at solving RPO problem



in the figure show that the proposed AFS-WOA variant has the fastest convergence compared to other algorithms. It converges in less than 80 generations, whilst the other algorithms require more than 120 generations to converge.

CONCLUSION AND RECOMMENDATIONS

This research focuses on developing enhanced WOA variant for improving the performance of original WOA in terms of convergence rate and global optimum to solve RPO problem in power system.

This paper presents a new enhanced WOA, referred to as AFS-WOA, to improve the convergence speed and enhance the global optimum of the original WOA by balancing exploitation and exploration processes. In the work, new procedure was suggested at the hunting stages of the original WOA to increase its lacking exploitation capability. This was done by including a *step* equation, taken from fish-inspired swarm behavior, into the standard WOA algorithm to balance out the effects exploitation and of exploration processes. The performance of the modified algorithm in terms of convergence speed and global optimum achievement were analyzed on 15 commonly used benchmark or test functions and on a complex real-world problem, Reactive Power Optimization (RPO) problem. The performance results have clearly exhibited superior performance of the proposed AFS-WOA in comparison to the other underwater swarm intelligent algorithms (AFSA, WOA and YSGA). Moreover, the efficiency of the algorithm at solving the RPO problem had vividly depicted the algorithm's practicality for solving optimization problem.

In the future, AFS-WOA shall be tested with other complex real-world application of various fields such as economic/emission load dispatch, fault estimation and digital IIR filter design prior to further confirm its robustness.

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