# AFSA-WOA Variants for Enhanced Global Optimization

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**Abstract:** Imbalanced exploitation in Metaheuristic Artificial Fish Swarm Algorithm (AFSA) inhibits it from producing good optimization performance. Therefore, this paper presents the proposal of a simple, yet improved AFSA variant for optimization, inspired by combining it with the Whale Optimization (WOA) algorithm. Originally, the standard AFSA algorithm imitates the hunting behavior of fish swarm, while the standard WOA algorithm imitates the whale hunting behavior in a natural environment. In this work, the spiral updating position technique of WOA is incorporated into the swarming and following behaviors of AFSA, creating three new variant algorithms referred to as AFSA-WOA-S, AFSA-WOA-F and AFSA-WOA-SF. The performances of the proposed variants are evaluated based on fifteen benchmark functions. The results have proven that the variants are able to improve the global optimization outputs compared to the standard AFSA and WOA. The best-performed variant among the proposed ones, is AFSA-WOA-F.

**Keywords:** Artificial Fish Swarm (AFSA), Whale Optimization Algorithm (WOA), Optimization, Benchmark Function

## 1. Introduction

Optimization plays an essential role in many aspects of living, either in the industry or academic, in finding the best or optimal solution for a problem [1-4]. Real-world optimization problems are complex, non-linear and quite challenging to find the exact optimized solution. Due to the computational costs of the existing numerical methods, researchers must rely on metaheuristic algorithms to solve complex optimization problems.

Metaheuristic optimization algorithms are introduced to solve the optimization problem by mimicking biological or physical phenomena. It is also known as a directional search algorithm towards the global best solution [5]. It is becoming more popular in engineering application because this algorithm is simple, easy to implement, can avoid the local optima and can be utilized in a wide range of problems in various disciplines[3-6].

These algorithms are categorized into three groups; evolution-based, physic-based, and swarm-based [6,9]. The evolution-based method is inspired by natural evolution laws. The most common algorithms are Genetic Algorithm (GA) [10], Evolution Strategy (ES) [11] and Biogeography-Based Optimizer (BBO) [12]. The search operation begins with a randomly generated population growing by the subsequent generations. This method is to lead the population over the generations based on the best individuals are always combined together to form the generation individuals.

On the other hand, the physic-based method imitates the physical principles in the universe. The most popular algorithms are Simulated Annealing (SA) [13], Gravitational Search Algorithm (GSA) [14], Black Hole (BH) algorithm [15] and Curved Space Optimization (CSO) [16]. Finally, the swarm-based method, also known as a nature-inspired method, mimic the social behavior of the groups of animals. The most popular algorithm is Particle Swarm Optimization (PSO), which is inspired by the social behavior of bird flocking [17]. PSO uses a number of particles to fly around the search space to find the best solution that represents the optimal solution. Meanwhile, they trace the best location along their path. Another popular algorithm is the Ant Colony Optimization (ACO). This algorithm was developed by Dorigo et al. [18], which inspired by the social behavior of ants in an ant colony. Artificial Fish Swarm Algorithm (AFSA) and Whale Optimization Algorithm (WOA) also categorized as a swarm-based method.

There are two phases involved in the metaheuristic algorithm search process; exploration and exploitation [19, 20]. In the exploration phase, the optimizer should always explore the search space globally, and the movements have to be randomly chosen and then followed by the exploitation phase. This phase is to investigate the found search space in detail. Basically, the exploitation is revisiting the region found by the exploration phase. However, the optimization process is stochastic in nature and it is a challenge to the metaheuristic algorithm in balancing the exploration and exploitation search process [21].

AFSA is a novel method for searching the global optimum proposed by Li et al.[22] in 2002. This algorithm had been formulated based on collective hunting and various social behaviors among fish swarm. It stimulated by the behavior of cooperative hunting of fishes in search of fish sources as well as protecting the group from threat during food hunting. Artificial fish (AF) can search for the global optimum effectively and has the adaptive ability for search space. AF individual behavior is to hunt for the local optimum. Hence, this algorithm has many advantages such as flexibility, high accuracy and high convergence speed [23]. However, artificial fish can be stuck into local optima when dealing with multimodal optimization problems. Since then, many modifications had been made by the researcher in order to enhance the optimization performance.

In 2016, WOA had been introduced by Mirjalili et al. [6]. This algorithm is mimicking the unique hunting behavior of humpback whales. It stimulated hunting behavior with the best search agent or randomly search agent to hunt the prey and stimulate a bubble net attacking mechanism using the spiral. This spiral called spiral updating position and used in the exploitation phase [6].

This paper introduces the variants algorithm that combines the Artificial Fish Swarm Algorithm (AFSA) and Whale Optimization Algorithm (WOA) named as AFSA-WOA variant. The main idea of this study is to integrate the WOA's exploitation capability with the AFSA's exploration capability to employ both strengths. Hence, this variant is able to enhance the optimization performance in term of the optimum value when the exploration and exploitation search process is balance.

The remaining of the paper is structured as follows. Section II illustrates the basic principle of standard AFSA and standard WOA algorithm. Section III outlines the proposed algorithm of variant AFSA-WOA. The simulation results of the proposed algorithms are presented in section IV. Finally, the last section draws the conclusion and future works.

## 2. Literature Review

### A. Artificial Fish Swarm Algorithm (AFSA)

Artificial fish swarm algorithm (AFSA) is one of the swarm intelligent algorithm based on fish hunting behavior to find the area with the most food source. The more fishes represent a certain area, it shows more food density. AFSA also known as a method for searching the global optimum [23].

Like another swarm intelligence methods, the AFSA searches the possible solution based on the cooperation and competition amongst the fish individuals. Each artificial fish can move around in the solution space. Suppose the state vector of an artificial fish (AF) swarm is $X = (x_1, x_2 \dots x_n)$, where $x_1, x_2 \dots x_n$ is the position of the fish in the population [24] and $n$ is the total number of AF population. The food concentration is determined by the object function $Y = f(X)$, where $Y$ represents the fitness value of each AF at position $X$. Each AF has been given a set of perception; *visual* and *step*. *Visual* is the visual distance of an artificial fish individual to gather the information to seek a better solution as well as determine the current situation of other companions. In the other hand, *step* represents the maximum step size of an artificial fish to approach a particular target position [24]. The other parameters involved in AFSA are crowding factor, *try_number* and iteration number *t*. Figure 1 shows the pseudo-code of the standard AFSA.

```
Random initialize the fish population
while (t < maximum number of iterations)
for each fish
Calculate the fitness of each fish
    Do AF_Swarm
        if (AF_Swarm fail)
            Do AF_Prey
        end if
        Output X1
    Do AF_Follow
        if (AF_Follow fail)
            Do AF_Prey
        end if
        Output X2
fish +1
end for
Update best fitness
t=t+1
end while
output optimal solution
```

**Fig. 1:** Pseudo-code of Standard AFSA

Three basic behaviors of AFSA involved in this work; preying, swarming and the following behavior. The current state and the next state of AF were named as $X_i$ and $X_j$, respectively. In contrast, $Y_i$ and $Y_j$ represent the fitness value for the current and next state. The selected state is randomly selected based on the specific value visual and step. In preying behavior, if $Y_i < Y_j$, AF will move forward a step to a new position. In contrast to swarming and the following behavior, the AF will move forward to a new position depends on the number of companions in the current neighbor of food (fitness value). In swarming behavior, the next state is, $X_c$, which is the center position of AF with higher fitness value, $Y_c$. Meanwhile, the next position for following, $X_j$ is the position with the highest food concentration and the surroundings is not very crowded, $Y_j$. All the equations for this behavior, as stated in [6].

**B. Whale Optimization Algorithm (WOA)**

WOA is another swarm intelligence algorithm proposed for continuous optimization problems. It is mimicking the preying behavior of a special species of whales called as "Humpback Whales'. The Humpback Whale is recognize the position of target and catch the prey in circular way [25]. There are two mechanism used by whale for search their prey; location and attack. Firstly, the preys are encircled the location and then create the bubble-nets to attack. Hence, in optimization the exploration in search space is performed when the whale looks for a prey while the exploitation occurs during the attack behavior [26]. Figure 2 shows the pseudo-code of the standard WOA.

```
Initialize the whale population
Calculate the fitness of each search agent
Calculate the best search agent
while (t < maximum number of iterations)
    for each search agent
    Update a, A, C, l, and p
        if (p<0.5)
            if (|A|<1)
                Update the position of the current search agent by the Eq. (2.1)
            else if (|A|>1)
                Select a random search agent (Xrand)
                Update the position of the current search agent by the Eq. (2.8)
            end
        else if (p>0.5)
            Update the position of the current search agent by Eq. (2.5)
        end if
    end for
    Calculate if any search agent goes beyond the search space and amend it
    Calculate the fitness of each search agent
    Update the best search agent if there is a better solution
    t=t+1
end while
output optimal solution
```

**Fig. 2:** Pseudo-code of Standard WOA

The most interesting fact about the humpback whale is their special hunting strategy. This hunting behavior is called 'bubble-net feeding method' [6, 27] and can only observed in Humpback Whale. They prefer to prey school of krill or small fishes near the surface. There are two approaches way to hunting the prey. The first approach named as Shrinking encircle mechanism. Humpback whales dive around 12m down and then start to create bubble in a spiral shape around the prey and swim up toward the surface. Then, they swim nearby the target within a shrinking circle and along a spiral-shaped path concurrently to create unique bubbles along a circle or "9"- shaped path [6, 27]. This is the second approach named as 'Spiral updating position' technique. WOA mimics the preying behavior to hunt the prey as well as the usage of a spiral to mimic bubble-net feeding method of behavior of whales. All the equations for this behavior, as stated in [28].

**3. Methodology**

**A. Proposed Algorithm**

In this work, the 'spiral updating position' technique [6] from the exploitation phase of WOA has been incorporated with the AFSA. The idea is to fit the exploration capability in AFSA with the exploitation capability of WOA to utilize both algorithm's strength. This technique is expected to enhance the optimum value of AFSA variant for multimodal function optimization (minimization). The incorporation of WOA is to improve the stability of exploration and exploitation in the algorithm. Hence, the algorithm is driven more quickly toward the best solution.

Three variants algorithms have been proposed in this work. There are AFSA-WOA-S, AFSA-WOA-F and AFSA-WOA-SF. The 'spiral updating position' technique was applied in the swarming behavior, following behavior and in both swarming and following behavior of standard AFSA. Figure 3 show the procedure of the proposed AFSA-WOA-S algorithm.

Step 1: Randomly initialize AF population
Step 2: Calculate fitness value
Step 3: Each artificial fish $i$ ($i$=1, 2, . . ., $N$)
  Step 3.1: Swarming behavior
    - Check the condition either meet the requirement or not
    - If so, apply WOA technique and update new fitness value ($X_1$)
    - Otherwise turn to step 3.3
  Step 3.2: Following behavior
    - Check the condition either meet the requirement or not
    - If so, evaluate the following equation and update new fitness value ($X_2$)
    - Otherwise turn to step 3.3
  Step 3.3: Evaluate preying behavior and update the new fitness value ($X_1$ or $X_2$)
Step 4: Compare the best fitness value ($X_1$ or $X_2$)
Step 5: Update the current best fitness value and location
Step 6: If maximum iteration reach, exit; otherwise, turn to Step 3

**Fig. 3:** Procedure of the algorithm for AFSA-WOA-S

**B. Simulation and Performance Assessment**

The simulation work was performed using MATLAB 2018b on an Intel ® Core ™ i7 CPU, 2.86Ghz 8GB RAM. The standard AFSA and proposed SLnO are run until 500 iterations for each function. Each function is run ten times independently to ensure that the AF is nit trapped in a local minimum. Table 1 shows the parameter settings for AFSA used in the simulation.

**Table 1.** Parameter setting for AFSA [29]

| **Parameter** | **Value** |
|---|---|
| Population | 50 |
| Step Size | 225 |
| Visual | 250 |
| *try_number* | 5 |
| Crowd factor, δ | 0.75 |
| Dimension | 30 |

Fifteen benchmark functions were used in the simulation to evaluate the performance of the proposed algorithm. These test functions have been widely utilized in global optimization[29-30]. Table 2 shows the list of the benchmark function used in this work. For each test function, the value of $f_{min}$ is the optimum value. An algorithm is considered performing good if is able to obtain the $f_{min}$ optimum value.

**Table 2.** Description of benchmark functions

| **Function** | **Range** | $f_{min}$ |
|---|---|---|
| $F1(x) = \sum_{i=1}^{D} {x_i}^2$ | [-5.12, 5.12] | 0 |
| $F2(x) = -20exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} {x_i}^2}\right) - exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right) + 20 + e$ | [-32.768, 32.768] | 0 |
| $F3(x) = \frac{1}{4000}\sum_{i=1}^{D} {x_i}^2 - \prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$ | [-600,600] | 0 |

| | | |
|---|---|---|
| $F4(x) = \sum_{i=1}^{D}[x_i^2 - 10\cos(2\pi x_i) + 10]$ | [-5.12, 5.12] | 0 |
| $F5(x) = \sum_{i=1}^{D-1}[100(x_i + 1 - x_i^2)^2 + (x_i - 1)^2]$ | [-2.048, 2.048] | 0 |
| $F6(x) = \sum_{i=1}^{D}(10^6)^{\left(\frac{i-1}{D-1}\right)} \,.\, x_i^2$ | [-100,100] | 0 |
| $F7(x) = \sum_{i=1}^{D}\lvert x_i \,.\sin(x_i) + 0.1 \,. x_i\rvert$ | [-100,100] | 0 |
| $F8(x) = \sum_{i=1}^{D}\lvert x_i\rvert^{(i+1)}$ | [-1,1] | 0 |
| $F9(x) = \sum_{i=1}^{D} i x_i^2$ | [-10,10] | 0 |
| $F10(x) = \sum_{i=1}^{D}\left(\sum_{j=i}^{i} x_j\right)^2$ | [-100,100] | 0 |
| $F11(x) = sin^2(\pi x_i) + \sum_{i=1}^{D}(x_i - 1)^2 [1 + 10(sin(\pi x_{i+1}) + 1)]^2 + (x_{i-1})^2 + [1 + sin^2\ (2\pi x_i)]$ | [-10,10] | 0 |
| $F12(x) = \sum_{i=1}^{D}(x_i - 1)^2 - \sum_{i=1}^{D} x_i\, x_{i-1}$ | [-10,10] | -4930 |
| $F13(x) = -cos\left(2\pi\sqrt{\sum_{i=1}^{D} x_i^2}\right) + 0.1\sqrt{\sum_{i=1}^{D} x_i^2}$ | [-2π, 2π] | 0 |
| $F14(x) = \sum_{i=1}^{D}(x_i^2 + x^2{}_{i+1})^{0.25}\{[sin50(x_i^2 + x^2{}_{i+1})^{0.1}]^2\ + 1\}$ | [-100,100] | 0 |
| $F15(x) = -0.1\sum_{i=1}^{D} cos\,(5\pi x_i) + \sum_{i=1}^{D} x_i^2$ | [-1,1] | -3 |

## 4. Results and Discussion

### A. Result Comparison of Proposed Variants AFSA-WOA

Table 3 shows the comparative performance of all proposed variant AFSA-WOA in term of the global optimum value. The results show that the AFSA-WOA-F and AFSA-WOA-SF are very competitive compared to AFSA-WOA-S. Based on the table, total best of global optimum value for AFSA-WOA-F and AFSA-WOA-SF are 13 and 12, respectively. Both variants successfully achieved the minimum global value at 0 for *F1*, *F4*, *F6*, *F7*, *F8*, *F9*, *F10*, *F13*, and *F14*.

On the other hand, AFSA-WOA-S is the worst-performed algorithm. This variant able to achieve the optimum global value only for two function, *F12* and *F15*. However, all variants reached the global minimum value of *F15*, successfully.

Thus, the result clearly shows that WOA is not suitable to be applied in swarming behavior alone. However, the result improved when the WOA incorporated into swarming and following behaviors. But, the performance of

AFSA-WOA-SF is defeated by AFSA-WOA-F because the minimum global value for *F5*. Hence, the best-proposed variant among the proposed is AFSA-WOA-F.

**Table 3.** Performance comparison of global optimum values amongst the propose variants.

| **Function** | **AFSA-WOA-S** | **AFSA - WOA-F** | **AFSA - WOA-SF** | **Optimum Value** [29], [30] |
|---|---|---|---|---|
| *F1* | 4.542E-11 | **0** | **0** | 0 |
| *F2* | 2.060E-06 | **8.882E-16** | **8.882E-16** | 0 |
| *F3* | 1 | 1 | 1 | 0 |
| *F4* | 1.509E-06 | **0** | **0** | 0 |
| *F5* | 2.147E-07 | **0** | 2.870E+01 | 0 |
| *F6* | 5.542E-05 | **0** | **0** | 0 |
| *F7* | 2.091E-06 | **0** | **0** | 0 |
| *F8* | 6.123E-14 | **0** | **0** | 0 |
| *F9* | 1.917E-08 | **0** | **0** | 0 |
| *F10* | 2.323E-02 | **0** | **0** | 0 |
| *F11* | 6.422E-10 | **1.500E-32** | **1.500E-32** | 0 |
| *F12* | **-2.867E+03** | -1.900E+03 | -1.500E+03 | -4930 |
| *F13* | 4.963E-06 | **0** | **0** | 0 |
| *F14* | 4.283E-01 | **0** | **0** | 0 |
| *F15* | **-3** | **-3** | **-3** | -3 |
| **Total best** | **2** | **13** | **12** | |

**B. Result Comparison of the Best-Proposed Variant with Other Algorithms.**

The performance of the best-proposed variant has been compared with the standard AFSA [30] and WOA [6] for verification. Table 4 show the comparative performance of the best-performed variant and standard algorithm. The result proved that the variant outperformed the standard AFSA and WOA for most of the function. Again, only AFSA-WOA-F achieved the minimum global at 0 value for *F1*, *F4*, *F5*, *F6*, *F7*, *F8*, *F9*, *F10*, *F13*, and *F14*. However, the performance of WOA is better result than AFSA-WOA-F in obtaining the global minimum value. WOA achieved global value at 0, while AFSA-WOA-F achieved global value at 1. Based on the table, most of the function able to reach near the minimum value for most of the function. Nevertheless, the AFSA-WOA-F proved that the variant able to improve the global optimization value compared to standard AFSA and WOA.

**Table 4.** Comparison of global optimum achievement for the best-proposed variants of ASFA-WOA-F with other algorithms.

| **Function** | **AFSA [**4] | **WOA** [6] | **AFSA - WOA-F** | **Optimum Value** [29], [30] |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| *F1* | 1.58E-11 | 1.41E-30 | **0** | 0 |
| *F2* | 2.50E-04 | 2.79E+01 | **8.882E-16** | 0 |
| *F3* | 2.49E-09 | **0** | 1 | 0 |
| *F4* | 3.20E-10 | 7.40E+00 | **0** | 0 |
| *F5* | 5.65E-12 | 2.89E-04 | **0** | 0 |
| *F6* | 1.61E-07 | - | **0** | 0 |
| *F7* | 6.41E-08 | - | **0** | 0 |
| *F8* | 2.94E-14 | - | **0** | 0 |
| *F9* | 3.78E-11 | - | **0** | 0 |
| *F10* | 1.98E-08 | - | **0** | 0 |
| *F11* | 1.39E-08 | - | **1.500E-32** | 0 |
| *F12* | - | - | **-1.900E+03** | -4930 |
| *F13* | - | - | **0** | 0 |
| *F14* | - | - | **0** | 0 |
| *F15* | - | - | **-3** | -3 |

## 5. Conclusion

Three variants of the standard AFSA algorithm have been proposed by incorporating the 'Spiral Updating Position' technique of WOA into AFSA's behavior. The proposed variants are named as AFSA-WOA-S, AFSA-WOA-F and AFSA-WOA-SF. The result reveal that best-proposed variant comes out to be AFSA-WOA-F, where the technique had been applied in following behavior. Its performance has been compared with the standard AFSA and WOA. The proposed variant is outstanding with successful achievement of better global optimum values for 10 benchmark functions. In conclusion, the global optimum value improves by incorporated the spiral updating position of WOA in AFSA's following behavior.

For future work, other types of test function will be applied such as valley-shape to evaluate the performance of the proposed variant. Besides, the proposed variant can be put on trial to solve real-world engineering problem such as electronic and power system.

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## References

1. J. Batra, R. Jain, V. A. Tikkiwal, and A. Chakraborty, "A comprehensive study of spam detection in e-mails using bio-inspired optimization techniques," Int. J. Inf. Manag. Data Insights, vol. 1, p. 100006, 2021.
2. M. Belna, A. Ndiaye, F. Taillandier, L. Agabriel, A. L. Marie, and G. Gésan-Guiziou, "Formulating multiobjective optimization of 0.1 μm microfiltration of skim milk," Food Bioprod. Process., vol. 124, pp. 244–257, 2020.
3. Ciardiello, F. Rosso, J. Dell'Olmo, V. Ciancio, M. Ferrero, and F. Salata, "Multi-objective approach to the optimization of shape and envelope in building energy design," Appl. Energy, vol. 280, p. 115984, 2020.
4. Z. Liu, J. Peng, X. Hua, and Z. Zhu, "Wind farm optimization considering non-uniformly distributed turbulence intensity," Sustain. Energy Technol. Assessments, vol. 43, p. 100970, 2021.
5. Rahman, J. Mohamad-Saleh, and N. Sulaiman, "Artificial Fish Swarm-Inspired Whale Optimization Algorithm for Solving Multimodal Benchmark Functions," 10th Int. Conf. Robot. Vision, Signal Process. Power Appl., pp. 59–65, 2019.

6. S. Mirjalili and A. Lewis, “The Whale Optimization Algorithm,” Adv. Eng. Softw., vol. 95, pp. 51–67, 2016.
7. Alzaqebah, R. Masadeh, and A. Hudaib, “Whale optimization algorithm for requirements prioritization,” 2018 9th Int. Conf. Inf. Commun. Syst. ICICS 2018, vol. 2018-Janua, pp. 84–89, 2018.
8. R. Masadeh, A. Alzaqebah, and A. Sharieh, “Whale optimization algorithm for solving the maximum flow problem,” J. Theor. Appl. Inf. Technol., vol. 96, no. 8, pp. 2208–2220, 2018.
9. S. Mirjalili, S. M. Mirjalili, and A. Lewis, “Grey Wolf Optimizer,” Adv. Eng. Softw., vol. 69, pp. 46–61, 2014.
10. R. Chen, B. Yang, S. Li, and S. Wang, “A self-learning genetic algorithm based on reinforcement learning for flexible job-shop scheduling problem,” Comput. Ind. Eng., vol. 149, p. 106778, 2020.
11. H.-G. Beyer and H.-P. Schwefel, “Evolution strategies - A comprehensive introduction,” Nat. Comput., vol. 1, no. 1, pp. 3–52, 2002.
12. D. Simon, “Biogeography-based optimization,” IEEE Trans. Evol. Comput., vol. 12, no. 6, pp. 702–713, 2008.
13. M. E. Çiftçi and V. Özkır, “Optimising flight connection times in airline bank structure through Simulated Annealing and Tabu Search algorithms,” J. Air Transp. Manag., vol. 87, p. 101858, 2020.
14. E. Rashedi, H. Nezamabadi-pour, and S. Saryazdi, “GSA: A Gravitational Search Algorithm,” Inf. Sci. (Ny)., vol. 179, no. 13, pp. 2232–2248, 2009.
15. Hatamlou, “Black hole: A new heuristic optimization approach for data clustering,” Inf. Sci. (Ny)., vol. 222, pp. 175–184, 2013.
16. F. F. Moghaddam, R. F. Moghaddam, and M. Cheriet, “Curved Space Optimization: A Random Search based on General Relativity Theory,” Comput. Sci., p. ArXiv:1208.2214, 2012.
17. J. Kennedy and R. Eberhart, “Particle swarm optimization,” Nat. Comput. Ser., pp. 97–102, 2018.
18. M. D. T. S. M. Birattari, “Ant Colony Optimization,” Quality, vol. 11, no. 4, pp. 1–16, 2004.
19. M. Alshraideh, B. A. Mahafzah, and S. Al-Sharaeh, “A multiple-population genetic algorithm for branch coverage test data generation,” Softw. Qual. J., vol. 19, no. 3, pp. 489–513, 2011.
20. M. A. Alshraideh, B. A. Mahafzah, H. S. E. Salman, and I. Salah, “Using Genetic Algorithm as Test Data Generator for Stored PL/SQL Program Units,” J. Softw. Eng. Appl., vol. 06, no. 02, pp. 65–73, 2013.
21. R. Masadeh, B. A. Mahafzah, and A. Sharieh, “Sea Lion Optimization algorithm,” Int. J. Adv. Comput. Sci. Appl., vol. 10, no. 5, pp. 388–395, 2019.
22. S. J. Li Xiaolei, “An optimizing method based on Autonomous Animals : Fish Swarm Algorithm,” Chin J Syst. Eng. Theory Pract., vol. 22, no. 11, pp. 32–38, 2002.
23. R. Moradi, Y. Alinejad-Beromi, and K. Kiani, “Artificial Fish Swarm Algorithm for solving the Economic Dispatch with Valve-Point Effect,” Int. J. Eng. Technol., vol. 2, no. 3, pp. 299–313, 2014.
24. Z. Huang and Y. Chen, “An Improved Artificial Fish Swarm Algorithm based on Hybrid Behavior Selection,” Int. J. Control Autom., vol. 6, no. 5, pp. 103–116, 2013.
25. H. J. Touma, “Study of The Economic Dispatch Problem on IEEE 30-Bus System using Whale Optimization Algorithm,” Int. J. Eng. Technol. Sci., vol. 5, no. 1, pp. 11–18, 2016.
26. Hudaib, R. Masadeh, and A. Alzaqebah, “WGW: A hybrid approach based on whale and grey wolf optimization algorithms for requirements prioritization,” Adv. Syst. Sci. Appl., vol. 18, no. 2, pp. 63–83, 2018.
    a. Kaveh and M. I. Ghazaan, “Enhanced whale optimization algorithm for sizing optimization of skeletal structures,” Mech. Based Des. Struct. Mach., vol. 45, no. 3, pp. 345–362, 2017.
27. M. Neshat, A. Adeli, G. Sepidnam, M. Sargolzaei, and A. N. Toosi, “A review of Artificial Fish Swarm Optimization methods and applications,” Int. J. Smart Sens. Intell. Syst., vol. 5, no. 1, pp. 107–148, 2012.
28. Y. Wu, X. Z. Gao, and K. Zenger, “Knowledge-based Artificial Fish-Swarm algorithm,” in The international Federation of Automatic Control, vol. 44, no. 1, pp. 14705–14710, 2011.
29. M. Mao, Q. Duan, P. Duan, and B. Hu, “Comprehensive improvement of artificial fish swarm algorithm for global MPPT in PV system under partial shading conditions,” Trans. Inst. Meas. Control, vol. 40, no. 7, pp. 2178–2199, 2018