TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 24, No. 1, February 2026, pp. 271~281
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v24i1.27594 ❒ 271

Anchovy-inspired filter algorithm: A bio-inspired optimization approach for high-dimensional benchmark functions

Azrul Mahfurdz[1], Muhammad Muizz Mohd Nawawi[1], Sunardi[2], Muhammad Azriq Abd Aziz[3]
[1]Department of Electrical Engineering, Politeknik Sultan Idris Shah, Sungai Lang, Sungai Air Tawar, Selangor, Malaysia
[2]Department of Electrical Engineering, Universitas Ahmad Dahlan, Yogyakarta, Indonesia
[3]Sapura Industrial Berhad, Bandar Baru Bangi, Selangor, Malaysia

Article Info

Article history:

Received Sep 10, 2025
Revised Oct 19, 2025
Accepted Dec 8, 2025

Keywords:

Anchovy-inspired filter
Bio-inspired optimization
Filter-based exploitation
Metaheuristics
Swarm intelligence

ABSTRACT

This paper presents the anchovy-inspired filter algorithm (AFA), a novel bio-inspired metaheuristic optimization method motivated by the filter-feeding behavior of anchovies. Unlike conventional swarm intelligence algorithms, AFA employs a filtering mechanism in which each agent generates multiple candidate solutions within a local sampling radius and selects the best, mimicking how anchovies filter microscopic prey from seawater. To evaluate its performance, AFA was benchmarked against particle swarm optimization (PSO) and genetic algorithm (GA) using six standard test functions: Sphere, Rosenbrock, Schwefel 1.2, Rastrigin, Griewank, and Ackley in 30-dimensional search spaces. Simulation results demonstrate that AFA consistently outperforms PSO and GA across unimodal and multimodal functions. For unimodal problems such as Sphere, Rosenbrock, and Schwefel 1.2, AFA achieved significantly lower best and mean fitness values, reflecting strong exploitation capability. For multimodal functions including Rastrigin, Griewank, and Ackley, AFA effectively avoided local minima, maintained robustness, and achieved stable convergence with lower variance. Convergence analysis further indicates that AFA steadily approaches near-global optima without premature stagnation. Overall, the results highlight the effectiveness of the filter-based exploitation mechanism in balancing exploration and exploitation. Future research will focus on adaptive filtering strategies, hybrid integration with other metaheuristics, and applications to real-world optimization problems.

Corresponding Author:

Azrul Mahfurdz
Department of Electrical Engineering, Politeknik Sultan Idris Shah
Sungai Lang, 45100 Sungai Air Tawar, Selangor, Malaysia
Email: azrul@psis.edu.my

1. INTRODUCTION

Metaheuristic optimization algorithms have gained increasing attention due to their ability to effectively handle complex, nonlinear, and multimodal optimization problems that are often intractable using conventional mathematical programming methods. Inspired by natural and biological processes, well-established approaches such as particle swarm optimization (PSO) [1], genetic algorithm (GA) [2], and ant colony optimization (ACO) [3] have been successfully employed in diverse domains including machine learning, engineering design, and scheduling tasks. Despite their success, these algorithms still face challenges in maintaining the balance between exploration and exploitation. Excessive exploration tends to delay convergence, whereas overly strong exploitation often results in premature convergence toward local optima [4]. This fundamental trade-off has motivated the search for novel bio-inspired paradigms that can provide alternative mechanisms for navigating the solution space more effectively.

Recent advances highlight the role of fish-inspired and filtering-based heuristics in addressing this issue. For instance, jellyfish search optimizer (JSO) [5] and simplified fish school search (SFSS) [6] employ unique movement operators to sustain population diversity and prevent stagnation. Similarly, filtering-based feature selection methods selectively retain the most informative candidates to reduce search complexity [7], [8]. Moreover, new fish-inspired designs such as the cuckoo catfish optimizer (CCO) [9] reflect the growing interest in marine-based behaviors for metaheuristic development. Metaheuristics continue to evolve with newer paradigms that address scalability, robustness, and convergence properties [10]. Recent advances highlight the adaptability of swarm-based methods across optimization domains, with novel variants designed to enhance convergence speed and maintain diversity [11].

In marine ecosystems, small pelagic fish such as anchovies and sardines feed by schooling in large groups while filtering plankton from surrounding water as demonstrated in Figure. 1. Unlike predators that chase individual prey, filter feeders continuously sample multiple particles and selectively retain only the beneficial fraction. Motivated by this unique strategy, we propose a new algorithm called the anchovy-inspired filter algorithm (AFA), which introduces filtering as a novel exploitation mechanism to improve convergence performance while preserving sufficient exploration.

Figure 1. A school of anchovies swims collectively

2. LITERATURE REVIEW

Swarm intelligence (SI) algorithms form an important class of metaheuristics inspired by collective behaviors observed in nature. Among them, PSO, GA, artificial fish swarm algorithm (AFSA), and fish school search (FSS) have received significant attention due to their ability to deal with high-dimensional and nonlinear problems. This section briefly reviews these approaches, emphasizing their underlying mechanisms, strengths, and limitations, while identifying the research gap that motivates the development of the AFA.

2.1. Particle swarm optimization

Introduced by Kennedy and Eberhart [1], PSO models the social dynamics of bird flocking and fish schooling. Each particle represents a solution that adjusts its trajectory based on its personal best and the global best. The algorithm is computationally efficient and easy to implement, but it is prone to premature convergence in multimodal search spaces [12].

2.2. Genetic algorithm

GA, proposed by Holland [2], applies principles of natural selection, crossover, and mutation to evolve a population of candidate solutions. It is versatile and has been applied in numerous optimization contexts. However, GA often demands careful parameter tuning and can become computationally expensive, particularly for large-scale problems [13].

2.3. Artificial fish swarm algorithm

The AFSA, originally proposed by Gao and Wen [14], imitates fish behaviors such as preying, swarming, and following, which enhances exploration in the solution space. Nevertheless, AFSA may suffer from slow convergence and the risk of stagnation if the balance between exploration and exploitation is not effectively managed [15], [16].

2.4. Fish school search

FSS, proposed by Filho *et al.* [17], draws from the collective behavior of fish schools. By incorporating feeding and coordinated swimming, FSS introduces mechanisms for balancing exploration and exploitation. Despite its potential, FSS can be highly sensitive to parameter selection and may underperform in complex multimodal landscapes [18], [19].

2.5. Research gap: filter-feeding mechanism

Although AFSA and FSS are both inspired by fish, they primarily model movement and foraging strategies rather than selective feeding. In contrast, anchovies and sardines employ a filter-feeding process, whereby each fish continuously samples plankton and selectively retains high value particles while discarding the rest [20], [21]. This mechanism represents an efficient natural filtering process that maximizes energy gain while minimizing cost. To the best of our knowledge, no existing metaheuristic explicitly incorporates filter feeding as an optimization operator. Fish-inspired algorithms such as AFSA and FSS capture aspects of group dynamics, but they lack the selective filtering mechanism. This gap highlights the potential of a new paradigm where filtering acts as a novel exploitation strategy such sampling widely (exploration) but only retaining promising candidates (exploitation). The proposed AFA addresses this gap, extending swarm intelligence with a biologically grounded filtering principle.

2.6. Anchovy-inspired filter algorithm

Motivated by the natural feeding behavior of anchovies, we propose an improved bio-inspired optimization method. Anchovies feed by filtering plankton suspended in the water. A school of anchovies swims collectively while each fish continuously filters water, retaining only edible particles and discarding the rest. This efficient filtering mechanism ensures survival while balancing focused exploitation (capturing plankton) and diverse exploration (school movement to new feeding grounds).

In optimization, this biological process is modeled:

a. Candidate generation (filtering intake): each anchovy samples multiple candidate solutions around its position, analogous to filtering water for plankton.
b. Filtering operator (selective feeding): only the best candidate is retained, mimicking the retention of nutritious plankton.
c. Schooling movement (collective exploration): anchovies adjust their positions collectively towards the global best, ensuring population-level search.
d. Dynamic filtering size: the filter step shrinks over time, promoting exploration in early stages and exploitation in later stages.
e. Elitism and local refinement: the best solutions are preserved each iteration, while the global best undergoes Gaussian-based local search for further refinement.

2.6.1. Initialization (school formation)

Each anchovy represents a solution vector. The initial school is randomly distributed in the search space:

$$x^0 \sim U\,(lb, ub)\,, i = 1,2,\dots,N \tag{1}$$

where N is the school size (population), and $[lb,\ ub]$ defines the ocean boundaries (search space). This corresponds to a school of anchovies initially scattered across the sea.

2.6.2. Fitness evaluation (plankton quality)

The nutritional value of plankton is represented by the fitness function:

$$f(x_i) = objective\ function\ (\,x_i) \tag{2}$$

where better fitness values correspond to more nutritious plankton captured by an anchovy.

2.6.3. Dynamic filter size (mouth aperture)

Anchovies regulate their mouth aperture dynamically. At the start, the filter is wide (exploration), but gradually narrows (exploitation) over time:

$$\delta(t) = \delta_{max} - \frac{t}{T}\,(\delta_{max} - \delta_{min}\,) \tag{3}$$

where t is the iteration index and T is the maximum number of iterations.

2.6.4. Candidate generation (plankton intake)

Each anchovy generates M candidate solutions within its filter radius as demonstrated in Figure 2.

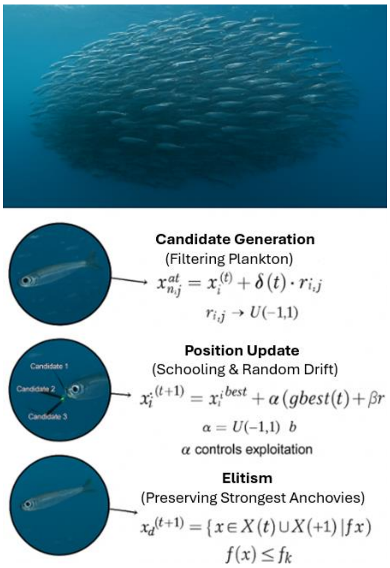

Figure 2. Anchovies filtering plankton as an analogy to candidate generation and selective filtering in AFA

$$x_{i,j}^{cand} = x_i\ (t) + \ \delta(t)\ .r_{i,j}\ , r_{i,j} \sim U(-1,1) \tag{4}$$

The best candidate solution (the most nutritious plankton particle) is selected.

$$x_i^{best}(t) = \arg min\ _j\ f\big(\ x_{i,j}^{cand}\ (t)\ \big) \tag{5}$$

2.6.5. Position update (schooling and random drift)

Anchovies synchronize with the global best while maintaining random drift.

$$x_i(t+1) = x_i^{best}\ (t) + \alpha\ .\Big(gbest(t) - x_i^{best}(t)\Big) + \beta.r\_i \tag{6}$$

where *gbest(t)* is the best anchovy in the school, $ri \sim U(-1,1)$, α controls exploitation, and β controls exploration.

2.6.6. Elitism (preserving strongest anchovies)

Elitism is applied to preserve the strongest anchovies representing high-quality solutions. This strategy ensures that the best solutions are not lost during the iterative update process. Consequently, elitism improves convergence consistency and overall optimization performance. To retain high-quality solutions, elitism is applied:

$$x_{elite}\ (t+1) = \{x \in X(t) \cup X(t+1) |\ f(x)\ \leq\ f_k\} \tag{7}$$

2.6.7. Local search on global best (anchovy mutation)

Anchovies refine their feeding by adjusting their filter mesh. The global best undergoes Gaussian mutation:

$$gbest'(t) = gbest\ (t) + \in (t)\ .N(0, I) \tag{8}$$

with a decaying perturbation factor:

$$\in (t) = \in_{max} \left(1\ - \frac{t}{T}\right) \tag{9}$$

Finally, the global best is updated by selecting the solution with the lowest fitness value among the previous global best and the mutated candidate:

$$gbest(t+1) = \arg min\{f(gbest(t)), f(gbest'(t))\} \quad (10)$$

3. ALGORITHM TESTING AND EVALUATION

Six benchmark functions were employed for the simulations, as defined in [21]–[26]. Table 1 provides the corresponding search domain, initialization range, and global optimum meanwhile Table 2 showed parameter setting for AFA, PSO and GA. All functions were tested in a 30-dimensional space under minimization. Among them, Sphere, Rosenbrock and Schwefel 1.2 are unimodal, whereas Rastrigin, Griewank, and Ackley are multimodal with numerous local minima.

$$F_{Sphere}\,(x) = \sum_{i=1}^{n} x_i^2 \quad (11)$$

$$F_{Rosenbrock}\,(x) = \sum_{i=1}^{n-1}[100(x_{i+1} - x^2) + (x_i - 1)^2 \quad (12)$$

$$F_{Schwefel\ 1.2}\,(x) = \sum_{i=1}^{n} (\sum_{j=1}^{i} x_j)^2 \quad (13)$$

$$F_{Rastrigin}\,(x) = 10n + \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i)] \quad (14)$$

$$F_{Griewank}\,(x) = 1 + \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos\left(\frac{x_i}{\sqrt{i}}\right) \quad (15)$$

$$F_{Ackley}\,(x) = -20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}) \quad (16)$$

$$\exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i) + 20 + e$$

Table 1. Functions used: search space, initialization range, and optima

Function	Parameters		
	Search space	Initialization	Optima
Sphere	-100≤ xi ≤100	[-50,50]	0.0^D
Rosenbrock	-30≤ xi ≤ 30	[15,30]	1.0^D
Schwefel 1.2	-100≤ xi ≤100	[50,100]	0.0^D
Rastrigin	5.12≤ xi ≤5.12	[-2.56,2.56]	0.0^D
Griewank	-600≤ xi ≤600	[-300,600]	0.0^D
Ackley	-32≤ xi ≤32	[-16,32]	0.0^D

Table 2. Parameter setting for AFA, PSO and GA

Algorithms	Population size (N)	Parameter	
AFA	50	(M) Candidates	15
		α (alpha)	0.6
		β (beta)	0.3
		δ_max	0.5
		δ_min	0.01
		Elite number	5
PSO	50	Inertia weight (w)	0.7
		Cognitive factor ($c1$)	1.5
		Social factor ($c2$)	1.5
GA	50	Crossover rate	0.8
		Mutation rate	0.1

4. SIMULATION RESULTS

The performance of the proposed AFA was compared against PSO and GA using six well-known benchmark functions: Sphere, Rosenbrock, Schwefel 1.2, Rastrigin, Griewank, and Ackley. The comparison was made based on best fitness mean, standard deviation, minimum, and maximum fitness values. For the Sphere function, AFA demonstrated superior convergence capability with the lowest mean fitness and standard deviation compared to PSO and GA (Table 3). The convergence behavior is further illustrated in Figure 3, where AFA rapidly reached near-optimal values while PSO and GA lagged significantly.

In the Rosenbrock function, which is a unimodal problem with a narrow valley, AFA again outperformed the other algorithms, yielding substantially lower best and mean fitness values (Table 4). The convergence plot in Figure 4 confirms AFA's ability to effectively navigate the challenging optimization landscape.

Table 3. Simulation results for sphere function

Algorithm	Best fitness mean	Standard deviation (std)	Minimum fitness	Maximum fitness
AFA	1.2340e-04	2.4167e-05	7.5755e-05	1.6364e-04
PSO	7.0828e-01	1.3879e+00	5.5781e-02	7.5132e+00
GA	9.8794e+04	1.1676e+04	7.9693e+04	1.2742e+05

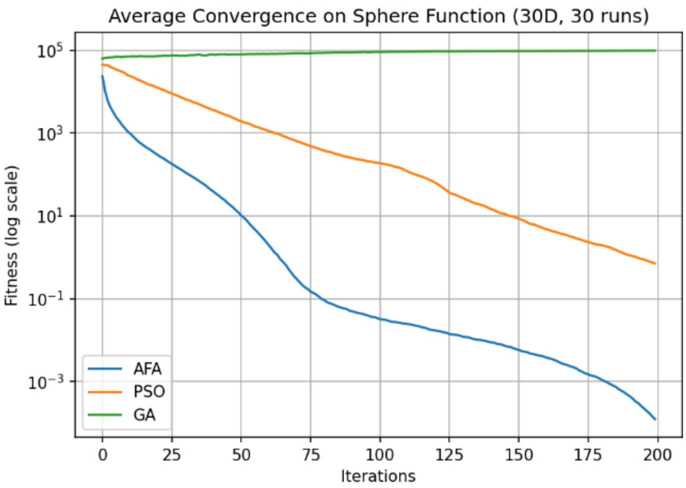

Figure 3. Convergence curve comparison for Sphere function

Table 4. Simulation results for Rosenbrock function

Algorithm	Best fitness mean	Standard deviation (std)	Minimum fitness	Maximum fitness
AFA	6.1512e+01	5.1125e+01	1.7130e-01	1.5687e+02
PSO	2.2489e+04	3.0820e+04	1.8793e+01	1.1116e+05
GA	3.4710e+06	1.0934e+06	1.7858e+06	5.5084e+06

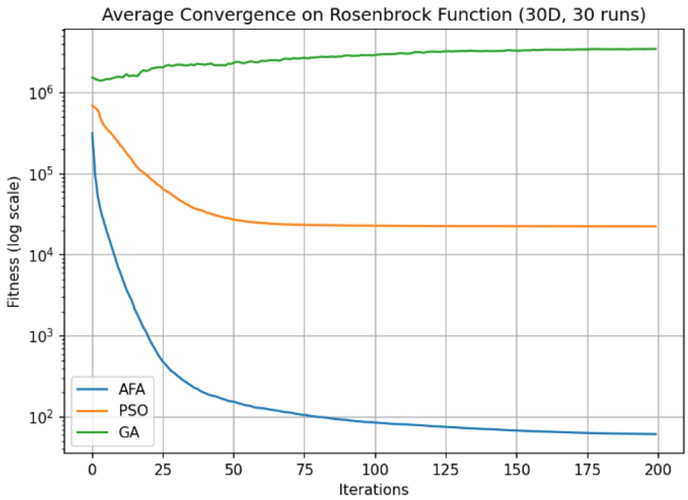

Figure 4. Convergence curve comparison for Rosenbrock function

For the Schwefel 1.2 function, AFA achieved a more stable performance with much smaller mean and variance than PSO and GA (Table 5). As shown in Figure 5, AFA consistently converged to lower fitness values, while PSO and GA fluctuated widely across iterations. The Rastrigin function, known for its multimodal landscape, further highlighted AFA's robustness. AFA attained the lowest mean fitness among all algorithms (Table 6). Figure 6 shows that AFA avoided local minima more effectively than PSO and GA, demonstrating strong exploration-exploitation balance.

Table 5. Simulation results for Schwefel 1.2 function

Algorithm	Best fitness mean	Standard deviation (std)	Minimum fitness	Maximum fitness
AFA	78.578	29.800	20.389	151.59
PSO	11155	4976.2	1.648.7	25819
GA	853620	8.22080	1.25450	3614400

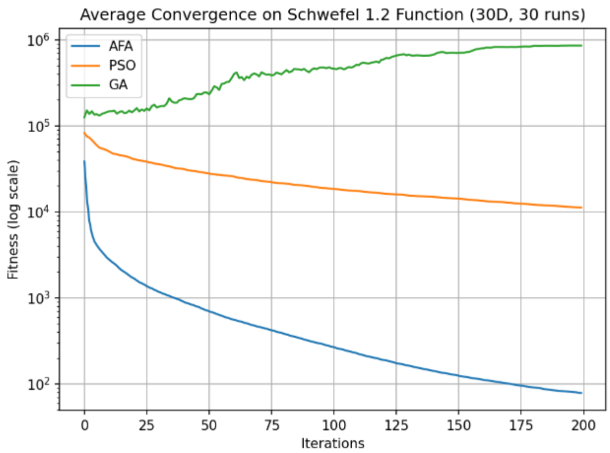

Figure 5. Convergence curve comparison for Schwefel 1.2 function

Table 6. Simulation results for Rastrigin function

Algorithm	Best fitness mean	Standard deviation (std)	Minimum fitness	Maximum fitness
AFA	1.7965e+01	4.7167e+00	8.2019e+00	2.7114e+01
PSO	1.0208e+02	3.2535e+01	4.8681e+01	1.8028e+02
GA	5.0714e+02	5.8857e+01	3.6608e+02	6.6018e+02

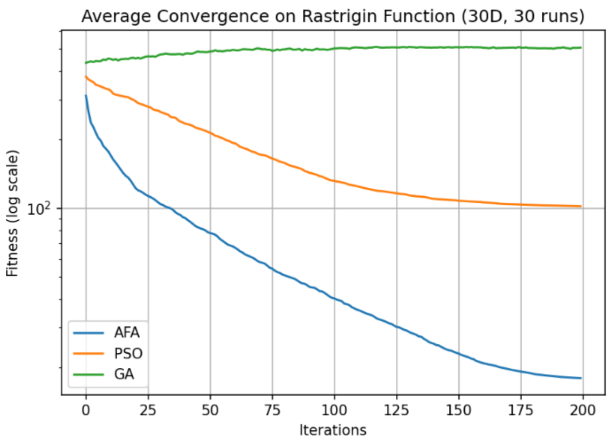

Figure 6. Convergence curve comparison for Rastrigin function

In the Griewank function, AFA once again obtained significantly lower mean and variance compared to PSO and GA (Table 7). The convergence curves in Figure 7 reinforce AFA's superior stability and accuracy in achieving near-global optima.

Finally, for the Ackley function, both AFA and PSO recorded competitive results, while GA produced substantially poorer outcomes (Table 8). As illustrated in Figure 8, AFA maintained consistent convergence with relatively low variance across runs. Overall, the simulation results across all six benchmark functions clearly indicate that AFA consistently outperforms PSO and GA in terms of convergence speed, accuracy, and stability.

Table 7. Simulation results for Griewank function

Algorithm	Best fitness mean	Standard deviation (std)	Minimum fitness	Maximum fitness
AFA	0.10265	0.076206	0.00078990	0.30514
PSO	3.3499	16.129	0.042825	90.191
GA	867.88	119.20	634.79	1071.3

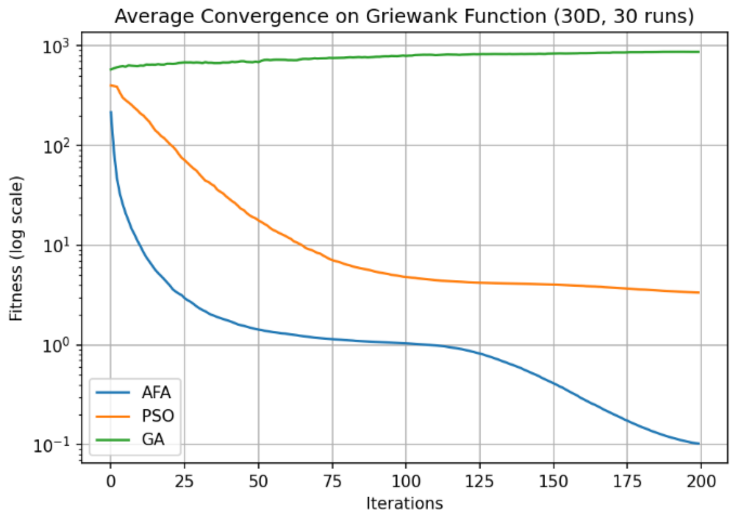

Figure 7. Convergence curve comparison for Griewank function

Table 8. Simulation results for Ackley function

Algorithm	Best fitness mean	Standard deviation (std)	Minimum fitness	Maximum fitness
AFA	2.8883	1.0182	0.00.67092	5.3508
PSO	2.1637	1.0197	0.63893	5.2479
GA	2.1.036	0.24934	20.521	21.546

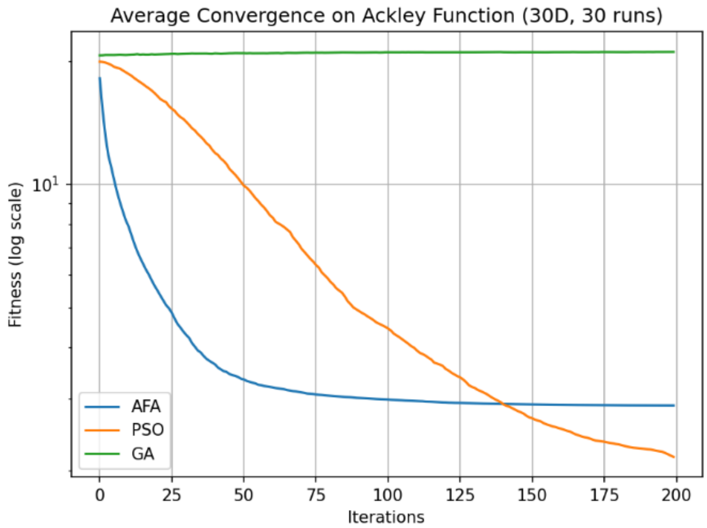

Figure 8. Convergence curve comparison for Ackley function

5. DISCUSSION

The comparative analysis of AFA, PSO, and GA across six benchmark functions highlights the distinct advantages of the proposed AFA approach. For unimodal functions such as Sphere, Rosenbrock, and Schwefel 1.2, AFA consistently achieved lower best and mean fitness values with smaller standard deviations. This indicates that AFA is highly effective in refining solutions towards the global optimum and demonstrates strong exploitation capability. In contrast, PSO exhibited slower convergence and larger variance, while GA struggled significantly in these problems due to premature convergence and weaker local search ability. For multimodal functions such as Rastrigin, Griewank, and Ackley, AFA again showed superior robustness. The ability of AFA to balance exploration and exploitation allowed it to escape local minima and converge closer to the global optimum. The convergence curves (Figures 6 to 8) confirm that AFA maintained stable progress across iterations, whereas PSO and GA often became trapped in suboptimal regions or displayed high fluctuations. Notably, in the Ackley function, PSO produced results relatively close to AFA, but GA remained significantly inferior in performance.

These findings demonstrate that the unique filter-based mechanism in AFA provides both diversity preservation and directional guidance, which improves global search capacity. The adaptive movement of candidate solutions in AFA prevents stagnation, ensuring a higher probability of reaching the global optimum compared to conventional PSO and GA.

6. CONCLUSION

The simulation results on six benchmark functions demonstrate that the proposed AFA significantly outperforms conventional PSO and GA in terms of convergence speed, accuracy, and stability. AFA consistently produced lower best and mean fitness values with reduced variance across unimodal and multimodal functions.

In unimodal problems, AFA exhibited strong exploitation ability by rapidly converging to the global optimum. For multimodal problems, AFA maintained robustness by effectively avoiding local minima and achieving better global search performance. Overall, these results confirm that AFA provides a competitive and reliable optimization tool, capable of addressing complex optimization landscapes more efficiently than traditional metaheuristic algorithms. Future work will focus on extending the application of AFA to real-world optimization problems and exploring hybrid variants that may further enhance its performance.

FUNDING INFORMATION

No funding is involved in this work.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Azrul Mahfurdz	✓	✓	✓	✓	✓	✓		✓	✓	✓				
Muhammad Muizz					✓			✓	✓	✓	✓			
Mohd Nawawi														
Sunardi					✓					✓	✓	✓		
Muhammad Azriq Abd Aziz		✓	✓	✓						✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author, Azrul Mahfurdz on request.

REFERENCES

[1] J. Kennedy and R. Eberhart, "Particle swarm optimization," *Proceedings of ICNN'95 - International Conference on Neural Networks*, Perth, WA, Australia, 1995, pp. 1942-1948 vol.4, doi: 10.1109/ICNN.1995.488968.

[2] J. H. Holland, "Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence," *The MIT Press edition*, vol. 89, no. 12, 1992.

[3] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization," in *IEEE Computational Intelligence Magazine*, vol. 1, no. 4, pp. 28-39, Nov. 2006, doi: 10.1109/MCI.2006.329691.

[4] X.-S. Yang, "Nature-Inspired optimization algorithms," *Nature-Inspired Optimization Algorithms*, 2014, doi: 10.1016/B978-0-12-416743-8.00017-8.

[5] J. S. Chou and A. Molla, "Recent advances in use of bio-inspired jellyfish search algorithm for solving optimization problems," *Scientific Reports*, vol. 12, no. 1, pp. 1-23, 2022, doi: 10.1038/s41598-022-23121-z.

[6] E. Figueiredo *et al.*, "A simplified fish school search algorithm for continuous single-objective optimization," *Computation*, vol. 13, no. 5, pp. 1–15, 2025, doi: 10.3390/computation13050102.

[7] M. A. Siddiqi and W. Pak, "Optimizing filter-based feature selection method flow for intrusion detection system," *Electronics*, vol. 9, no. 12, pp. 1–18, 2020, doi: 10.3390/electronics9122114.

[8] C. Yan *et al.*, "A novel hybrid filter/wrapper feature selection approach based on improved fruit fly optimization algorithm and chi-square test for high dimensional microarray data," *Current Bioinformatics*, vol. 16, no. 1, pp. 63–79, 2021, doi: 10.2174/1574893615666200324125535.

[9] T. L. Wang, S. W. Gu, R. J. Liu, L. Q. Chen, Z. Wang, and Z. Q. Zeng, "Cuckoo catfish optimizer: a new meta-heuristic optimization algorithm," *Artificial Intelligence Review*, vol. 58, no. 10, 2025, doi: 10.1007/s10462-025-11291-x.

[10] T. Dokeroglu, E. Sevinc, T. Kucukyilmaz, and A. Cosar, "A survey on new generation metaheuristic algorithms," *Computers & Industrial Engineering*, vol. 137, 2019, doi: 10.1016/j.cie.2019.106040.

[11] Z. Gao and B. Wang, "Multi-strategy-driven salp swarm algorithm for global optimization," *Journal of Computer and Communications*, vol. 11, no. 07, pp. 88–117, 2023, doi: 10.4236/jcc.2023.117007.

[12] D. Bratton and J. Kennedy, "Defining a standard for particle swarm optimization," *2007 IEEE Swarm Intelligence Symposium*, Honolulu, HI, USA, 2007, pp. 120-127, doi: 10.1109/SIS.2007.368035.

[13] F. Pourpanah, R. Wang, C. P. Lim, X. Z. Wang, and D. Yazdani, "A review of artificial fish swarm algorithms: recent advances and applications," *Artificial Intelligence Review*, vol. 56, no. 3, pp. 1867–1903, 2023, doi: 10.1007/s10462-022-10214-4.

[14] S. Gao and Y. Wen, "An improved artificial fish swarm algorithm and its application," *2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS)*, Singapore, 2018, pp. 649-652, doi: 10.1109/ICIS.2018.8466458.

[15] J. Tang, G. Liu, and Q. Pan, "A review on representative swarm intelligence algorithms for solving optimization problems: applications and trends," in *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 10, pp. 1627-1643, October 2021, doi: 10.1109/JAS.2021.1004129.

[16] Y. Li, J. Zhang, Y. Yin, and L. Wang, "An improved artificial fish-swarm algorithm and its applications," *2021 China Automation Congress (CAC)*, Beijing, China, 2021, pp. 5725-5730, doi: 10.1109/CAC53003.2021.9728495.

[17] C. J. A. B. Filho, F. B. d. L. Neto, A. J. C. C. Lins, A. I. Nascimento, and M. P. Lima, "Fish school search," *Nature-Inspired Algorithms for Optimisation*, vol. 193, pp. 261–277, 2009, doi: 10.1007/978-3-642-00267-0_9.

[18] B. A. M. Menezes, F. Wrede, H. Kuchen, and F. B. L. Neto, "Parameter selection for swarm intelligence algorithms: Case study on parallel implementation of FSS," *International Journal of Swarm Intelligence Research (IJSIR)*, vol. 9, no. 4, pp. 1–20, 2018, doi: 10.4018/IJSIR.2018100101.

[19] J. B. M. Filho, I. M. C. d. Albuquerque, F. B. d. L. Neto, and F. V. S. Ferreira, "Optimizing multi-plateau functions with FSS-SAR (stagnation avoidance routine)," *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, Athens, Greece, 2016, pp. 1-7, doi: 10.1109/SSCI.2016.7850272.

[20] N. Carey and J. A. Goldbogen, "Kinematics of ram filter feeding & beat-glide swimming in the northern anchovy Engraulis mordax," *Journal of Experimental Biology*, vol. 220, no. 15, pp. 2717–2725, 2017, doi: 10.1242/jeb.158337.

[21] D. Costalago and I. Palomera, "Feeding of European pilchard (sardina pilchardus) in the northwestern Mediterranean: from late larvae to adults," *Scientia Marina*, vol. 78, no. 1, pp. 41–54, 2014, doi: 10.3989/scimar.03898.06d.

[22] C. J. A. B. Filho, F. B. d. L. Neto, A. J. C. C. Lins, A. I. S. Nascimento, and M. P. Lima, "A novel search algorithm based on fish school behavior," *2008 IEEE International Conference on Systems, Man and Cybernetics*, Singapore, 2008, pp. 2646-2651, doi: 10.1109/ICSMC.2008.4811695.

[23] R. H. Abiyev and M. Tunay, "Optimization of high-dimensional functions through hypercube evaluation," *Computational Intelligence and Neuroscience*, vol. 2015, no. 1, 2015, doi: 10.1155/2015/967320.

[24] M. A. Arasomwan and A. O. Adewumi, "Improved particle swarm optimization with a collective local Unimodal search for continuous optimization problems," *The Scientific World Journal*, vol. 2014, no. 1, 2014, doi: 10.1155/2014/798129.

[25] S. G. De-Los-Cobos-Silva, M. Á. Gutiérrez-Andrade, R. A. Mora-Gutiérrez, P. Lara-Velázquez, E. A. Rincón-García, and A. Ponsich, "An efficient algorithm for unconstrained optimization," *Mathematical Problems in Engineering*, vol. 2015, no. 1, 2015, doi: 10.1155/2015/178545.

[26] M. I. Jarrah *et al.*, "A novel explanatory hybrid artificial bee colony algorithm for numerical function optimization," *The Journal of Supercomputing*, vol. 76, no. 12, pp. 9330–9354, 2020, doi: 10.1007/s11227-019-03083-2.

BIOGRAPHIES OF AUTHORS

Azrul Mahfurdz received a degree in Electrical Engineering with Honours from Universiti Tun Hussein Malaysia (UTHM) in 2004. Received his Master's in Technical and Vocational Education from Universiti Tun Hussein Onn Malaysia (UTHM) in 2006 and Ph.D. in Electrical Engineering from Universiti Malaysia Pahang (UMP). Currently, he serves as a senior lecturer at the Department of Electrical Engineering, Politeknik Sultan Idris Shah. His research interests include machine learning, IOT system and signal processing. He can be contacted at email: azrul@psis.edu.my.

Muhammad Muizz Mohd Nawawi received a degree in Electrical Engineering Control, Instrumentation, and Automation with Honours from Universiti Teknikal Malaysia Melaka (UTeM) in 2007. Received his Master's in Technical and Vocational Education from Universiti Tun Hussein Onn Malaysia (UTHM) in 2009. and Ph.D. in Electrical Engineering from International Islamic University Malaysia (IIUM). Currently serve as a senior lecturer at the Department of Electrical Engineering, Politeknik Sultan Idris Shah. He can be contacted at email: muizznawawi@psis.edu.my.

Sunardi received his Bachelor's degree in Electrical Engineering from Universitas Gadjah Mada, Yogyakarta, Indonesia, in 1999. He obtained his Master's degree in Electrical Engineering from Institut Teknologi Bandung, Bandung, Indonesia, in 2003, and later earned his Ph.D. in Electrical Engineering from Universiti Teknologi Malaysia, Johor Bahru, Malaysia, in 2011.He is currently a Professor at the Department of Electrical Engineering, Universitas Ahmad Dahlan, Yogyakarta. His research interests include information processing, and communication systems. He can be contacted at email: sunardi@mti.uad.ac.id.

Muhammad Azriq Abd Aziz received his Diploma in Electronic Engineering (Computer) from Politeknik Sultan Idris Shah. He is currently working with Sapura Industrial Berhad. He has experience and expertise in Python programming, with particular research and development interests in image processing and face recognition. He can be contacted at email: azriqaziz0405@gmail.com.