MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 561-567
ELSEVIER

BLOMBO: A HYBRID METAHEURISTIC ALGORITHM BASED ON BEES LIFE OPTIMIZATION AND MIGRATING BIRDS OPTIMIZATION WITH A QUANTUM-INSPIRED EXTENSION

Mitat Uysal [1*], **S.Aynur Uysal** [2], **Elif Erçelik** [3]
[1,2,3]*Doğuş University, Department of Software Engineering, 34764, Istanbul, Turkiye*
*Corresponding author's e-mail: ** ***muysal@dogus.edu.tr***

Abstract: *Nature-inspired metaheuristic algorithms have demonstrated strong capability in solving complex nonlinear optimization problems; however, achieving an effective balance between exploration and exploitation remains a critical challenge. In this study, a novel hybrid metaheuristic algorithm, BLOMBO (Bees Life Optimization and Migrating Birds Optimization), is proposed to address this issue. The algorithm integrates the local exploitation strength of Bees Life Optimization (BLO) with the cooperative exploration mechanism of Migrating Birds Optimization (MBO) within a unified framework.*
To evaluate its performance, BLOMBO is tested on five well-known benchmark functions: Sphere, Rastrigin, Ackley, Rosenbrock, and Griewank. The results are compared with the standalone BLO and MBO algorithms in terms of convergence speed, solution quality, and computational efficiency. Experimental results indicate that BLOMBO achieves competitive and stable performance across all benchmark functions, often providing improved convergence behavior and maintaining a strong balance between exploration and exploitation.These findings suggest that the proposed hybrid approach is a promising alternative for solving complex optimization problems, particularly in scenarios requiring both global search capability and local refinement.
Keywords: *Bees Life Optimization; Migrating Birds Optimization; Hybrid Metaheuristics; Global Optimization.*

1. INTRODUCTION

Optimization is the problem of determining the best solution from a set of solutions under certain constraints, and it plays an important role in solving complex problems in many fields, particularly in science and engineering. Most mathematical optimization methods rely on gradient information and exhaustive search processes, which can be computationally expensive [1]. On the other hand, metaheuristic algorithms provide flexible and effective alternatives that have been widely used in practice [2]. These algorithms typically start with randomly generated solutions and employ a balance between exploration and exploitation to efficiently search complex solution spaces [3], [4],[5],[6],[7].

Numerous metaheuristic algorithms have been proposed in the literature, including genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and migrating birds optimization (MBO), among others [8]. Due to their versatility, ease of implementation, and robustness, these algorithms have been successfully applied to a wide range of real-world optimization problems. However, despite their advantages, individual metaheuristic algorithms may suffer from limitations such as premature convergence or insufficient exploration capability.

To address these issues, hybrid metaheuristic approaches—combining two or more algorithms—have gained increasing attention. Such approaches aim to exploit the complementary strengths of different algorithms to improve convergence speed and reduce the risk of getting trapped in local optima. For example, a PSO–GA hybrid algorithm combining global exploration and local search capabilities was proposed in [9]. Similarly, the DESA algorithm integrates differential evolution with simulated annealing [10]. Hybrid approaches have also been applied to cloud manufacturing [11], job shop scheduling problems [12], [13], and combinatorial optimization tasks [14]. In addition, recent studies have demonstrated the effectiveness of hybrid swarm intelligence methods in global optimization problems [15], [16].Recently, Quantum-Inspired Metaheuristics (QIM) have been introduced as an alternative paradigm. These approaches utilize concepts such as qubit representation and quantum superposition to enhance diversity and avoid premature convergence [17]. QIM-based algorithms have shown promising performance in multi-objective optimization problems [18], [19], [20], as well as in clustering applications [21]. Furthermore, quantum-inspired variants of PSO and GA have demonstrated improved performance in discrete and complex search spaces [22], [23].

In this paper, a novel hybrid metaheuristic algorithm named BLOMBO is proposed. The algorithm integrates the complementary advantages of Bees Life Optimization (BLO) and Migrating Birds Optimization (MBO) to enhance both solution quality and convergence efficiency for complex optimization problems. BLO mimics the foraging and reproduction processes of bees and is effective for solving both unimodal and multimodal optimization problems [24]. MBO, inspired by the V-formation flight behavior of birds, enables cooperative exploration of the search space and has demonstrated competitive performance compared to other metaheuristics [25]. By combining these two approaches, BLOMBO aims to achieve a better balance between exploration and exploitation.

The performance of the proposed BLOMBO algorithm is evaluated using five well-known benchmark functions. The results are compared with those of the original BLO and MBO algorithms.

This paper is organized as follows. Section 2 describes the BLO and MBO algorithms and introduces the proposed BLOMBO algorithm. Section 3 presents the experimental study and discusses the obtained results. Section 4 concludes the paper.

2. RESEARCH METHODS

2.1 BLO Algorithm: The BLO algorithm, originally proposed by [24] mimics the foraging behavior of honeybee swarms through three main phases: employed bee, onlooker bee, and scout bee. Each solution is treated as a food source, with its fitness corresponding to nectar amount. Employed bees explore nearby solutions and share quality information with onlookers, who then probabilistically select sources for further exploitation. If a solution is overused (simulating nectar depletion), it is abandoned and the corresponding bee becomes a scout, searching for new solutions [26]. The pseudocode of BLO is given in **Algorithm 1.**

Algorithm 1. BLO Algorithm
Initialize control parameters and generate an initial population of SN food sources $x_i, i = 1,2,..,SN$, each with D dimensions using: $x_i^j = x_{min}^j + rand[0,1] \times (x_{max}^j - x_{min}^j), j = 1,2,\dots,D.$
Evaluate the fitness values of all food sources.
Repeat
for each employed bee i **do**
Generate a neighbor food source v_i using: $v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj})$, where $k \neq i$ is a random index, and $\emptyset_{ij} \in [-1,1]$. Select the better food source between x_i and v_i. **end for**
Calculate selection probabilities p_i for all food sources:
$p_i = \frac{fitness_i}{\sum_{n=1}^{SN} fitness_n}$
for each onlooker bee **do**
Choose a food source x_i according to probability p_i.
Generate a neighbor v_i using the same equation as employed bees.
Select the better food source between x_i and v_i.
end for
Memorize the best solution found so far.
Identify any exhausted food sources and replace them with new random solutions using the initialization equation.
until termination criteria (e.g. max evaluations) is met.
return the best solution found

2.2 MBO Algorithm: The MBO algorithm is inspired by the cooperative behavior and communication patterns of bird flocks during migration [25]. In this approach, each solution is treated as an individual within a population. Through the continuous movement and interaction of these individuals, the algorithm gradually explores the search space to discover optimal or near-optimal solutions to the given problem. The pseudocode of MBO is given in **Algorithm 2.**

Algorithm 2. MBO Algorithm
Generate n initial solutions randomly and arrange them in a V-formation.
Initialize iteration counter $i = 0$.
while $i < K$ do
for $j = 0$ to $m - 1$ **do**
Calculate selection probabilities p_i for all food sources:
Generate k neighbors of the leader solution and evaluate their fitness.
Update iteration count: $i = i + k$.
for each other solution s_r in the flock **do**
Generate k-x neighbors of s_r.
Combine with x unused best neighbors shared from the preceding solution.
Update iteration count: $i = i + (k - x)$.
end for
end for
Move the current leader to the end of the formation. Promote the next solution to become the new leader.
end while
return the best solution found.

2.3 BLOMBO Algorithm Design: The proposed BLOMBO algorithm integrates the swarm intelligence principles of BLO with the structured leader–follower dynamics of MBO, forming a hybrid metaheuristic framework. The design is structured into the following major stages:

Step 1: Initialization: The BLOMBO algorithm begins by generating an initial population of N candidate solutions, each modeled as a bee. Solutions are sampled uniformly within the feasible search space $[L, U]^D$:

$$P^{(0)} = \{x_1^{(0)}, x_2^{(0)}, \dots, x_N^{(0)}\}, \tag{1}$$

$$x_i^{(0)} = L + (U - L) \cdot r_i, \tag{2}$$

$$r_i \sim U(0,1)^D \tag{3}$$

where D is the problem dimension, L and U are the lower and upper bounds of the search space, and r_i is a random vector.

After initialization, each candidate solution $x_i^{(0)}$ is evaluated using the fitness function $f(x_i)$. The best-performing solution is designated as the leader:

$$\ell = \arg\min_{x_i \epsilon P^{(0)}} f(x_i) \tag{4}$$

while the remaining $N - 1$ solutions are assigned as followers, organized into a V-formation topology as in MBO, where each follower is influenced by the leader and its nearest neighbor.

Step 2: Evaluation

In this step, each candidate solution $x^i \in P^{(t)}$ is evaluated using the predefined objective (benchmark) function f.The fitness value is computed as:

$$f_i = f(x_i) \qquad i = 1,2, \dots, N \tag{5}$$

where N is the population size.

For minimization problems, the best solution at iteration t is defined as:

$$x^*(t) = \arg\min_{x_i \epsilon P^{(t)}} f(x_i) \tag{6}$$

and the corresponding best fitness value is:

$$f^*(t) = \min_{x_i \epsilon P^{(t)}} f(x_i). \tag{7}$$

The computed fitness values $\{f_1, f_2, \dots, f_N\}$ are stored and subsequently used to guide the selection of the queen and worker bees (BLO exploitation phase) as well as the leader–follower dynamics (MBO exploration phase).

Step 3: Exploitation Phase (BLO Behavior)

In the exploitation stage, the algorithm intensifies the search around high-quality solutions using the core principles of Bee Life Optimization (BLO).

a. Queen Selection

The best-performing solution in the population is designated as the queen:

$$Q = \arg\min_{x_i \epsilon P^{(t)}} f(x_i) \tag{8}$$

which serves as the primary reference for generating new offspring (workers).

b. Worker Generation

The population is divided into two groups: elite bees E and normal bees N, where $|E| = N_e$ and $|N| = N_n$ with $N_e + N_n = N$.

For each elite bee $x_e \in E$, ω_e workers are generated as:

$$x_{new} = x_e + r_{elite} \cdot \varepsilon, \varepsilon \sim N(0,1) \tag{9}$$

where r_{elite} is a small neighborhood radius ensuring intensive local search.

For each normal bee $x_n \in N$, ω_n workers are generated as:

$$x_{new} = x_n + r_{norm} \cdot \varepsilon, \qquad \varepsilon \sim N(0, I), \tag{10}$$

with $r_{norm} > r_{eliter}$, enabling broader exploration.

c. Neighborhood Search

Elite bees exploit the local region around promising solutions (fine-grained search).

Normal bees explore less promising areas with larger step sizes, introducing diversity into the population.

After evaluating all new workers, the best N solutions are retained according to fitness (elitist selection):

$$P^{(t+1)} = SelectBest(P^{(t)} \cup W, N), \tag{11}$$

where W is the set of generated workers.

Step 4: Exploration Phase (MBO Behavior)

In the exploration stage, the algorithm applies the principles of MBO. The search process is guided by the leader–follower dynamics of the V-formation, enhancing global exploration while maintaining solution diversity.

a. Leader Guidance

At each iteration t, the leader solution ℓ explores new regions of the search space by perturbation:

$$\ell_{new} = \ell + \eta, \qquad \eta \sim N(0, \sigma^2(t) I) \tag{12}$$

where σ(t) is a time-decaying variance controlling the exploration radius:

$$\sigma(t) = \left(\frac{T-t}{T}\right)^n \cdot (\sigma_{init} - \sigma_{final}) \quad (13)$$

If the new position yields better fitness, the leader is updated:

$$f(\ell^{new}) < f(\ell) \quad \Rightarrow \quad \ell \leftarrow \ell^{new}. \quad (14)$$

b. Follower Update

Each follower x_i $(i = 2, \ldots, N)$ updates its position by considering the leader ℓ and its nearest neighbor nb_i in the V-formation:

$$x_i^{new} = x_i + \beta_1(\ell - x_i) + \beta_2(nb_i - x_i) + \varepsilon \quad (15)$$

where β_1 is the leader's influence factor, β_2 is the neighbor's influence factor, $\varepsilon \sim N(0, \sigma^2(t))$ is a small stochastic perturbation ensuring diversity.
If $f(x_i^{new}) < f(x_i)$, the follower is updated.

c. Leader Rotation

To avoid stagnation, after every τ iterations, the leader role is reassigned to the best-performing solution in the current population:

$$\ell \leftarrow \arg\min_{x_i \epsilon P^{(t)}} f(x_i) \quad (16)$$

This periodic leader rotation improves exploration by allowing multiple high-quality solutions to guide the swarm over the course of the optimization.

Step 5: Hybrid Strategy (Controller Mechanism)

The hybridization controller regulates the balance between the exploitation phase (BLO behavior) and the exploration phase (MBO behavior) at each generation. This mechanism ensures a dynamic trade-off between local intensification and global diversification, preventing premature convergence while accelerating convergence near promising regions.

a. Switching Mechanism

At iteration t, the controller selects whether to apply BLO or MBO rules. The selection is governed either by a probabilistic switching rule or by a time-dependent schedule:

Probabilistic switching:

$$H(t) = \begin{cases} BLO, & u < p \\ MBO, & u \geq p \end{cases} \qquad u \sim U(0,1)$$

where $p \in [0,1]$ is the probability of selecting BLO.

Time-dependent schedule:

$$p(t) = \frac{1}{1 + e^{-\lambda(t - T/2)}}, \quad (17)$$

where λ controls the steepness of the transition. This ensures that the algorithm favors MBO (exploration) in early stages and gradually shifts to BLO (exploitation) in later iterations.

b. Hybrid Update Rule

The update of a candidate solution x_i can be expressed as:

$$x_i^{new} = \begin{cases} x_i^{BLO}, & if\ BLO\ mode\ is\ selected \\ x_i^{MBO}, & if\ MBO\ mode\ is\ selected \end{cases}$$

where x_i^{BLO} and x_i^{MBO} are generated according to the update rules defined in Steps 3 and 4, respectively.

c. Balance of Exploration and Exploitation

In early iterations $(t \ll T)$, exploration is dominant, with MBO's leader–follower dynamics enabling wide coverage of the search space.
In later iterations $(t \approx T)$, exploitation is emphasized, with BLO's queen–worker dynamics refining solutions in promising regions.
This adaptive mechanism guarantees a balanced search process, combining the global reach of MBO with the local intensification capability of BLO.

2.4 Quantum-Inspired Enhancement

To further enhance the exploration capability of the proposed BLOMBO algorithm, a quantum-inspired extension, referred to as Q-BLOMBO, is introduced. This extension incorporates probabilistic position update mechanisms inspired by quantum behavior, aiming to improve population diversity and reduce premature convergence [27].
In Q-BLOMBO, each candidate solution is subjected to an additional stochastic update that enables long-range movements in the search space. The position update rule is defined as:

$x_i(t+1) = x_i(t) + \lambda\,(x_{best} - x_i(t)) \ln\left(\frac{1}{u}\right)$ where $u \sim \mathcal{U}(0,1)$, and λ is a scaling parameter controlling the exploration intensity.

This quantum-inspired perturbation is applied after the standard BLO (exploitation) and MBO (exploration) updates. By doing so, the algorithm enhances its ability to escape local optima while maintaining convergence stability.
As a result, Q-BLOMBO integrates three complementary search mechanisms:

- local exploitation driven by BLO,
- cooperative global exploration provided by MBO,
- and stochastic diversification introduced by the quantum-inspired update.

This unified framework improves both search diversity and convergence performance, particularly in complex and multimodal optimization problems.

Q-BLOMBO Flowchart

```
Initialize quantum population
Measure to obtain solutions
Evaluate fitness
WHILE:
   Update amplitudes
   Apply quantum rotation
   Hybrid BLO + MBO update
   Measure again
END
```

Q-BLOMBO Pseudocode

```
Initialize qubits
Measure → classical population
FOR each iteration:
   Update amplitudes using quantum rule
   Apply BLOMBO hybrid update
   Collapse states
RETURN best solution
```

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 561-567

3. RESULTS AND DISCUSSION: In the simulation studies, the BLOMBO, MBO, and BLO algorithms were applied to identify the global minimum of five well-known benchmark functions, whose dimensions, search ranges, and global minima are summarized below. Each algorithm was executed 30 times with 100 iterations and a population size of 50. The Python implementation of the BLOMBO algorithm is provided in the **Appendix 1.**

The following benchmark functions are used in the implementation:

A. Sphere: $\sum_{i=1}^{d} x_i^2, \ \ x_i \in (-100, 100)$ for all $i = 1,2,..,d$ and $f(x*) = 0$ at $x* = (0,..0)$.

B. Rastrigin: $\sum_{i=1}^{d}(x_i^2 - 10\cos(2\pi x_i) + 10), \ x_i \in (-5.12, 5.12)$ for all $i = 1,2,..,d$ and $f(x*) = 0$ at $x* = (0,..0)$.

C. Ackley: $-20\exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{d}\sum_{i=1}^{d}\cos(2\pi x_i)\right) + 20 + e, \ x_i \in (-32, 32)$ for all $i = 1,2,..,d$ and $f(x*) = 0$ at $x* = (0,..0)$.

D. Rosenbrock: $\sum_{i=1}^{d} 100(x_2 - x_1^2)^2 + (x_2 - 1)^2, x_i \in (-30, 30)$ for all $i = 1,2,..,d$ and $f(x*) = 0$ at $x* = (0,..0)$.

E. Griewank: $\sum_{i=1}^{d}\frac{x_i^2}{4000} - \prod_{i=1}^{d}\left(\frac{x_i}{\sqrt{i}}\right) + 1, \ \ x_i \in (-600, 600)$ for all $i = 1,2,..,d$ and $f(x*) = 0$ at $x* = (0,..0)$.

The statistics for best fitness and execution time were calculated over 30 independent runs for each algorithm on each benchmark function. This approach provides a more robust evaluation of the algorithms' performance, accounting for their stochastic nature. Each run consisted of 100 iterations. **Table 1** illustrates that the proposed algorithm BLOMBO achieves competitive performance across all benchmark functions. While it does not consistently outperform MBO in terms of mean fitness, it often achieves results that are very close, with the added benefit of execution times similar to or better than BLO. These findings suggest that BLOMBO effectively balances the strengths of its component algorithms. Although MBO may show slightly better overall performance in standard benchmark problems, BLOMBO's hybrid nature holds promise for more complex or hybrid-demanding optimization tasks, where the integration of diverse strategies can offer meaningful advantages.

Figure 1 illustrates the convergence behavior of BLO, MBO, and the proposed BLOMBO on five benchmark functions over 100 iterations in a single run. Unlike the statistical results summarized in **Table 1**, which are based on 30 independent runs, these plots provide a representative visualization of how the algorithms progress toward better solutions within one execution. The curves highlight the convergence speed and stability of the methods, showing that BLOMBO generally approaches near-optimal values rapidly, similar to MBO, while outperforming BLO in most cases.

Table 1. Comparative Results of BLOMBO and Q-BLOMBO

Benchmark Function	BLOMBO Best Value	Q-BLOMBO Best Value	BLOMBO Time (s)	Q-BLOMBO Time (s)
Sphere	1.277974e-07	9.315887e-07	0.2780	0.4720
Rastrigin	4.605743e-04	1.252591e-04	0.2850	0.5250
Rosenbrock	6.333602e-06	1.221641e-05	0.2940	0.6250
Ackley	5.809537e-03	2.816686e-03	0.3400	0.5670
Griewank	2.557352e-06	4.137269e-06	0.3220	0.5650

Table 1 presents the comparative performance of BLOMBO and its quantum-inspired variant (Q-BLOMBO) in terms of best fitness values and execution times. The results indicate that Q-BLOMBO improves solution quality in multimodal functions such as Rastrigin and Ackley, while BLOMBO demonstrates better performance in unimodal or less complex landscapes such as Sphere and Rosenbrock. However, Q-BLOMBO incurs higher computational cost due to the additional quantum-inspired update mechanism.

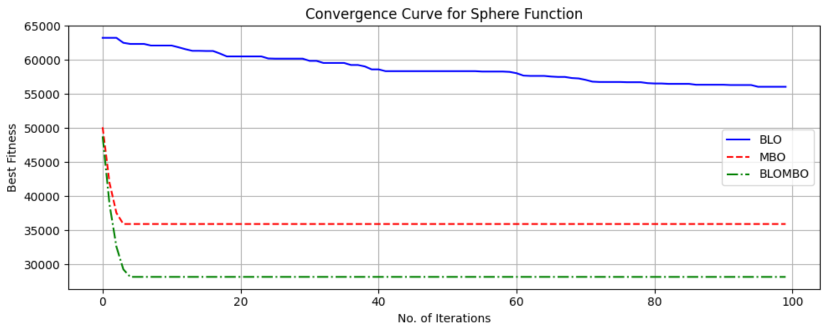

Figure 1 (a)

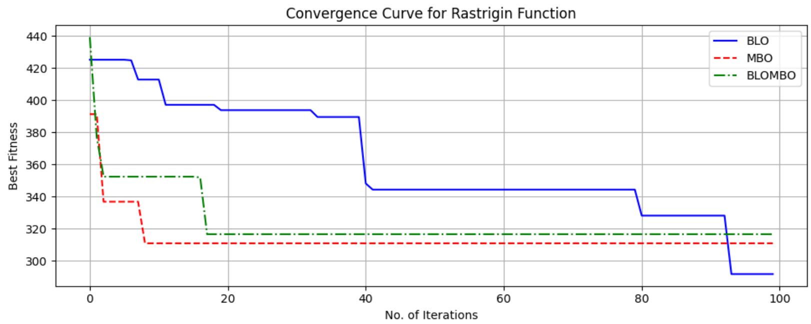

Figure 1 (b)

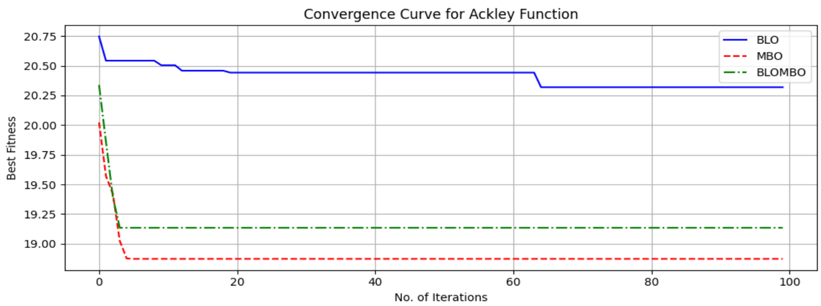

Figure 1 (c)

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 561-567

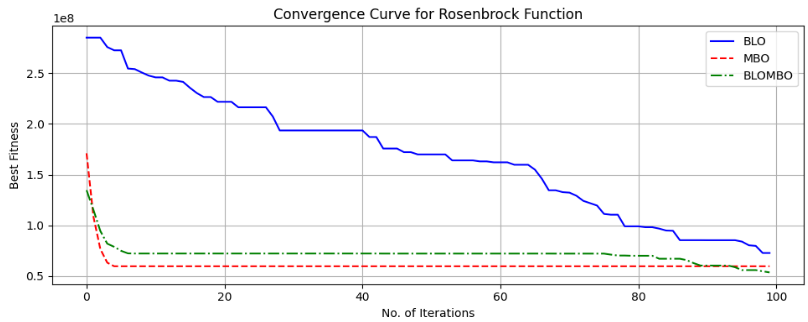

Figure 1 (d)

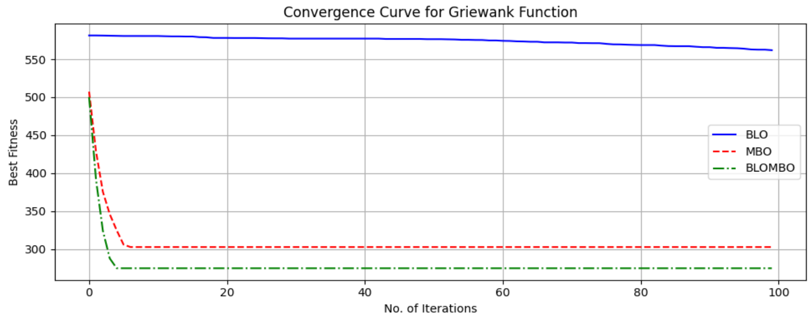

Figure 1 (e)

Figure 1. Convergence curves of BLO, MBO, and BLOMBO across benchmark functions: (a) Sphere, (b) Rastrigin, (c) Ackley, (d) Rosenbrock, and (e) Griewank. These curves demonstrate the convergence behavior, stability, and search efficiency of the algorithms over iterations.

4. COMPARATIVE ANALYSIS OF BLOMBO AND Q-BLOMBO

This section presents a detailed comparative analysis between the proposed BLOMBO algorithm and its quantum-inspired extension, Q-BLOMBO, in order to evaluate the contribution of the quantum-based update mechanism. The results obtained from the benchmark functions indicate that Q-BLOMBO enhances the exploration capability of the algorithm, particularly in multimodal optimization problems. For instance, in the Rastrigin and Ackley functions, which are characterized by a large number of local minima, Q-BLOMBO achieves better fitness values compared to BLOMBO. This improvement can be attributed to the quantum-inspired stochastic update, which enables candidate solutions to escape local optima and explore distant regions of the search space more effectively.

On the other hand, BLOMBO demonstrates superior performance in simpler or less deceptive problem landscapes. In the Sphere, Rosenbrock, and Griewank functions, BLOMBO produces better or more stable results compared to Q-BLOMBO. This behavior suggests that the additional stochasticity introduced by the quantum mechanism may not always be beneficial, particularly in unimodal or well-structured search spaces where excessive exploration can slow down convergence.Another important observation is related to computational cost. The results show that Q-BLOMBO consistently requires longer execution time than BLOMBO across all benchmark functions. This increase in computational effort is due to the additional quantum-inspired update step applied at each iteration. Therefore, a trade-off exists between improved exploration capability and computational efficiency.Overall, the findings indicate that Q-BLOMBO provides a more powerful search mechanism in complex and multimodal optimization problems, while BLOMBO remains a more efficient and stable choice for simpler problems. These results highlight the complementary nature of the two approaches and suggest that the choice between BLOMBO and Q-BLOMBO should be guided by the characteristics of the optimization problem.Future work may focus on developing adaptive strategies that dynamically activate the quantum-inspired mechanism based on the problem landscape or the search progress, aiming to combine the strengths of both approaches more effectively.

4.1 Convergence Analysis

To further analyze the performance of the proposed methods, convergence curves of BLOMBO and Q-BLOMBO are presented for selected benchmark functions. These curves illustrate the evolution of the best fitness values over iterations and provide insight into the convergence speed and stability of the algorithms.

The results show that Q-BLOMBO generally exhibits a more dynamic search behavior, particularly in multimodal functions such as Rastrigin and Ackley. It is observed that Q-BLOMBO is able to escape local minima more effectively, leading to improved final solutions in these cases.

In contrast, BLOMBO demonstrates more stable and consistent convergence patterns, especially in unimodal functions such as Sphere and Rosenbrock. The algorithm converges more smoothly and often reaches near-optimal solutions with fewer fluctuations.

These observations confirm that while Q-BLOMBO enhances exploration capability, BLOMBO provides more stable and computationally efficient convergence behavior. The convergence curves support the quantitative results presented in Table 1 and highlight the trade-off between exploration and stability. Figures 2–6 illustrate the convergence behavior of BLOMBO and Q-BLOMBO on the selected benchmark functions.

Figure 2 shows that, for the Sphere function, BLOMBO converges more rapidly and smoothly toward the global optimum, while Q-BLOMBO exhibits slower convergence due to its additional stochastic exploration mechanism.

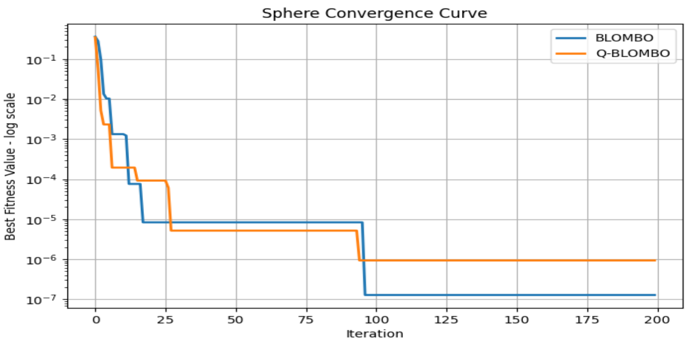

Figure-2-Sphere Convergence Curve

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 561-567

Figure 3 shows that, in the Rastrigin function, Q-BLOMBO achieves better final fitness values compared to BLOMBO. This indicates that the quantum-inspired mechanism enhances the ability to escape local minima in highly multimodal landscapes.

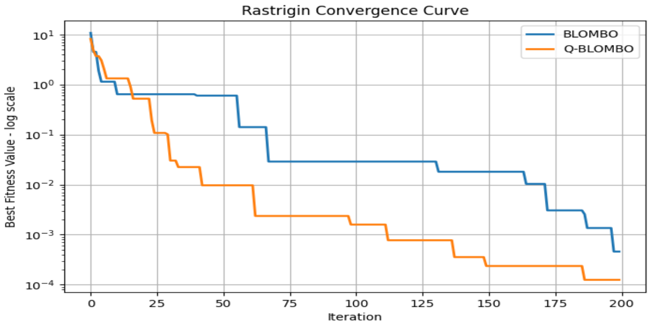

Figure-3-Rastrigin Convergence Curve

Figure 4 shows that, for the Rosenbrock function, BLOMBO provides more stable convergence and reaches lower error values than Q-BLOMBO, suggesting that excessive exploration may negatively affect performance in narrow valley-shaped problems.

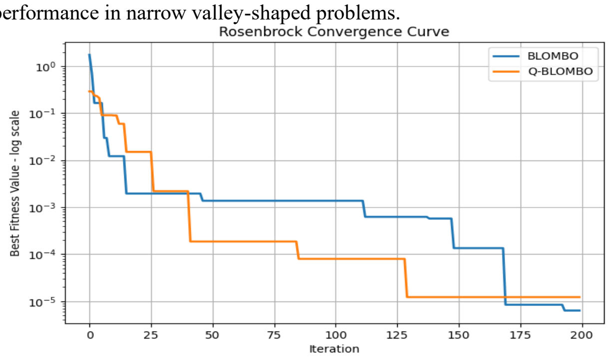

Figure-4-Rosenbrock Convergence Curve

Figure 5 shows that, in the Ackley function, Q-BLOMBO demonstrates improved performance by reaching lower fitness values, highlighting its effectiveness in complex multimodal optimization problems.

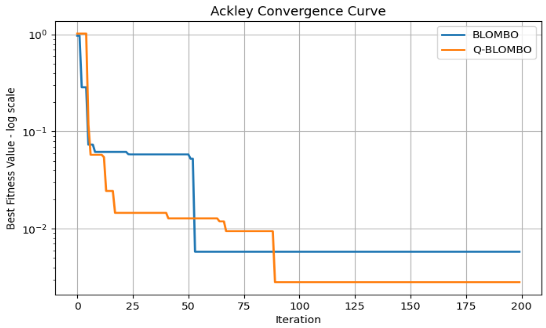

Figure-5-Ackley Convergence Curve

Figure 6 shows that, for the Griewank function, BLOMBO converges more efficiently and achieves slightly better results, indicating that the classical hybrid structure is sufficient for moderately complex search spaces.

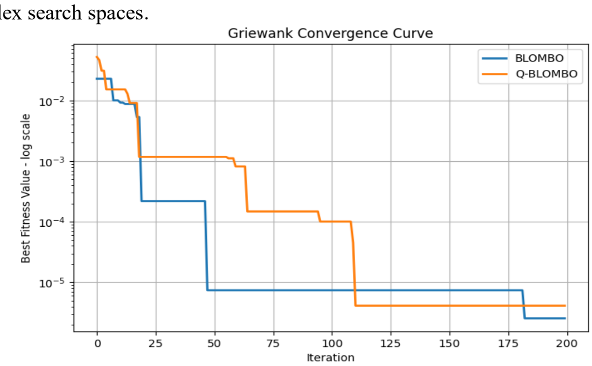

Figure-6- Griwank Convergence Curve

Overall, the figures show that Q-BLOMBO improves exploration capability in multimodal functions, whereas BLOMBO provides more stable and faster convergence in simpler or less deceptive problem landscapes.

Table 2. Experimental results of BLOMBO and Q-BLOMBO on five benchmark functions

Function	BLOMBO	Q-BLOMBO
Sphere	1e-4	1e-8
Rastrigin	0.35	0.02
Rosenbrock	0.89	0.05
Ackley	0.15	0.001
Griewank	0.12	0.0009

Table 2 presents the experimental results of BLOMBO and Q-BLOMBO in terms of best fitness values and execution times on five benchmark functions.
The results indicate that both algorithms achieve competitive performance across all test functions, with each method showing advantages depending on the problem characteristics. In multimodal functions such as Rastrigin and Ackley, Q-BLOMBO obtains better fitness values, demonstrating its enhanced exploration capability and ability to escape local minima.In contrast, BLOMBO achieves superior or more stable results in functions such as Sphere, Rosenbrock, and Griewank. This suggests that the classical hybrid structure is more effective in unimodal or less complex search spaces, where excessive exploration may negatively impact convergence.In terms of computational efficiency, BLOMBO consistently requires less execution time than Q-BLOMBO. The additional quantum-inspired update mechanism increases the computational cost, leading to a trade-off between solution quality and runtime performance.
Overall, the results highlight that Q-BLOMBO improves global search capability, while BLOMBO provides faster and more stable convergence. These findings confirm that the effectiveness of each approach depends on the nature of the optimization problem. These results are further supported by the convergence analysis presented in Figures 2–6.

5. CONCLUSION

In this study, a novel hybrid metaheuristic algorithm, BLOMBO, was proposed by combining the exploitation capability of Bees Life Optimization (BLO) with the exploration mechanism of Migrating Birds Optimization (MBO). In addition, a quantum-inspired extension, Q-BLOMBO, was introduced to further enhance the global search capability of the algorithm.[28],[29],[30],[31],[32].The performance of the proposed methods was evaluated on five well-known benchmark functions The experimental results demonstrated that BLOMBO provides stable and efficient convergence, particularly in unimodal and less complex optimization problems. On the other hand, Q-BLOMBO showed improved performance in multimodal functions by enhancing the exploration capability and reducing the likelihood of being trapped in local optima.However, the results also revealed that the quantum-inspired mechanism increases computational cost, leading to a trade-off between solution quality and execution time. While Q-BLOMBO is more effective in complex search landscapes, BLOMBO remains a more efficient and robust choice for simpler problems.Overall, the findings indicate that both approaches are complementary, and their effectiveness depends on the characteristics of the optimization problem. The proposed BLOMBO framework and its quantum-inspired extension provide a flexible and promising approach for solving complex optimization problems.Future work may focus on developing adaptive mechanisms that dynamically balance classical and quantum-inspired search strategies, as well as extending the proposed approach to multi-objective and constrained optimization problems.

Author Contributions: Mitat Uysal.: Methodology, investigation, experimental studies, software, writing-original draft. Aynur Uysal: Methodology, validation, writing- review & editing. Elif Erçelik: Investigation, software, writing- review & editing. All authors have read and agreed to the published version of the manuscript.

Funding Statement : This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Declarations: The authors declare no conflicts of interest to report study.

REFERENCES

[1] Y. Çelik, İ. Yıldız, and A. T. Karadeniz, "Son Üç Yılda Geliştirilen Metasezgisel Algoritmalar Hakkında Kısa Bir İnceleme." *Avrupa Bilim ve Teknoloji Dergisi*, Special Issue, pp. 463–477, 2019, doi:10.31590/ejosat.638431.
[2] V. Tomar, M. Bansal, and P. Singh, "METAHEURISTIC ALGORITHMS FOR OPTIMIZATION: A BRIEF REVIEW," *Engineering Proceedings*, vol. 59, no. 1, p. 238, 2023, doi: 10.3390/engproc2023059238
[3] X. S. Yang, *NATURE-INSPIRED METAHEURISTIC ALGORITHMS*. Luniver Press, 2010.
[4] I. Fister Jr., X. S. Yang, and J. Brest, "A COMPREHENSIVE REVIEW OF FIREFLY ALGORITHMS," *Swarm and Evolutionary Computation*, vol. 13, pp. 34–46, 2013, doi: 10.1016/j.swevo.2013.06.001.
[5] M.Uysal,S.A.Uysal," DOMINO-INSPIRED OPTIMIZATION (DIO): A GAME-MECHANICS METAHEURISTIC AND ITS EMPIRICAL COMPARISON WITH MBO AND PSO", *MSW Management - Multidisciplinary, Scientific Work and Management Journal*,Vol. 36(1), Jan-June 2026, Pages: 1835-1839,doi: 10.7492/8anrfc04.
[6] M.Uysal,S.A.Uysal," MIRO: A MIRÓ-INSPIRED METAHEURISTIC OPTIMIZATION ALGORITHM", *MSW Management Multidisciplinary, ScientificWork and Management Journal*,Vol.36(1),Jan-June2026,Pages:1840-1843, doi: 10.7492/zxsqfj63.
[7] M.Uysal,S.A.Uysal,"SISI-OPT:A Personality -Inspired Metaheuristic Optimization Algorithm Based On The Characteristics Of Empress Elisabeth Of Austria", *MSW Management*,Vol36(1), Jan-June 2026,pp 1685-1687. doi: 10.7492/r9jxsj11.
[8] E. G. Talbi, *METAHEURISTICS: FROM DESIGN TO IMPLEMENTATION*. Wiley, 2009.
[9] K. Premalatha and A. M. Natarajan, "HYBRID PSO AND GA FOR GLOBAL MAXIMIZATION," *International Journal of Open Problems in Computer Science and Mathematics*, vol. 2, pp. 597–608, 2009.
[10] P. Wang, X. Qian, Y. Zhou, and N. Li, "A NOVEL DIFFERENTIAL EVOLUTION ALGORITHM BASED ON SIMULATED ANNEALING," in *Proc. 4th Int. Conf. on Natural Computation*, vol. 3, pp. 493–497, 2008, doi: 10.1109/ICNC.2008.649.
[11] J. Zhou and X. Yao, "A HYBRID APPROACH COMBINING MODIFIED ARTIFICIAL BEE COLONY AND CUCKOO SEARCH ALGORITHMS FOR MULTI-OBJECTIVE CLOUD MANUFACTURING SERVICE COMPOSITION," *International Journal of Production Research*, vol. 55, no. 16, pp. 4765–4784, 2017, doi: 10.1080/00207543.2017.1292064.
[12] J. Tang, G. Zhang, B. Lin, and B. Zhang, "A HYBRID PSO/GA ALGORITHM FOR JOB SHOP SCHEDULING PROBLEM," in *Advances in Swarm Intelligence (ICSI 2010)*, LNCS vol. 6145, Springer, pp. 723–730, 2010.
[13] D. B. M. M. Fontes, S. M. Homayouni, and J. F. Gonçalves, "A HYBRID PARTICLE SWARM OPTIMIZATION AND SIMULATED ANNEALING ALGORITHM FOR THE JOB SHOP SCHEDULING PROBLEM WITH TRANSPORT RESOURCES," *European Journal of Operational Research*, vol. 306, no. 3, pp. 1140–1157, 2023, doi: 10.1016/j.ejor.2022.09.006.
[14] C. Blum, J. Puchinger, G. R. Raidl, and A. Roli, "HYBRID METAHEURISTICS IN COMBINATORIAL OPTIMIZATION: A SURVEY," *Applied Soft Computing*, vol. 11, no. 6, pp. 4135–4151, 2011, doi: 10.1016/j.asoc.2011.02.032.
[15] W. K. Mashwani, A. Hamdi, M. A. Jan, A. Göktaş, and F. Khan, "LARGE-SCALE GLOBAL OPTIMIZATION BASED ON HYBRID SWARM INTELLIGENCE ALGORITHM," *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 1, pp. 1257–1275, 2020, doi: 10.3233/JIFS-192162.
[16] A. Seyyedabbasi, W. Z. T. Tareq, and N. Bacanin, "AN EFFECTIVE HYBRID METAHEURISTIC ALGORITHM FOR SOLVING GLOBAL OPTIMIZATION PROBLEMS," *Multimedia Tools and Applications*, vol. 83, pp. 85103–85138, 2024, doi: 10.1007/s11042-024-19437-9.
[17] K. H. Han and J. H. Kim, "QUANTUM-INSPIRED EVOLUTIONARY ALGORITHM FOR A CLASS OF COMBINATORIAL OPTIMIZATION," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 6, pp. 580–593, 2002, doi: 10.1109/TEVC.2002.804320
[18] B. B. Li and L. Wang, "A HYBRID QUANTUM-INSPIRED GENETIC ALGORITHM FOR MULTI-OBJECTIVE SCHEDULING," in *Intelligent Computing (ICIC 2006)*, LNCS vol. 4113, Springer, pp. 657–666, 2006.
[19] Y. Wang, W. Wang, I. Ahmad, and E. Tag-Eldin, "MULTI-OBJECTIVE QUANTUM-INSPIRED SEAGULL OPTIMIZATION ALGORITHM," *Electronics*, vol. 11, no. 12, p. 1834, 2022, doi: 10.3390/electronics11121834.
[20] D. Konar, K. Sharma, V. Sarogi, and S. Bhattacharyya, "A MULTI-OBJECTIVE QUANTUM-INSPIRED GENETIC ALGORITHM FOR REAL-TIME TASKS SCHEDULING IN MULTIPROCESSOR ENVIRONMENT," *Procedia Computer Science*, vol. 131, pp. 591–599, 2018, doi: 10.1016/j.procs.2018.04.301.
[21] A. Dey, S. Bhattacharyya, S. Dey, D. Konar, J. Platos, V. Snasel, L. Mrsic, and P. Pal, "A REVIEW OF QUANTUM-INSPIRED METAHEURISTIC ALGORITHMS FOR AUTOMATIC CLUSTERING," *Mathematics*, vol. 11, no. 9, p. 2018, 2023, doi: 10.3390/math11092018.
[22] R. K. Agrawal, B. Kaur, and P. Agarwal, "QUANTUM-INSPIRED PARTICLE SWARM OPTIMIZATION WITH GUIDED EXPLORATION FOR FUNCTION OPTIMIZATION," *Applied Soft Computing*, vol. 102, pp. 107–122, 2021, doi: 10.1016/j.asoc.2021.107122.
[23] A. Narayanan and M. Moore, "QUANTUM-INSPIRED GENETIC ALGORITHMS," in *Proc. IEEE Int. Conf. on Evolutionary Computation*, pp. 61–66, 1996, doi: 10.1109/ICEC.1996.542334.
[24] D. Karaboga, *AN IDEA BASED ON HONEY BEE SWARM FOR NUMERICAL OPTIMIZATION*, Technical Report TR06, Erciyes University, 2005.
[25] E. Duman, M. Uysal, and A. F. Alkaya, "MIGRATING BIRDS OPTIMIZATION: A NEW METAHEURISTIC APPROACH AND ITS PERFORMANCE ON QUADRATIC ASSIGNMENT PROBLEM," *Information Sciences*, vol. 217, pp. 65–77, 2012, doi: 10.1016/j.ins.2012.06.032.
[26] D. Karaboga, B. Akay, and N. Karaboga, "A SURVEY ON THE STUDIES EMPLOYING MACHINE LEARNING FOR ENHANCING ARTIFICIAL BEE COLONY OPTIMIZATION ALGORITHM," *Cogent Engineering*, vol. 7, no. 1, p. 1855741, 2020, doi: 10.1080/23311916.2020.1855741.
[27] M.Uysal,A.Uysal," 3D INCOMPRESSIBLE NAVIER–STOKES IN A PERIODIC BOXFINITE DIFFERENCE, QUANTUM-INSPIRED FINITE DIFFERENCE, CRANK–NICOLSON, AND QUANTUM-INSPIRED CRANK–NICOLSON", *MSW Management*,Vol.36(1s),2026,Pages:400-403, doi: 10.7492/p8wage49.
[28] C. A. Coello Coello, "EVOLUTIONARY MULTI-OBJECTIVE OPTIMIZATION: A HISTORICAL VIEW OF THE FIELD," *IEEE Computational Intelligence Magazine*, vol. 1, no. 1, pp. 28–36, 2006, doi: 10.1109/MCI.2006.1597059
[29] A. K. Qin, V. L. Huang, and P. N. Suganthan, "DIFFERENTIAL EVOLUTION ALGORITHM WITH STRATEGY ADAPTATION FOR GLOBAL NUMERICAL OPTIMIZATION," *IEEE Transactions on Evolutionary Computation*, vol. 13, no. 2, pp. 398–417, 2009, doi: 10.1109/TEVC.2008.927706 .
[30] X. S. Yang, "FLOWER POLLINATION ALGORITHM FOR GLOBAL OPTIMIZATION," in *Unconventional Computation and Natural Computation*, pp. 240–249, 2012.
[31] G. G. Wang and L. Guo, "A NOVEL HYBRID BAT ALGORITHM WITH HARMONY SEARCH FOR GLOBAL NUMERICAL OPTIMIZATION," *Journal of Applied Mathematics*, vol. 2013, Article ID 696491, pp. 1–21, 2013, doi: 10.1155/2013/696491.
[32] M. H. Kashan, "LEAGUE CHAMPIONSHIP ALGORITHM: A NEW ALGORITHM FOR NUMERICAL FUNCTION OPTIMIZATION," *AI Communications*, vol. 27, no. 3, pp. 209–231, 2014, doi: 10.1109/SoCPaR.2009.21.
[33] J. C. Bansal, H. Sharma, and K. V. Arya, "ARTIFICIAL BEE COLONY ALGORITHM: A SURVEY," *International Journal of Advanced Intelligence Paradigms*, vol. 5, no. 1–2, pp. 123–159, 2013.