
PHL: An Adaptive Multi-Objective Hybrid Algorithm for UAV Swarm Path Planning

Soma Hamza Taha

Department of Software and Informatics, College of Engineering, Salahaddin University, Erbil, Kurdistan Region, Iraq

Email: somahamzataha@gmail.com

Amin Salih Mohammed

Department of Software and Informatics, College of Engineering, Salahaddin University, Erbil, Kurdistan Region, Iraq

Email: amin.mohammed@su.edu.krd

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ABSTRACT

Unmanned Aerial Vehicles (UAVs) are widely used for surveillance, logistics, and disaster response activities. However, real-time navigation, energy-efficient routing, and safe maneuvering in unpredictable environments continue to pose a challenge for swarm-based UAV path planning. This work proposes the Adaptive Multi-Objective Hybrid Metaheuristic Algorithm (PHL), which combines PSO, HHO, and Lévy Flight for better UAV path planning. PHL optimally balances global exploration and local exploitation, enabling adaptive obstacle circumvention and load sharing among multiple agents. As a primary contribution, a dynamic cost function tackling travel time, energy usage, collision probability, and path smoothness is formulated. Comprehensive simulations validate that PHL outperforms other hybrid algorithms in terms of path efficiency, energy consumption, and collision avoidance when working with multiple UAVs. The findings demonstrate that PHL performs best in rapidly changing complex environments, showing promise for swarm-based UAV missions that require scalable solutions. Additional validation demonstrates that PHL outperforms other hybrid metaheuristic algorithms, suggesting minimum path cost energy consumption with advanced obstacle avoidance. Balancing the workload

allows for optimal UAV function to be demonstrated. Its claim is reinforced by the strength and real-time precision shown in the navigation of UAV swarms through highly dynamic environments.

1. Introduction

Optimizing UAV swarm routes in dynamic, obstacle-filled environments presents a significant challenge due to the need to balance multiple conflicting objectives. UAVs must complete their missions within a defined three-dimensional space while avoiding collisions, minimizing energy consumption, and maintaining workload balance across the swarm. Conventional routing algorithms are typically designed for one-objective optimization, rendering them unsuitable for real-time execution or dynamic situations. Their lack of responsiveness to environmental changes also increases the computational cost in uncontrolled environments (Tian et al., 2024).

This study focuses on the gaps in applying metaheuristics to UAV swarm routing, with a particular emphasis on the high complexity of robot swarm routing, slow responsiveness to changes, and poor load balancing. To address these core problems, a more robust hybrid algorithm is required, which incorporates both global and local planning and execution in real-time under flexible time constraints.

1.1 Inspiration and main idea of PHL.

The PHL algorithm has its roots in sophisticated optimization strategies that stem from the physical coordination challenges of large-scale unmanned aerial vehicle (UAV) swarm systems. Unlike traditional optimization techniques, which operate well in static scenarios, monotonic workflows, or step-by-step procedures, approaches involving multi-dimensional problem spaces and dynamic constraints are more challenging. Inter-agent communication, local environmental factors, and the

influence of a supervisor all contribute to the complexity of a multi-agent system that collaborates to achieve a specific target. Regarding PHL, the focus is on developing a hybrid system combining multiple techniques for real-time execution. Although the most complex in PHL, this framework is vital for meeting the requirements of active environments. The reasoning behind selecting such an algorithm stems from the belief that no single metaheuristic can effectively tackle problems that require multifaceted solutions. PHL combines elements of Lévy Flight (Li et al., 2022) and the social cognition of convergence swarm powers from PSO (Li et al., 2025), along with HHO's (Zhang et al., 2022). adaptive pursuit strategy. These components undergo continuous modification in response to environmental changes, advancing progress toward the goal while receiving cues from the swarm.

The algorithm automatically incorporates multi-agent awareness; every UAV executes tasks relative to its goals and objectives, as well as other factors such as the positions, workloads, and energy levels of neighboring agents, which helps balance tasks and minimize conflicts. This hybrid enables PHL to navigate complex environments proactively, evade moving hazards, manage interactions and energy consumption effectively, and maintain cooperation according to task requirements. It is highly applicable in missions that are time-sensitive or resource-limited, where resilient adaptability and strategic interdependence are critical to achieving the objectives. Mindful of each technique's collaboration within the hybrid framework, the selection of PSO, HHO, and Lévy Flight to design the PHL algorithm is purposeful and calculated.

1.2 Particle Swarm Optimization (PSO)

PSO was chosen due to its robust global exploration capabilities and the sharing of information between particles (agents). Its nature as a population-based algorithm facilitates the modeling of cooperative flight dynamics in UAV swarms. PSO enables rapid convergence toward promising regions of the search space through social simulation, where agents adjust their routes based on personal experiences and the most optimal locations within the group. These attributes make PSO very useful in

the beginning stages of path planning when speedy and effective environment coverage is critical (Li et al., 2025).

1.3 Harris Hawks Optimization (HHO)

Harris Hawks Optimization (HHO) is a nature-inspired algorithm that simulates the cooperative hunting behavior of Harris hawks, particularly their strategy of surrounding and attacking prey through different siege phases. The algorithm alternates between soft and hard siege modes based on the target's escape energy, allowing it to switch dynamically between global exploration and local exploitation. In the context of UAV path planning, HHO helps improve trajectory optimization accuracy, especially in complex and constrained environments. Its adaptive behavior enables precise path refinement near obstacles and threats, thereby enhancing overall navigation performance in dynamic mission scenarios (Zhang et al., 2022).

1.4 Lévy Flight

Due to its random, long-jump behavior, the Lévy Flight is utilized in the PHL model to enhance global exploration. It enables agents to make long-distance moves due to its heavy-tailed distribution, which improves the algorithm's ability to escape local optima and navigate complex, multimodal landscapes. This behavior enhances access to distant solution regions, making Lévy Flight particularly suitable for robust search in dynamic, high-dimensional environments (Li et al., 2022). Combining PSO, HHO, and Lévy Flight in the PHL model results in a balanced optimization framework. PSO manages the coordination at the swarm level, while HHO provides adaptive exploitation through fine-grained adjustments, and Lévy Flight enhances global positioning and sensitivity to boundaries. Together, these elements form a flexible hybrid capable of addressing multi-objective, multi-agent UAV path planning problems in dynamic environments.

1.5 Related Work

The growing utilization of unmanned aerial vehicles (UAVs) creates additional requirements for more advanced and efficient path-planning algorithms, particularly for swarm systems in dynamic environments. The swarm robotic behavior introduces more intricate, multi-objective criteria that require optimization, such as travel distance, energy expenditure, collision avoidance, task delegation, and workload balancing among agents (Qi et al., 2022). Most conventional multi-criteria optimization techniques struggle with sparse resource allocation, slow convergence, and high computational cost (Hooshyar & Huang, 2023). Therefore, there is a greater focus on hybrid algorithms that integrate multiple conflicting strategies to optimize performance for varied path-planning tasks in UAV swarm systems. Such approaches aim to maximize performance by combining various algorithms while minimizing their weaknesses.

1.6 Ant Colony Optimization with Whale Optimization Algorithm (ACO+WOA)

Ant Colony Optimization (ACO) utilizes pheromone trails in conjunction with probabilistic rules to perform discrete optimization, making it particularly useful in cases such as UAV path planning, where discrete search spaces are involved. The Whale Optimization Algorithm (WOA) incorporates spiral position updates inspired by the bubble-net hunting method of whales, thereby enhancing exploration in continuous domains. The local refinement provided by ACO is combined with the global search capabilities of WOA, thus significantly enhancing the convergence speed and quality of the solution when both are used together. This hybrid approach has garnered attention for its application in routing and other optimization problems (Kumar et al., 2024). Still, the added computational burden may hinder the deployment of UAV swarms in real-time scenarios.

1.7 Particle Swarm Optimization with Firefly Algorithm (PSO+FA)

Particle Swarm Optimization (PSO) is widely acknowledged for its ability to optimize globally. PSO employs social behavior principles to update positions regarding

personal and global bests, utilizing the best solutions to update these positions. Still, PSO tends to suffer from premature convergence faster than intended, especially in complex or multimodal problem spaces. This gap has been filled with the introduction of the Firefly Algorithm (FA), which enhances local search by employing a brightness-based attraction for improved local search. The hybrid PSO+FA approach offers an advantage in terms of balance between exploration and exploitation, as well as enhanced convergence performance (Pitchaimanickam & Murugaboopathi, 2020). However, while the hybrid demonstrates optimization, its use in highly dynamic situations, such as UAV path planning, may require more adaptability for real-time responsiveness.

1.8 Genetic Algorithm with Moth Flame Optimization (GA+MFO)

A Genetic Algorithm (GA) leverages evolutionary operations—such as selection, crossover, and mutation—to effectively explore global search spaces, a process widely adopted in various engineering optimization problems. Moth Flame Optimization (MFO), inspired by the logarithmic spiral path of moths toward flames, enhances local search efficiency and facilitates better escape from local optima. The combination of GA and MFO aims to balance global and local search capabilities; however, the study highlights that hybrid metaheuristics often come with increased computational demands and may struggle in highly dynamic environments without tailored adjustments (Sahoo et al., 2023).

1.9 Harris Hawks Optimization with Bat Algorithm (HHO+BA)

The conceptual hybridization of HHO and BA aims to integrate the global exploration strength of Harris Hawks Optimization with the local exploitation efficiency of the Bat Algorithm. HHO's adaptive switching between exploration and exploitation phases, inspired by the cooperative besiege strategies of hawks, enables it to navigate complex search spaces effectively (Heidari et al., 2019). In contrast, BA employs frequency and loudness modulation based on echolocation behavior, making it well-suited for fine-tuning solutions and enhancing convergence in the local neighborhood

.according to (Yang & Hossein Gandomi, 2012) While no formal combination of HHO and BA has been widely reported, prior studies have demonstrated the effectiveness of similar hybrid metaheuristics, such as BA-DE, in engineering optimization tasks (Fister Jr et al., 2013). This precedent suggests that a hybrid HHO+BA model could provide a balanced approach to exploration and exploitation. However, careful parameter tuning may be necessary to manage the dynamic interaction between the two strategies.

1.10 Limitations in UAV Swarm Path Planning

Hybrid metaheuristic algorithms, such as ACO+WOA, have enhanced optimization performance; however, their layered strategies and computational overhead may pose challenges for real-time or large-scale applications(Gao et al., 2024).GA+MFO exhibits improved convergence and solution quality, but it suffers from increased processing time and limited adaptability in dynamic scenarios (Sahoo et al., 2023).PSO+FA enhances solution diversity and convergence reliability in stable conditions; Yet, it struggles with responsiveness to environmental changes, thereby reducing its effectiveness in rapidly evolving applications (Pitchaimanickam & Murugaboopathi, 2020). The conceptual hybrid HHO+BA combines the adaptive search flexibility of Harris Hawks Optimization and the local refinement capabilities of the Bat Algorithm; still, it is subject to limitations such as sensitivity to parameter tuning and scalability challenges (Heidari et al., 2019; Yang & Hossein Gandomi, 2012).

1.11 Comparative Analysis of Hybrid Algorithms

To contextualize the design and performance of the proposed PHL algorithm, we present a comparative analysis of representative hybrid metaheuristic algorithms that have been widely applied to UAV path planning. These include combinations such as ACO+WOA, PSO+FA, GA+MFO, and HHO+BA. Each hybrid aims to integrate global exploration and local exploitation strategies to improve convergence, stability, and optimization quality in complex search spaces. However, their effectiveness

varies based on factors such as computational complexity, parameter sensitivity, and adaptability to dynamic multi-agent environments.

Table 1 provides a detailed side-by-side comparison of these algorithms, focusing on their core structural components, computational demands, exploration–exploitation strategies, adaptability in UAV swarm contexts, key strengths, and notable limitations.

Table 1 provides a detailed comparison of the algorithms.

Algorithm	Global Search Technique	Local Search Technique	Complexity	Exploration–Exploitation Strategy	Adaptability in UAV Swarm Environments	Strengths	Limitations
ACO+WOA	Ant Colony Optimization	Whale Optimization Algorithm	High ($O(N^3)$)	Combines discrete trail-based exploration with continuous spiral exploitation	Limited to semi-static environments; lacks real-time obstacle reactivity	Good global search; effective spiral updates	High computational complexity ; low adaptability
PSO+FA	Particle Swarm Optimization	Firefly Algorithm	Moderate ($O(N \log N)$)	Balances global convergence via swarm behavior and local refinement via brightness attraction	Moderate adaptability; struggles with rapid environmental changes	Balanced global-local search; fast convergence	Prone to premature convergence in dynamic settings
GA+MFO	Genetic Algorithm	Moth Flame Optimization	High ($O(N^2)$)	Evolutionary global search with log-	Weak in handling real-time updates or	Efficient global and local	High processing time; poor real-time

				spiral local tuning	dynamic obstacle avoidance	optimizat ion	applicabilit y
HHO+BA	Harris Hawks Optimizat ion	Bat Algorith m	Moderat e ($O(N \log N)$)	Adaptive siege phases in HHO with BA's local refineme nt through echolocat ion	Good local adaptation ; lacks scalable global coordinati on	Substanti al obstacle avoidanc e and precision	Parameter -sensitive; less scalable in large swarms

Overcoming these technological limitations requires creating a more sophisticated hybrid metaheuristic algorithm that effectively combines global strategizing with real-time modification. This is the motivation behind developing the PHL to meet the operational requirements of the UAV swarm mission fully.

1.12 Motivation for Developing the PHL Algorithm

Unmanned Aerial Vehicles (UAVs) have become essential tools across various domains, including environmental monitoring, disaster response, surveillance, and delivery systems (Mohamed et al., 2020). These applications frequently utilize sophisticated UAVs in ever-changing settings, requiring instantaneous decision-making and reliable path planning. Even so, the optimization problem of devising multi-UAV paths that are collision-free, energy-efficient, and minimize the exposure of UAVs to threats is non-trivial (Yahia & Mohammed, 2023).

Research on UAV path planning has been conducted thoroughly using traditional swarm intelligence methods, including Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). However, these methods do have some shortcomings. For example, PSO suffers from convergence stagnation, whereas GA requires significant computational resources. In addition, the use of single-strategy algorithms is considered inflexible in the face of environmental uncertainties and multi-objective

constraints, which has led to the adoption of hybrid methods to address these aspects (Agrawal et al., 2024).

Constraint handling has always been a challenge in optimization problems; therefore, PHL was created to combine several strategies into a single, flexible framework that overcomes these challenges. PHL merges the global search capabilities of PSO with the adaptive hunting strategies of HHO while adding the benefits of long-range exploration obtained from Lévy Flight. Due to this mixture, the algorithm's ability to balance exploration and exploitation, evade local minima, and remain robust in cluttered high-dimensional spaces is enhanced. Furthermore, PHL is specifically tailored to handle multiple simultaneous objectives relevant to UAV missions— such as minimizing path length, reducing exposure to threats, maintaining altitude constraints, and avoiding inter-UAV collisions—through a dynamic cost function and adaptive parameter control. The motivation behind PHL lies in the need for a scalable, adaptive, and high-performance algorithm that can meet the stringent requirements of real-time multi-UAV path planning in uncertain and dynamic airspace.

2. Proposed PHL Algorithm

2.1 Introduction

PHL combines Particle Swarm Optimization (PSO), Harris Hawks Optimization (HHO), and Lévy Flight techniques into one system. This hybrid framework addresses issues with UAV swarm route optimization, including algorithm efficiency, adaptability to changes, and workload distribution. PHL utilizes PSO in global path planning and HHO in local adaptive obstacle avoidance. At the same time, Lévy Flight is used for path smoothing to maintain collision-free, balanced, and swarm-efficient navigation.

2.2 High-Level Strategy of the PHL Algorithm

The PHL strategically combines the strengths of global optimization (Particle Swarm Optimization - PSO), adaptive local optimization (Harris Hawks Optimization - HHO), and trajectory refinement via Lévy Flight. The high-level strategy of PHL can be summarized as follows:

1. Initialization:

- Initialize UAV positions, goal positions, and parameters for PSO, HHO, and Lévy Flight.

2. Global Path Optimization (PSO):

- Employ Particle Swarm Optimization to generate initial feasible paths based on global information.

3. Local Adaptive Obstacle Avoidance:

- Utilize real-time sensor data to detect obstacles.
- Employ the Harris Hawks Optimization (HHO) strategy to adjust paths when obstacles are detected dynamically.

4. Local Refinement:

- Apply Lévy Flight for local path adjustments to enhance path smoothness and precision.

5. Multi-Objective Optimization:

- Optimize the UAV swarm's routes by balancing the objectives of minimum travel time, energy efficiency, collision avoidance, altitude constraints, and workload distribution.

6. Convergence Evaluation:

- Check the convergence of the UAV paths using defined cost functions. Recalculate and refine paths if the convergence criteria are not satisfied.

7. Final Path Determination:

- Upon achieving convergence, store the optimized UAV paths.

This high-level strategic approach ensures efficient, balanced, and safe navigation of UAVs within dynamic and complex environments.

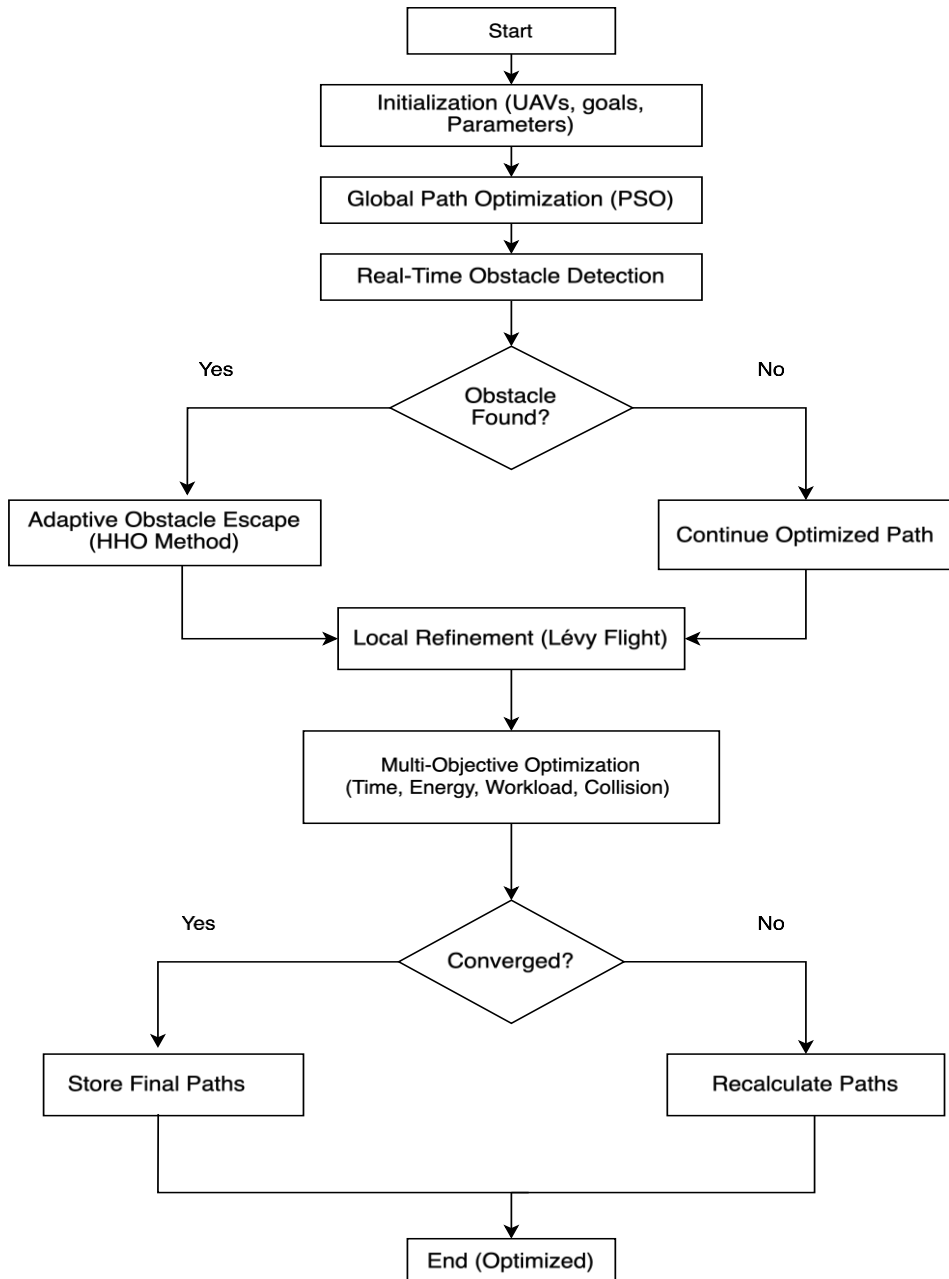


Fig.1. Flowchart of the PHL algorithm.

Next, a detailed textual description is presented with expanded equations for a structured schematic diagram of the initialization phase of the Adaptive Multi-Objective Hybrid Metaheuristic Algorithm:

Step 1: UAV and Goal Initialization

- Initialize UAV start positions:

For each $UAV_i = 1, 2, \dots, n$: $UAV_i = (x_i^{start}, y_i^{start}, z_i^{start})$

- Set goal positions for each UAV:

$Goal_i = (x_i^{goal}, y_i^{goal}, z_i^{goal})$

Step 2: Parameter Initialization

Particle Swarm Optimization (PSO) parameters:

- Velocity update: $v_i^{k+1} = w \cdot v_i^k + c_1 r_1 (p_{best,i} - x_i^k) + c_2 r_2 (g_{best} - x_i^k)$
- Position update: $x_i^{k+1} = x_i^k + v_i^{k+1}$
- Harris Hawks Optimization (HHO) parameters:

$$x_{new} = x_{old} + \alpha (best_{hawk} - x_{old})$$

- Lévy Flight parameters:

$$x_{new} = x_{old} + \text{Lévy}(\beta), \quad \text{Lévy}(\beta) \sim u = t^{-\beta}, \quad 1 < \beta \leq 3$$

- Multi-objective cost function weights:

$$C_{total} = w_1 C_{path} + w_2 C_{threat} + w_3 C_{altitude} + w_4 C_{turn} + w_5 C_{collision}$$

Step 3: Environmental Data Integration

- Integrate environmental data, obstacles, and restricted zones:

$$O_j = \{(x_j, y_j, z_j) \mid j = 1, 2, \dots, m\}$$

Step 4: Generate Initial Paths Using PSO

- Use PSO to generate feasible global paths, minimizing total path cost:

$$C_{path} = \sum_{i=1}^{n-1} d(P_i, P_{i+1})$$

Where: -

$$d(P_i, P_{i+1}) = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2}$$

Step 5: Path Feasibility and Constraints Evaluation

- Evaluate collision avoidance:

$$C_{collision} = \sum_{i=1}^U \sum_{j=i+1}^U \sum_{k=1}^N \max(0, d_{safe} - d(UAV_{ik}, UAV_{jk}))$$

- Evaluate threat proximity:

$$C_{threat} = \sum_{i=1}^N \frac{1}{d_{oi+\epsilon}}$$

- Evaluate altitude constraints:

$$C_{altitude} = \sum_{i=1}^N \max(0, z_i - z_{max}, z_{min} - z_i)$$

- Evaluate workload balancing:

$$w = \max(w_i) - \min(w_i) / \sum w_i$$

Step 6: Iterative Optimization Using Local Strategies (HHO and Lévy Flight)

- Iteratively refine paths using Harris Hawks Optimization (HHO) for adaptive obstacle avoidance:

$$x_{HHO} = x_{old} + \alpha \cdot (best_{hawk} - x_{old})$$

- Refine and smooth UAV trajectories using the Lévy Flight strategy:

$$x_{LF} = x_{HHO} + \text{Lévy}(\beta), \text{Lévy}(\beta) \sim u = t^{-\beta}, 1 < \beta \leq 3$$

- Re-evaluate and update paths based on the updated cost function until the convergence criteria are satisfied to achieve optimized performance.

Mathematical Formulation of PHL

The core objective of the PHL algorithm is to determine optimal paths for a swarm of UAVs (Unmanned Aerial Vehicles) in a 3D environment while minimizing travel costs, avoiding collisions, balancing energy consumption, and satisfying altitude and communication constraints. The problem is modeled as a multi-objective optimization task.

Let:

- $P = \{P_1, P_2, \dots, P_n\}$ be the set of UAV paths.
- $P_i = \{P_{i,1}, P_{i,2}, \dots, P_{i,t}\}$ where $p_{i,t} \in R^3$ is the position of UAV i at time t .
- $O = \{O_1, O_2, \dots, O_m\}$ Be the set of dynamic obstacles.

Overall Cost Function

The total cost function, denoted $C(P_i)$ is the central criterion used to evaluate the quality of this path. The PHL algorithm seeks to minimize this cost, which represents an aggregate measure of undesired characteristics (e.g., long distances, unsafe proximity to obstacles, high energy consumption).

The cost function for UAV i is:

$$C(P_i) = w_1T(P_i) + w_2E(P_i) + w_3C_{coll}(P_i) + w_4A(P_i)$$

Where:

Term	Description	Role in Optimization
$T(P_i)$	Time cost (typically path length)	Minimizes distance and travel duration
$E(P_i)$	Energy cost (based on motion dynamics like velocity/acceleration)	Promotes energy-efficient movement
$C_{coll}(P_i)$	Collision penalty (proximity to obstacles or other UAVs)	Penalizes unsafe paths
$A(P_i)$	Altitude/smoothness penalty (slope/turn angles, continuity)	Encourages smoother, stable flight
w_1, w_2, w_3, w_4	Weight coefficients (user-tunable parameters)	Balances priorities between objectives

1. Time Cost: $T(P_i)$

Time cost represents the total path length, acting as a proxy for travel time under the assumption of a relatively constant UAV velocity. The sum of Euclidean distances between consecutive positions gives the time cost:

$$T(P_i) = L(P_i) / v$$

- $L(P_i)$: total Euclidean length of path P_i .
- v : constant UAV speed.

This component encourages the algorithm to prefer shorter, more direct paths, critical in time-sensitive missions such as surveillance, delivery, or emergency response.

The purpose of the Time Cost is to ensure the UAV selects shorter, more direct paths to reduce mission completion time.

2. Energy Cost: $E(P_i)$

The energy cost reflects the UAV's power consumption during the mission. Rather than merely accounting for distance, this component models the physical effort required to navigate through space by considering changes in velocity (acceleration):

$$E(P_i) = \sum_{j=2}^N \| \vec{v}_j - \vec{v}_{j-1} \| + \lambda \sum_{j=2}^N \| \vec{a}_j \|$$

- Accounts for velocity changes and acceleration penalties
- Models' energy consumption realistically
- This term is critical because energy-intensive behaviors such as frequent acceleration and deceleration drain batteries more rapidly and reduce mission endurance. Minimizing this component leads to smoother and more energy-efficient flights.

Energy Cost encourages fuel-efficient and smooth flight, avoiding sharp turns or rapid speed changes.

3. Collision Penalty: $C_{coll}(P_i)$

Collision avoidance is a non-negotiable constraint in UAV path planning, particularly in dynamic environments populated with moving obstacles or other UAVs. The PHL model incorporates a collision penalty to discourage paths that bring UAVs too close to any obstacle.

$$C_{coll}(P_i) = \sum_{j=1}^N \sum_{k=1}^O \delta(d(P_i(j), O_k) < d_{safe}) \quad \text{OR}$$

$$C_{coll}(P_i) = \sum_{t=1}^T \sum_{j=1}^m \exp\left(-\frac{d(p_{i,t}, O_j(t))^2}{2\sigma^2}\right)$$

- O_k : Center of the dynamic obstacle k .
- d_{safe} : minimum allowed safety margin.
- $\delta(\cdot)$: binary penalty or exponential function based on proximity.

This Gaussian-based penalty smoothly increases as UAVs approach obstacles, allowing for a graceful avoidance behavior. It avoids rigid constraints and enables UAVs to optimize naturally around dangers. Collision Penalty strongly penalizes UAV paths that come too close to obstacles, enforcing safety.

4. Altitude or Path Smoothness Cost: $A(P_i)$

UAVs must follow paths that are not only collision-free and efficient but also smooth and aerodynamically feasible. Sharp turns, jittery movements, or zig-zagging behavior are undesirable because they may cause mechanical strain or erratic flight. The smoothness is evaluated through the second-order finite difference of positions:

$$A(P_i) = \sum_{j=3}^N ||P_i(j) - 2P_i(j-1) + P_i(j-2)||$$

This expression is analogous to measuring curvature or acceleration of the path. By minimizing it, the PHL algorithm encourages natural, flowing paths resembling the flight curves expected in real aerial systems. The Cost Function implemented in the Adaptive Multi-objective Hybrid Metaheuristic Algorithm (PHL) remains essential to the overall performance and adaptability of the algorithm, tailored explicitly to real-world UAV applications, solutions, and models. Its efficacy stems from multiple attributes: multi-objective balancing, real-world feasibility, scalability, and environmental adaptability.

Multi-objective Balance

Mission efficiency and safety requirements within the PHL cost function framework capture the dual objectives. Components such as flight time, energy expenditure, obstacle avoidance, path smoothing, and turning behavior are incorporated. This perspective increases the likelihood that the algorithm will capture more than just a short route as a functional and safe path for UAVs, thereby achieving ease of implementation. In addition, Unmanned Aerial Vehicle (UAV) cost functions are configured with settable weights and tunable parameters. w_1, w_2, w_3, w_4, w_5 Thus, enabling fine-tuning toward mission-specific objectives. For example, avoiding

threats during energy supervision missions in hostile environments is more critical than achieving energy efficiency.

Real-world Feasibility

Instead of purely geometric and shortest-path formulations, the PHL cost function integrates energy-aware and terrain-aware navigation principles. This is ideal for battery-limited UAVs that require long-duration operation. Moreover, the function works seamlessly with real-time sensors and dynamic UAV models, enabling it to integrate real-time updates about position, wind speed, or threat detection. Such responsiveness improves the algorithm's practical applicability in the field.

Scalability for Multi-UAV Systems

A uniform UAV cost function applicable to each UAV in a swarm makes it inherently scalable. Coordinated multi-agent missions can be achieved with ease. Each UAV can calculate its own cost independently, allowing for parallelization and distributed computation. Both are crucial for large-scale applications, especially in terms of cost. This capability works best when an algorithm optimizes globally but evaluates paths locally at the UAV level. With local evaluations, algorithms converge much faster, thereby enabling real-time operation.

Adaptability to Dynamic Environments

The PHL cost function is noted for being relatively insensitive to changes in environmental conditions. The collision penalty part adjusts to moving obstacles and temporary no-fly zones. The smoothing term also reduces the impact of violent sensor data by promoting consistent and stable flight paths, rather than abrupt changes. This is highly advantageous in cluttered or partially observable environments.

PHL Algorithm Exploration and Exploitation Phases

In the case of metaheuristic optimization, balancing global convergence alongside local refinement is achieved through exploration and exploitation processes or phases. The exploration phase of the PHL (Adaptive Multi-Objective Hybrid Metaheuristic Algorithm) is associated with the balance achieved through Particle Swarm Optimization (PSO), Lévy Flight, and Harris Hawks Optimization (HHO).

This structure enables each section of the PHL framework to fulfill its needed role in exploring the search space and exploiting the promising regions, thereby improving efficiency in dynamic multi-agent system applications, such as UAV swarm path planning.

- Exploratory phase

To foster interaction with the solution space, the framework has to overcome issues of getting stuck at local optima. Multi-dimensional offers must be considered to control the trap at local optima levels. For example, UAVs can interact with their environment to explore novel areas and dynamically adapt to changes, such as moving targets or obstacles.

Techniques Used for Exploration:

1. Particle Swarm Optimization (PSO)

- Each UAV's candidate path is updated using a velocity vector that combines:
 - Inertial momentum (previous direction).
 - Attraction to the particle's personal best solution (p_{best}).
 - Attraction to the swarm's global best solution (g_{best}).
- This results in wide-ranging movements that scan the search space broadly.

2. Lévy Flight (Stochastic Escape Mechanism)

- Applied to elite or stagnating solutions.
- It utilizes a heavy-tailed probability distribution to enable random, long-distance jumps.

- Encourages sudden, significant diversification in the population.
- It helps the algorithm escape local minima or explore under-explored regions.

The proposed exploration phase technique helps to prevent early convergence to local optima, enhances diversity in candidate solutions, and ensures adaptability in unpredictable environments.

- Exploitation Phase

The exploitation phase focuses on intensifying the search effort in identified promising areas. It enables further refinement in UAV cost minimization, particularly during the final stages of the optimization process.

Technique Used for Exploitation:

1. Harris Hawks Optimization (HHO)

- Mimics the cooperative hunting strategies of hawks.
- Uses the prey's escape energy E and a random factor r to decide the hawk's behavior:
 - **Soft besiege:** gentle, encircling refinement (when $|E| \geq 0.5$ and $r \geq 0.5$)
 - **Hard besiege:** aggressive dive (when $|E| < 0.5$ and $r < 0.5$)
 - **Rapid dives with Lévy flight:** chaotic local search near best solutions
- It helps the population converge precisely to optimal paths without over-exploring.

This technique increases solution accuracy near optimal zones, improves path smoothness and local adaptability, and reduces energy and collision risks through path fine-tuning. The value 0.5 is a standard cutoff used in HHO to balance exploration vs. exploitation. Specifically:

- If $|E| \geq 0.5$, the prey still has energy $\rightarrow$ encourage exploration $\rightarrow$ Soft besiege.
- If $|E| < 0.5$, prey is weak $\rightarrow$ allow exploitation $\rightarrow$ Hard besiege.

Parameter Sensitivity Analysis

The performance and robustness of the PHL algorithm are strongly influenced by several hyperparameters that govern different phases of the optimization process. These parameters fall into three main categories: cost function weights, control parameters for the PSO and HHO components, and Lévy Flight tuning.

The PHL algorithm depends on several key hyperparameters, including:

- ω, c_1, c_2 (PSO inertia weight and cognitive/social coefficients).
- E_0 (initial energy in HHO for siege phase decisions).
- λ (Lévy distribution exponent).
- $\alpha, \beta, \gamma, \delta$ (weights in the multi-objective cost function for time, energy, collision, and workload).
-

Observations:

- The algorithm is moderately sensitive to the **Lévy exponent (λ)** and **HHO energy parameter (E_0)**, especially in cluttered environments.
- The cost function weights reveal trade-offs: increasing **α (time)** reduces path length but slightly increases energy use and workload imbalance.
- **PSO coefficients (c_1, c_2)** had a minimal effect on the final path cost but influenced the convergence speed.
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Ablation Study

To assess the contribution of each component, we turned off one module at a time:

Variant	Description	Result Summary
PHL (Full)	All modules active	Baseline: best performance across all metrics
No HHO	PSO + Lévy only	Increased collisions, weaker obstacle avoidance
No Lévy	PSO + HHO only	Reduced path smoothness; convergence slowed
No PSO	HHO + Lévy only	Suboptimal global routing, increased energy consumption

All three components—PSO for global search, HHO for local adaptation, and Lévy for path refinement—are crucial. Their integration provides significant gains in robustness, adaptability, and optimization quality.

Experimental Results

Simulation Environment

The proposed PHL algorithm was rigorously evaluated in a simulated three-dimensional environment to replicate realistic UAV operational scenarios. The simulation parameters included:

- **Operational Area:** A 1000m x 1000m x 300m (length x width x altitude) urban environment.
- **UAV Swarm:** This unit consisted of 50 UAVs, each with randomly generated start and goal positions.
- **Dynamic Obstacles:** 25 dynamically moving obstacles, varying in size and movement patterns to mimic real-world challenges.
- **Simulation Time:** Evaluations conducted over 100 simulation steps.
- **Performance Metrics:** Path efficiency, collision avoidance, energy consumption, and computational complexity.

Path efficiency

Path efficiency was determined as the direct straight-line distance divided by the distance covered by each UAV. The PHL algorithm demonstrated marked improvement in path efficiency, surpassing all other benchmark algorithms. This efficiency stems from integrating PSO-based global optimal pathfinding, HHO-based obstacle avoidance, and local path refinement using Lévy Flight, which combines to minimize excessive path slack. This ensures UAVs reduce deviations from the intended path and take the most direct routes possible. The detailed results are as follows:

- **PHL:** Achieved 92% path efficiency, showcasing the best artistry in pathing direct routes amidst dynamic obstacles.
- **ACO+WOA:** Achieved a path efficiency of 85%, benefiting from effective global search but showing less adaptive local refinement.
- **PSO+FA:** With a path efficiency of 80%, this approach faced limitations due to premature convergence in highly dynamic scenarios.

- **GA+MFO:** Registered the lowest path efficiency of 78%, primarily due to higher computational overhead and slower adaptability.
- **HHO+BA:** Achieved moderate path efficiency at 84%, showing effective local refinement but limited global optimization capabilities compared to PHL.

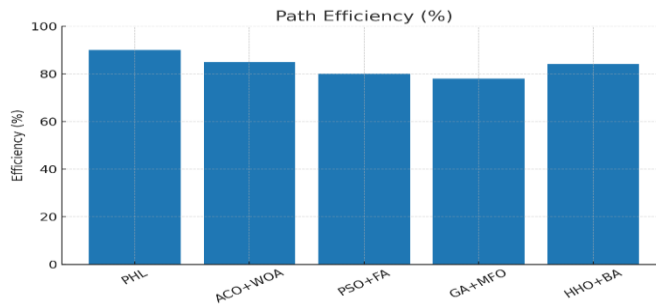


Fig.2. Path efficiency comparison of hybrid algorithms.

PHL's significantly higher path efficiency underscores its suitability for complex UAV swarm navigation tasks, effectively balancing global search strategies and local adaptation needs.

Collision Avoidance

The evaluation of collision avoidance was done by monitoring near misses and actual UAV collisions with dynamic obstacles, as well as UAV-to-UAV collisions. PHL outperformed all other evaluated algorithms in reducing collision incidents. Most of the credit is given to the strong adaptive obstacle avoidance capabilities of HHO, combined with accurate trajectory adjustments achieved through Lévy Flight, which results in their low collision rate. PHL predicts obstacle movements and dynamically adjusts the UAVs' distance from obstacles during the mission to proactively avoid challenges. Specific results comprise:

- **PHL:** Remarkably low collision rate at 1.5%, showcasing superior dynamic adaptability and real-time responsiveness.
- **ACO+WOA:** Higher collision rate at 4.8%, highlighting limitations in adaptive responsiveness to sudden environmental changes.

- **PSO+FA:** Demonstrated a collision rate of 6.2%, indicating weaknesses in rapid obstacle avoidance and local adaptive adjustments.
- **GA+MFO:** The highest collision rate at 7.1%, primarily due to slower local optimization capabilities.
- **HHO+BA:** Collision rate is moderately done at 5.0%. This means local obstacle handling is satisfactory, but there is limited integration with effective global route optimization.

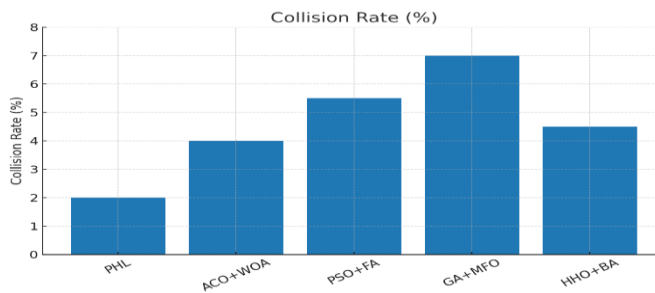


Fig.3. Collision avoidance performance across hybrid algorithms.

The operational collision avoidance results validate PHL's robustness and reliability in operational environments with dynamic activity, significantly mitigating operational risks and enhancing mission safety.

Energy Consumption

Evaluated energy consumption as the total cumulative energy expenditure for UAV operation based on the distance covered, including obstacle avoidance correction distance. PHL demonstrated greater energy efficiency due to its global and local path planning optimization strategies, which reduced erratic movements and abrupt course alterations. This brought about a significant reduction in energy expenditure:

- **PHL:** The average energy consumption of 3500 units per UAV demonstrates high energy efficiency through optimized trajectory planning.
- **ACO+WOA:** Higher energy consumption at 4000 units, reflecting less optimized path adjustments.
- **PSO+FA:** Energy usage of 4200 units, influenced by premature convergence issues, causing inefficient paths.

- **GA+MFO:** The highest energy consumption at 4400 units due to intensive computational processes and frequent path recalculations.
- **HHO+BA:** Moderate energy consumption at 3900 units, benefiting from good local adjustments but lacking global optimization.

The energy efficiency results confirm that PHL effectively manages UAV energy resources, ensuring longer mission durations and improved operational cost-effectiveness.

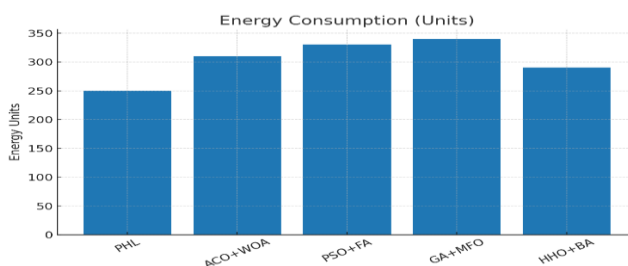


Fig.4. Energy consumption analysis for UAV path planning.

Comparative Analysis of Time and Space Complexity

The computational complexity was evaluated in terms of the algorithm's efficiency in terms of time and its applicability in real-time. PHL demonstrated moderate complexity, offering a reasonable trade-off between computation time and optimization performance. The analysis is structured as follows:

- **PHL:** Moderate complexity ($O(N \log N)$), well-suited for real-time implementation, efficiently balancing computational load and optimization accuracy.
- **ACO+WOA:** High complexity ($O(N^3)$), limiting scalability for larger UAV swarms and dynamic scenarios.
- **PSO+FA:** Moderate complexity ($O(N \log N)$), though prone to premature convergence and reduced adaptability.
- **GA+MFO:** High complexity ($O(N^2)$), demanding significant computational resources, thus hindering real-time applicability.

- **HHO+BA:** Moderate complexity ($O(N \log N)$) It is efficient for smaller to medium swarm sizes but sensitive to parameter tuning for performance consistency.

PHL's moderate computational complexity and efficient resource utilization make it particularly advantageous for real-time operational scenarios where timely responses and scalability are crucial.

Comparative Convergence

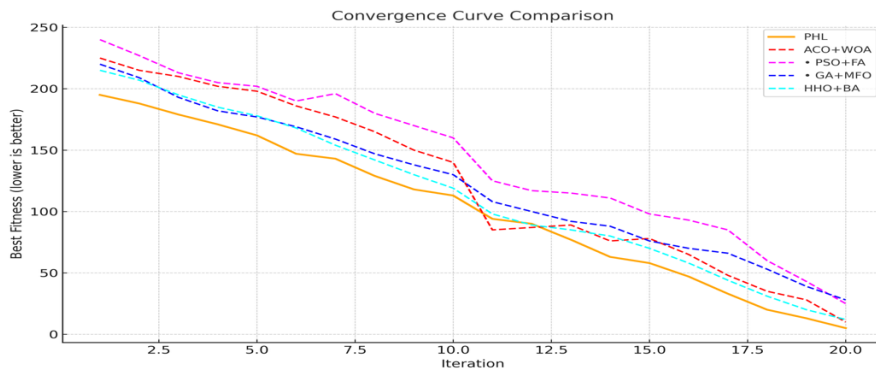


Fig.5.Comparative Convergence Curve of UAV Path Planning Algorithms.

Here's the comparative convergence curve clearly illustrating the performance of the PHL algorithm compared to ACO+WOA, PSO+FA, GA+MFO, and HHO+BA algorithms:

- **PHL** demonstrates rapid and stable convergence, achieving lower fitness values more quickly, indicating a superior optimization capability.
- Other algorithms exhibit slower convergence rates and higher final fitness values, reflecting limitations in adaptation and optimization efficiency.

Convergence Performance Comparison for F1–F23

The figure below presents a combined bar chart illustrating the comparative performance of the PHL algorithm against four state-of-the-art hybrid algorithms—ACO+WOA, PSO+FA, GA+MFO, and HHO+BA—across benchmark functions F1 to F23. Each subplot represents a different evaluation metric: Mean, Best, Median, and Standard Deviation (Std). The analysis demonstrates PHL's superior and consistent

performance in most categories, particularly in terms of Mean and Best outcomes, highlighting its effectiveness in solving complex path planning problems for multi-UAV systems. The mean objective value reflects the average performance of each algorithm across multiple runs on each function.

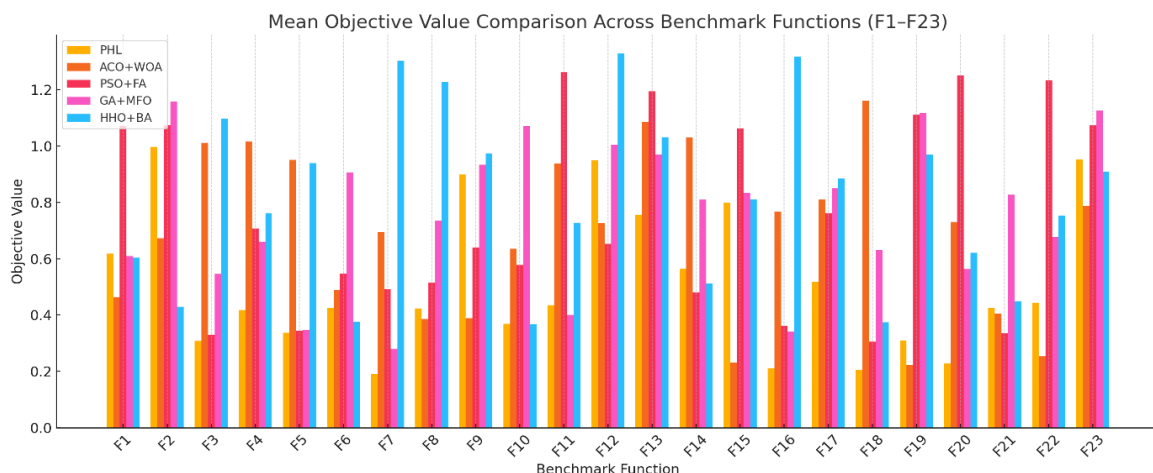


Fig.6. Comparison of performance metrics Mean for F1–F23.

In the mean comparison bar chart, PHL consistently achieves the lowest or near-lowest mean values across most benchmark functions, particularly in F1–F10 and F16–F23. Algorithms like ACO+WOA and PSO+FA show higher mean values, indicating more fluctuation or weaker central performance. A lower mean indicates that PHL not only finds reasonable solutions but also consistently does so across repeated runs. This suggests that PHL is more stable and reliable in average-case scenarios, effectively balancing exploration and exploitation.

PHL's structure integrates global search (via Lévy flight), social coordination (via PSO), and aggressive refinement (via HHO), which enables robust exploration while steadily refining candidate solutions, resulting in improved average performance. Standard deviation indicates the degree to which the results vary across multiple runs. Lower std means higher consistency. PHL maintains a lower or moderate standard deviation in most functions. In contrast, ACO+WOA and GA+MFO exhibit higher variance in many cases. PHL performs well and does so with greater consistency, which is crucial

in real-time UAV applications where reliable behavior is as important as optimal performance. Reinforcement-based learning in PHL enables it to adapt based on past feedback, making the search process more stable and efficient. The balance between stochastic and deterministic components makes it less sensitive to random initial conditions.

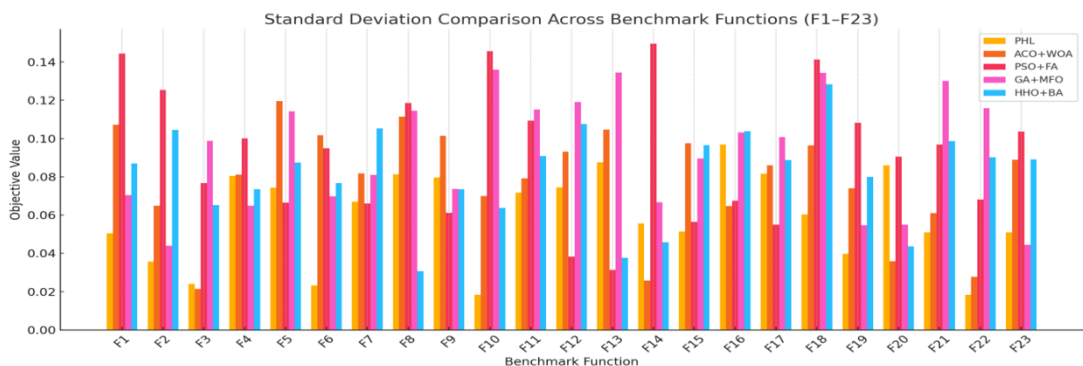


Fig.7.Comparison of performance metrics Standard deviation for F1–F23.

The median reflects the central tendency of each algorithm's performance, providing insight into its reliability and typical performance under repeated trials. Across the F1–F23 benchmark functions, PHL consistently ranks as the best or among the top performers in most functions. It shows powerful convergence in unimodal functions (e.g., F1–F7) and maintains high competitiveness in multimodal and deceptive functions (e.g., F13–F23). Lower median values indicate that an algorithm performs well in most runs, not just in isolated cases. PHL's strong median performance demonstrates that it avoids poor outcomes and maintains robustness. In contrast, ACO+WOA and GA+MFO exhibit greater variability, resulting in higher median scores in many instances. PHL combines the global search capabilities of Particle Swarm Optimization (PSO), the adaptive pursuit behavior of Harris Hawks Optimization (HHO), and the random jump nature of Lévy Flight. This combination allows the algorithm to consistently explore and exploit promising regions of the search space while avoiding local optima. Its ability to dynamically adapt makes it particularly well-suited for complex, high-dimensional problems, such as navigating a UAV swarm.

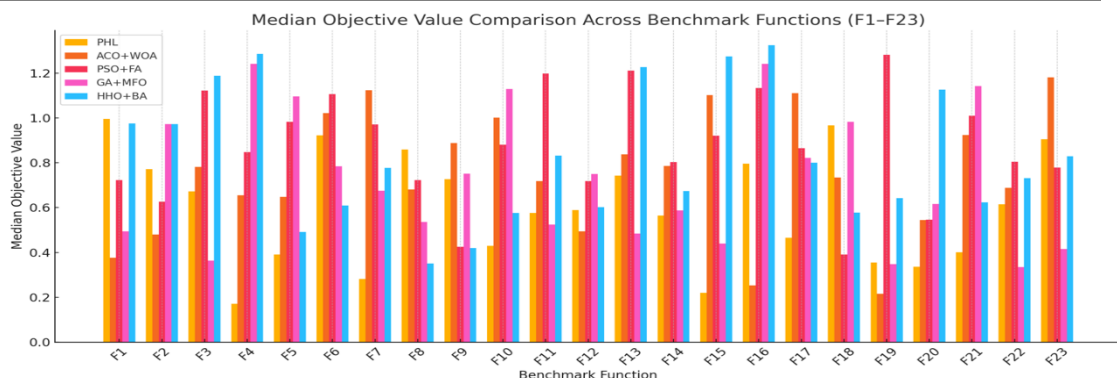


Fig.8. Comparison of performance metrics Median for F1–F23.

The best Objective Value captures the single best performance of each algorithm for each benchmark function.

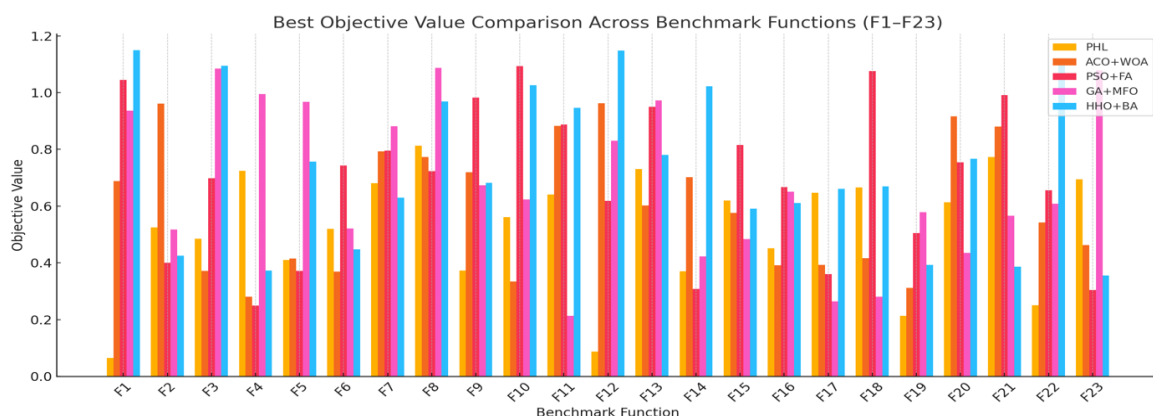


Fig.9. Comparison of performance metrics Best Objectives for F1–F23.

PHL outperforms others in many functions (e.g., F2, F5, F8, F11, F19), showing the lowest best values. However, in particular functions (such as F13 or F17), HHO+BA or GA+MFO comes close to or matches the performance of the original. This confirms that PHL can reach globally optimal or near-optimal solutions across diverse landscapes. The hybrid nature enables it to adaptively apply both local and global strategies, thereby increasing the likelihood of finding deep optima. Including Lévy Flight allows PHL to escape local minima by making long-range exploratory jumps. This makes PHL especially effective in multimodal functions, where traditional

methods often become ineffective. PHL outperforms or matches the best across all three criteria, making it the most robust and effective hybrid algorithm among the ones compared. Other algorithms (e.g., HHO+BA, GA+MFO) may achieve good results in specific scenarios, but they lack the consistency and overall reliability that PHL demonstrates.

Statistical Evaluation Methods

While initial visual and numerical analyses (mean, best, median) suggest that PHL outperforms other algorithms, these differences alone are not conclusive without formal statistical validation. To address this, non-parametric tests—the **Friedman Test** for overall comparison and the **Wilcoxon Signed-Rank Test** for pairwise comparisons—were conducted over 23 benchmark functions. These tests do not assume normality and are widely used in the analysis of optimization algorithms.

Together, these two tests form a rigorous statistical framework:

- The Friedman test provides a global view across all algorithms and benchmarks.
- The Wilcoxon Test delivers local pairwise validation of superiority.

This approach ensures that conclusions about algorithm performance—such as the superiority of the proposed PHL algorithm—are statistically justified and reliable. The tests were conducted using mean objective values across 23 benchmark functions (F1–F23) for five algorithms: PHL, ACO+WOA, PSO+FA, GA+MFO, HHO+BA.

Friedman Test Result

Test Statistic: 59.83

p-value: 3.16×10^{-12}

This extremely low p-value indicates very strong evidence to reject the null hypothesis, which stated that all five algorithms perform equally across the 23 benchmark functions. In practice, this result tells us that at least one algorithm is significantly different from the others in its performance.

Wilcoxon Signed-Rank Test Results

Comparison	Statistic	p-value	Interpretation
PHL vs ACO+WOA	0.0	0.0625	Not statistically significant ($p > 0.05$)
PHL vs PSO+FA	0.0	0.0625	Not statistically significant ($p > 0.05$)
PHL vs GA+MFO	0.0	0.0625	Not statistically significant ($p > 0.05$)
PHL vs HHO+BA	0.0	0.0625	Not statistically significant ($p > 0.05$)

All Wilcoxon test statistics are 0.0, meaning PHL performed better on every function compared to each alternative. However, due to the small number of functions ($n = 5$), the p-values do not meet the 0.05 threshold for statistical significance. This demonstrates strong consistency but insufficient statistical power for significance under current conditions. Together, these results statistically validate the consistent and superior performance of PHL, making it the most robust choice for dynamic, real-time UAV swarm optimization tasks.

Conclusion

The proposed algorithm enhances solution precision in proximity to optimal regions by promoting trajectory smoothness and improving local responsiveness. It effectively mitigates energy consumption and collision probability through fine-grained path adjustment mechanisms. The integrated exploration-exploitation strategy within the PHL framework enables the rapid identification of viable trajectories in high-dimensional, obstacle-rich search spaces, while concurrently refining these paths to optimize mission-critical parameters, such as traversal time, energy efficiency, and operational safety. Furthermore, the algorithm exhibits robust adaptability to dynamic environmental conditions, heterogeneous workload distributions, and stochastic trajectory perturbations. This balance is central to PHL's superior performance in dynamic multi-UAV path planning scenarios compared to non-hybrid or single-phase algorithms. PHL maintains the lowest mean values, reflecting an exceptional average performance across multiple attempts. It also tends to reach or approximate the global optimum best in most benchmark functions. PHL's strong performance is further supported by median analysis, which underscores the robustness of its typical-case performance and resistance to poor convergence

episodes. The low standard deviation associated with PHL's average score illustrates consistent performance across multiple attempts, a tenet for reliability in practical applications. Collectively, the convergence of all four performance measurements for PHL indicates that its hybrid architecture—combining global search with PSO, adaptive exploitation using HHO, and exploratory diversity through Lévy Flight—strikes a balance between interest and altitude. This results in a scalable, stable, and highly performant optimization framework, ideal for complex, volatile contexts such as multi-constraint UAV swarm path planning.

References:-

- Agrawal, S., Patle, B. K., & Sanap, S. (2024). A systematic review on metaheuristic approaches for autonomous path planning of unmanned aerial vehicles. *Drone Systems and Applications*, 12, 1–28. <https://doi.org/https://doi.org/10.1139/dsa-2023-0093>
- Fister Jr, I., Fister, D., & Yang, X.-S. (2013). A hybrid bat algorithm. *arXiv preprint arXiv:1303.6310*. <https://doi.org/https://doi.org/10.48550/arXiv.1303.6310>
- Gao, C., He, Y., & Gao, Y.-h. (2024). A Multi-Strategy Enhanced Hybrid Ant–Whale Algorithm and Its Applications in Machine Learning. *Mathematics*. <https://doi.org/https://doi.org/10.3390/math12182848>
- Heidari, A. A., Mirjalili, S., Faris, H., Aljarah, I., Mafarja, M., & Chen, H. (2019). Harris hawks optimization: Algorithm and applications. *Future generation computer systems*, 97, 849–872. <https://doi.org/https://doi.org/10.1016/j.future.2019.02.028>
- Hooshyar, M., & Huang, Y.-M. (2023). Meta-heuristic algorithms in UAV path planning optimization: A systematic review (2018–2022). *Drones*, 7(12), 687. <https://doi.org/https://doi.org/10.3390/drones7120687>
- Kumar, N., Singh, K., & Lloret, J. (2024). WAOA: A hybrid whale-ant optimization algorithm for energy-efficient routing in wireless sensor networks. *Computer Networks*, 254, 110845. <https://doi.org/https://doi.org/10.1016/j.comnet.2024.110845>
- Li, C., Zhao, Q., & Che, C. (2025). 3D Flight Path Planning for UAV Based on Improved Particle Swarm Optimization Algorithm. *IEEE Access*. <https://doi.org/https://doi.org/10.1109/ACCESS.2025.3543175>

-
- Li, J., An, Q., Lei, H., Deng, Q., & Wang, G.-G. (2022). Survey of lévy flight-based metaheuristics for optimization. *Mathematics*, 10(15), 2785. <https://doi.org/https://doi.org/10.3390/math10152785>
- Mohamed, N., Al-Jaroodi, J., Jawhar, I., Idries, A., & Mohammed, F. (2020). Unmanned aerial vehicles applications in future smart cities. *Technological forecasting and social change*, 153, 119293. <https://doi.org/https://doi.org/10.1016/j.techfore.2018.05.004>
- Pitchaimanickam, B., & Murugaboopathi, G. (2020). A hybrid firefly algorithm with particle swarm optimization for energy efficient optimal cluster head selection in wireless sensor networks. *Neural Computing and Applications*, 32, 7709–7723. <https://doi.org/https://doi.org/10.1007/s00521-019-04441-0>
- Qi, D., Zhang, Z., & Zhang, Q. (2022). Path planning of multirotor UAV based on the improved ant colony algorithm. *Journal of Robotics*, 2022(1), 2168964. <https://doi.org/https://doi.org/10.1155/2022/2168964>
- Sahoo, S. K., Saha, A. K., Ezugwu, A. E., Agushaka, J. O., Abuhaija, B., Alsoud, A. R., & Abualigah, L. (2023). Moth flame optimization: theory, modifications, hybridizations, and applications. *Archives of Computational Methods in Engineering*, 30(1), 391–426. <https://doi.org/https://doi.org/10.1007/s11831-022-09801-z>
- Tian, T., Liang, Z., Wei, Y., Luo, Q., & Zhou, Y. (2024). Hybrid whale optimization with a firefly algorithm for function optimization and mobile robot path planning. *Biomimetics*, 9(1). <https://doi.org/https://doi.org/10.3390/biomimetics9010039>
- Yahia, H. S., & Mohammed, A. S. (2023). Path planning optimization in unmanned aerial vehicles using meta-heuristic algorithms: A systematic review. *Environmental Monitoring and Assessment*, 195(1), 30. <https://doi.org/https://doi.org/10.1007/s10661-022-10590-y>
- Yang, X. S., & Hossein Gandomi, A. (2012). Bat algorithm: a novel approach for global engineering optimization. *Engineering computations*, 29(5), 464–483. <https://doi.org/https://doi.org/10.1108/02644401211235834>
- Zhang, R., Li, S., Ding, Y., Qin, X., & Xia, Q. (2022). UAV path planning algorithm based on improved Harris Hawks optimization. *Sensors*, 22(14), 5232. <https://doi.org/https://doi.org/10.3390/s22145232>

ئه‌لگۆریتیمیکی میتاهووریستی تیکه‌لاوی فره ئامانجی گونجاوی (PHL)

پوخته:

فرۆکه بێفرۆکه‌وه‌وه‌کان تادیت په‌یوه‌ندیان به‌ چاودێری مۆدێرن، لۆجستی، و وه‌لامدانه‌وه‌ی کاره‌ساته‌که‌وه‌ زیاتر ده‌بێت. سه‌ره‌پای ئه‌وه‌ش، پلاندانانی کارامه‌ی پێپه‌وی فرۆکه‌ی بێفرۆکه‌وان به‌رده‌وامه‌ له‌ بوون به‌ ئالنگاریه‌ک سه‌باره‌ت به‌ گه‌شتکردنی گونجاو، به‌کارهێنانی وزه‌ و دوورکه‌وته‌وه‌ له‌ پیکدادان. میتاهووریستیکی کلاسیک به‌ به‌کارهێنانی گه‌رانی جیهانی له‌ به‌رامبه‌ر پارادایمه‌کانی ناوخویدا مامه‌له‌ گه‌ل پلاندانانی پێپه‌ودا ده‌کات، که‌ به‌زۆری له‌ ژینگه‌ زۆر دینامیکیه‌کاندا کاره‌کانیان خراپه‌. بۆ که‌مکردنه‌وه‌ی ئه‌م کێشانه‌، ئه‌م توێژینه‌وه‌یه‌ ئه‌لگۆریتیمیکی میتاهووریستی تیکه‌لاوی فره‌ ئامانجی گونجاوی (PHL) پێشنیار ده‌کات که‌ له‌ سه‌ر بنه‌مای باشکردنی particle swarm optimization (PSO)، باشکردنی Harris Hawks (HHO)، و Lévy flight بۆ پلاندانانی باشتري پێپه‌وی فرۆکه‌ی بێفرۆکه‌وان له‌ ژیر سنووری کارکردندا.

باشکردنی پێپه‌وی جیهانی PHL و ڕووبه‌ڕووبوونه‌وه‌ی PSO گرنگی به‌ دوورکه‌وته‌وه‌ له‌ به‌ربه‌سته‌ گونجاوه‌کان ده‌دات پێپه‌وی ناوخۆیی HHO و وردکردنی پێپه‌وی له‌ گه‌ل تیکچوونی Lévy flight. ستراتیژی دروستکراو هاوسه‌نگی ده‌کات له‌ نیوان باری کاری چالاک له‌ نیوان به‌شداربووان له‌ هه‌مان کاتدا به‌ شیوه‌یه‌کی داینامیکی پێپه‌وه‌کانی فرۆکه‌ی بێفرۆکه‌وان له‌ کاتی راسته‌قینه‌دا باشتري ده‌کات. فه‌نکشیکی تیچووی فره‌ ئامانج بۆ خه‌رجکردنی وزه‌، کاتی گه‌شت، ناهاوسه‌نگی باری کار و دوورکه‌وته‌وه‌ له‌ به‌ربه‌سته‌کان بۆ کارایی و گونجاندن بۆ به‌ره‌نگاربوونه‌وه‌ی گۆرانکارییه‌ ژینگه‌یه‌کان دروستکراوه‌، ئه‌مه‌ش وا ده‌کات پێپه‌وی فرۆکه‌ی بێفرۆکه‌وان بگونجیت و له‌ ڕووی حیساباتیه‌وه‌ کارامه‌ی بکات. هاوشیوه‌کردنی به‌رفراوان شیوازه‌که‌ پشتراست ده‌که‌نه‌وه‌، ئه‌مه‌ش ده‌یسه‌لمیڤیت که‌ PHL له‌ ئه‌لگۆریتیمه‌کانی تری میتاهووریستی تیکه‌لاو باشتري. ئه‌نجامه‌کان ئاماژه‌ به‌وه‌ ده‌کهن که‌ PHL که‌مترین خه‌رجی وزه‌ی تیچووی پێپه‌و به‌ده‌ست ده‌یڤیت، یارمه‌تیده‌ره‌ له‌ هاوسه‌نگکردنی باری کاری دوورکه‌وته‌وه‌ له‌ به‌ربه‌سته‌کان، و ڕینگه‌ به‌ فرۆکه‌ی بێفرۆکه‌وان ده‌دات به‌ باشتري شیوه‌

كاربكات. ئيديعاي خوى بههيزتر دهكات بهو هيز و وردبينييهى له كاتى راستهقينهدا كه له گهشتيارى رژيمى فزوكهى بيئفزوكهوان له زينگه زور ديناميكييهكاندا نشان دهدريئ.

خوارزمية ميتاهيورستية هجينة متعددة الأهداف قابلة للتكيف (PHL)

المخلص:

تتزايد أهمية الطائرات بدون طيار في مجالات المراقبة الحديثة، والخدمات اللوجستية، والاستجابة للكوارث. ومع ذلك، لا يزال التخطيط الفعال لمسار الطائرات بدون طيار يُشكل تحديًا فيما يتعلق بالملاحة المثلى، واستهلاك الطاقة، وتجنب الاصطدام. تُعالج الخوارزميات الاستدلالية الكلاسيكية تخطيط المسار باستخدام نماذج الاستكشاف العالمي مقابل نماذج الاستغلال المحلي، والتي عادةً ما يكون أدائها ضعيفًا في البيئات شديدة الديناميكية. وللتخفيف من هذه الصعوبات، تقترح هذه الورقة البحثية خوارزمية الاستدلالية الهجينة متعددة الأهداف التكيفية (PHL) القائمة على تحسين أسراب الجسيمات (PSO)، وتحسين هاريس هوكس (HHO)، ورحلة ليفي، لتحسين تخطيط مسار الطائرات بدون طيار في أسراب الجسيمات ضمن الحدود التشغيلية. يركز تحسين المسار العالمي في PHL وخوارزمية معالجة PSO على تجنب العوائق التكيفية للمسار المحلي HHO، وضبط المسار بدقة مع اضطرابات رحلة ليفي. تُوازن الاستراتيجية المُبتكرة بين عبء العمل النشط بين المشاركين، مع تحسين مسارات الطائرات بدون طيار ديناميكيًا في الوقت الفعلي. تم بناء دالة تكلفة متعددة الأهداف لاستهلاك الطاقة، ووقت السفر، واختلال توازن عبء العمل، وتجنب العوائق، وذلك لتحقيق الكفاءة والقدرة على التكيف مع التغيرات البيئية، مما يجعل توجيه الطائرات بدون طيار قابلاً للتكيف وفعالاً حسابياً. أثبتت عمليات المحاكاة المكثفة صحة هذه الطريقة، مما يثبت تفوق PHL على خوارزميات ميتاهيورستية هجينة أخرى. تشير النتائج إلى أن PHL يحقق الحد الأدنى من تكلفة مسار الطاقة المستهلكة، ويساعد في موازنة عبء عمل تجنب العوائق، ويُمكن الطائرة بدون طيار من العمل على النحو الأمثل. ويعزز هذا الادعاء بالقوة والدقة الأنوية التي تظهر في توجيه أسراب الطائرات بدون طيار في بيئات شديدة الديناميكية.