JCARM
Journal of Contemporary Academic Research and Methodologies

An Online Peer Reviewed / Refereed Journal
Volume 1 | Issue 1 | February 2026
Website: www.journal.jcarm.in

Research

A Comparative Analysis of Bio-Inspired Algorithms in Flying Ad Hoc Networks

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Abstract: Flying Ad Hoc Networks (FANETs) composed of unmanned aerial vehicles (UAVs) provide flexible and infrastructure-free communication that is applicable to disaster management, environmental monitoring, and surveillance. Nevertheless, the node mobility is high, and topology change is frequent, hence reliable routing and coordination are difficult. The bio-inspired optimization algorithms have been extensively explored to solve these problems because of their flexibility and decentralized character [1], [2]. This paper offers a comparative performance study of the Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC) algorithms in the FANET settings. To simulate the behaviour of a UAV swarm in several terrains, such as mountain terrain, urban terrain, desert terrain, and ocean terrain, a MATLAB simulation framework is created. The algorithms are compared according to the convergence rate, network connectivity, stability, and optimization of the trajectory. The findings of the simulations suggest that PSO can converge much faster, ACO can give very effective path optimization, and ABC can be more adaptable in highly dynamic environments. The paper identifies trade-offs between the chosen algorithms and offers recommendations on appropriate algorithms to choose when using various FANET applications. Results can be used to design intelligent and energy-efficient coordination schemes for the future UAV networks.

Keywords: Flying Ad Hoc Networks, Unmanned Aerial Vehicles, Bio-Inspired Optimization, Ant Colony Optimization, Particle Swarm Optimization, Artificial Bee Colony, swarm intelligence, UAV Communication, Routing Optimization, Trajectory Planning, Network Connectivity, Multi-Terrain Simulation, MATLAB Simulation, Distributed Systems, Aerial Networking.

 https://doi.org/10.5281/zenodo.18900329

INTRODUCTION

The use of Unmanned Aerial Vehicles (UAVs) has gained greater significance in civilian and military applications because of their versatility, low cost of deployment, and tolerance to unfriendly or unreachable zones. When several UAVs are integrated without the use of infrastructures, they create a Flying Ad Hoc Network (FANET). FANETs can be used in search and rescue, traffic monitoring, agricultural surveying, and battlefield reconnaissance applications [1], [3].

The FANETs have distinct peculiarities, such as three-dimensional mobility, high velocity, dynamic topology, and limited onboard energy, unlike Mobile Ad Hoc Networks (MANETs) and Vehicular Ad Hoc Networks (VANETs) (1). These characteristics result in frequent link breakages and unstable paths of communication. Conventional routing schemes like AODV and DSR, which were initially created to be used in the MANETs, are not effective in the FANET environments because control overheads are too large and route recovery is too slow [4].

Effective coordination and reliable communication between UAVs is a key to the effective execution of missions. There are routing, formation control, and trajectory planning that should be done dynamically based on environmental barriers and communication limitations. As such, the dynamism of FANETs demands the use of adaptive as well as distributed optimization methods.

The bio-inspired algorithms that simulate natural foraging activities of ants, birds, and bees have also demonstrated high ability in finding solutions to complex optimization problems. These algorithms will be by nature robust, scalable, and self-organizing [5]. Due to this, they can fit a decentralized system like FANETs.

The Ant Colony Optimization (ACO) employs the pheromone trails to determine the route to follow and has been broadly used in the network routing issues [6]. PSO is a method based on collective motion and is characterized by rapid convergence in a multidimensional search space [7]. Artificial Bee Colony (ABC) is a simulation of bee foraging behavior and an effective trade-off between exploration and exploitation [8].

These algorithms have been separately used in some studies in UAV networks. Nevertheless, there is limited research on comparative research in unified conditions of simulation and multi-terrain. The majority of the currently available works are scenario-specific and fail to give consistent performance appraisals.

The purpose of this paper is to fill this gap and provide a comparative analysis in detail of ACO, PSO, and ABC in FANET settings in a common simulation framework. A multi-terrain model of MATLAB is created to be realistic, with various environmental conditions tested on the algorithm.

The principal findings of the paper are as follows:

- Architecture of a centralized simulation environment of FANET.
- Application of three bio-inspired algorithms to the coordination of UAVs.
- Multiple terrain performance analysis.
- Determination of the strengths and weaknesses of every algorithm.

The rest of the paper has the following structure. Section 2 is literature related. Section 3 discusses the principles of working of the choice algorithms. Section 4 reports on simulation settings. The fifth section is a discussion of experimental results. Section 6 concludes the paper.

2. RELATED WORKS

Over the last ten years, Flying Ad Hoc Networks have received much research interest. One of the first extensive reviews of FANET architectures, communication issues, and routing protocols was given by Bekmezci et al. [1]. The researchers have highlighted that aerial networks require different solutions besides the traditional MANET-based ones. Zeng et al. [3] talked about opportunities and challenges of UAV communications and identified the problems tied to mobility, energy consumption, and spectrum management. Their efforts formed the basis of optimization-based solutions in the future. A number of researchers have investigated the issue of ACO-based routing in FANETs. Gunes et al. [6] have shown that ACO is able to stabilize the route and minimize the loss of packets due to dynamically updating pheromones. Nevertheless, they find that large networks also have increased computational complexity.

PSO has been broadly used in UAV formation control and trajectory optimization. A population-based optimization technique was proposed by Kennedy and Eberhhardt [7]. Subsequently, Zhang et al. used PSO in planning UAV paths and showed that the convergence was much faster than genetic algorithms [9]. Although it has its benefits, PSO can experience premature convergence in a highly dynamic environment. ABC algorithms were presented by Karaboga and Basturk [8] and were applied to UAV systems and wireless networks. Sharma and Kumar [10] used ABC to do energy-based routing in ad hoc networks and indicated enhanced flexibility. Nevertheless, ABC-based techniques are prone to thorough parameter optimization.

There have also been proposals of hybrid solutions to the problem, where bio-inspired algorithms are used together with standard routing mechanisms. Oubbati et al. [11] incorporated UAVs into vehicular networks as an effort to improve connectivity in the cities. They focused their work on adaptive strategies of coordination.

Despite the several studies conducted regarding single algorithms, there are limited comparative studies performed under the same environmental and network system conditions. Besides, the majority of the current literature fails to consider multi-terrain conditions that have a pronounced impact on the UAV mobility and communication. Thus, comparative evaluation of algorithm performance in FANETs requires a systematic comparison based on a common simulation platform that would objectively compare their performance.

3. COMPARATIVE ANALYSIS

This section outlines the principles of ACO, PSO, and ABC working principles in the proposed simulation framework.

3.1 Working of ACO in FANET

The Ant Colony Optimization is based on the foraging behavior of ants that leave pheromones along the paths in order to attract the other ants to food sources [6]. UAVs become artificial ants in FANETs and search for the best paths to a destination. Within the adopted model, every UAV has a pheromone value, which indicates the quality of its path to the target. A direction of movement is chosen depending on the intensity of the pheromones and the distance to the target. It is by the evaporation of the pheromones that stagnation is avoided and that exploration is encouraged. Due to the closeness of UAVs to the destination, pheromone values are reinforced to influence others to take efficient paths. The given mechanism allows optimizing distributed paths and enhancing route robustness. Nevertheless, ACO is slow to converge and could be slow to respond in the case of rapid changes in topology. Figure 1 depicts the working of ACO.

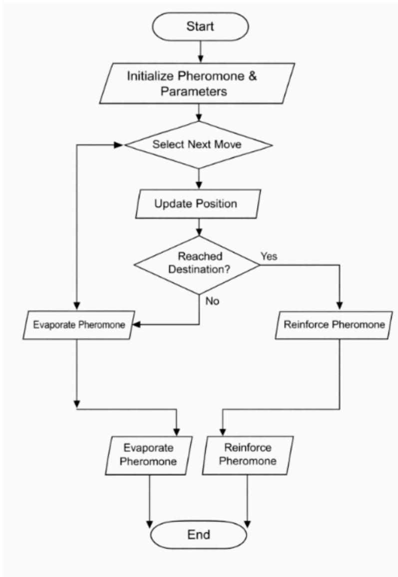

Figure 1. ACO in FANET

3.2 Working of PSO in FANET

Particle Swarm Optimization imitates bird flock social behavior and fish schools [7]. Every UAV is a specific particle whose features are position and velocity. The UAV velocities in the suggested model are updated around three variables, namely inertia, cognitive learning (personal best), and social learning (global best). The UAVs vary their course according to their best position and the best position of the swarm. This process allows the speedy arrival at the target. PSO has good search ability globally and minimal computational complexity. Nonetheless, overdependence on global best information can result in less diversity and eventual convergence in dynamism. Figure 2 represents the functioning of PSO.

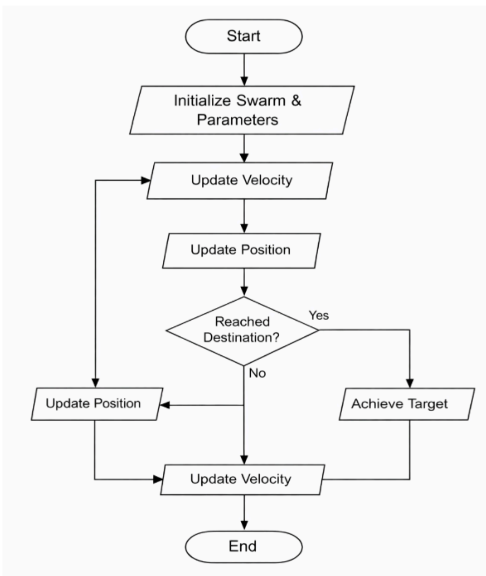

Figure 2. PSO in FANET

3.3 Working of ABC in FANET

The optimization of Artificial Bee Colony is a behavior that resembles honey bees' foraging behavior [8]. UAVs are categorized into employed bees, onlooker bees, and scout bees. Employed bees follow existing paths, observers choose interesting paths depending on fitness scores, and scouts explore new areas randomly. Fitness is calculated on the distance to the target and the quality of communication. Such a structure allows searching the space efficiently and enhances flexibility. ABC gets along especially well in surroundings where there are unforeseeable impediments. However, ABC might be slower than PSO, and it needs more computational resources. Figure 3 represents the working of ABC.

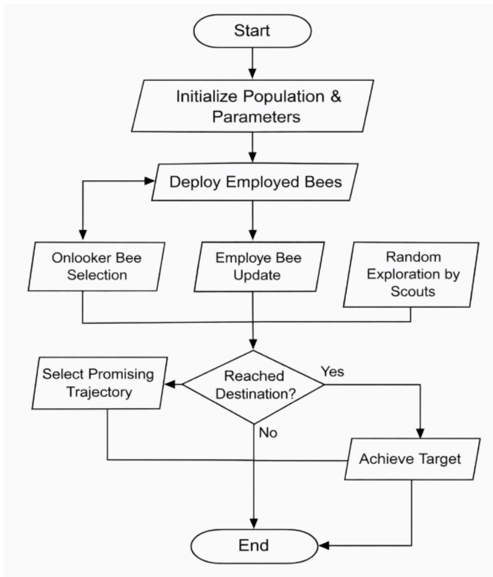

Figure 3. ABC in FANET

4. SIMULATION SETTINGS

A detailed MATLAB-based simulation model was created to assess the ability of bio-inspired optimization algorithms to optimize Flying Ad Hoc Networks. The realistic UAV mobility, communication limitations, and terrain variations are modelled within the simulation environment in order to provide meaningful and repeatable results.

The size of the horizontal plane is taken to be a 240 x 240 unit simulation space. Vertical dimension is adaptively set, depending on the conditions of the terrain elevation and UAV altitude. The number of UAVs deployed randomly in this space at the start of each simulation is twenty. Initial horizontal coordinates are evenly spread, and initial altitudes have been generated with reference to the terrain height in order to prevent ground collisions.

There are four types of terrain that are discussed, which include mountain, urban, desert, and ocean. The mountain terrain is created with the help of the sinusoidal functions to illustrate the irregular heights. The urban environment is represented by randomly spread obstacles to model buildings. The desert terrain has smooth undulations, unlike the ocean terrain, which has low-amplitude waves. These landforms determine the UAV height and movement pattern and, hence, the network performance.

The destination area is presented as a cylindrical area whose center, radius, and height are predetermined. UAVs must fly to this area, having to avoid the obstacles on the terrain. When they enter the destination zone, the assumption is that UAVs have completed their mission successfully, and they are forced to land.

In every UAV, there is a communication module that has a limit of 60 units of the maximum range of transmission. The connection of communication is formed dynamically with the fall of UAVs into this range. These connections make up the FANET topology and are revised on each iteration. Network links are plotted after a predefined time of starting to analyze the patterns of connectivity.

The simulation will operate with 400 iterations, and this is enough to note convergence behavior and network stabilization. The UAV positions are dynamic at each iteration, depending on the velocity vectors calculated using the optimization algorithm used. To simulate disturbances in the atmosphere and real flight dynamics, small sinusoidal changes in the altitude are added.

Parameters related to the algorithm are chosen based on generally accepted parameters in the literature. In the case of ACO, the rate of pheromone evaporation, heuristic parameters, and the parameter of reinforcement are established. In the case of PSO, the weight of inertia and the acceleration coefficients will be adjusted so that exploration and exploitation can be balanced. In the case of ABC, mechanisms of fitness probability and random exploration are adopted.

The main performance metrics considered in this study include:

- Convergence speed
- Average distance to target
- Network connectivity ratio
- Stability of UAV trajectories

- Communication link persistence
- Energy consumption trends (estimated)

Each combination of algorithms and terrains is tested in multiple simulation runs, and average results are collected to minimize statistical bias. This arrangement makes the comparison and reproducibility fair.

Table – 1. Simulation Settings

Category	**Parameter**	**Value**	**Unit / Remarks**
Network Setup	Number of UAVs	20	–
	Simulation Area	240 × 240	Units
	Maximum UAV Altitude	70	Units
	Total Iterations	400	Iterations
	Communication Range	60	Units
	FANET Activation Time	120	Iterations
Initial Deployment	Initial X–Y Position	Random in [0, 240]	Uniform distribution
	Initial Altitude	Terrain height to +70	Relative to terrain
	Initial Velocity	(0, 0, 0)	Stationary
Destination Parameters	Goal Center	(180, 180)	Units
	Goal Radius	12	Units
	Goal Height	45	Units
	Base Height Offset	Terrain height + 2	Units
Terrain Models	Mountain Terrain	Sinusoidal surface	Code-defined
	Urban Terrain	Random blocks (10–40)	Height range
	Desert Terrain	Smooth undulations	Code-defined
	Ocean Terrain	Wave surface	Code-defined
ACO Parameters	Initial Pheromone Value	1	–
	Pheromone Weight	1	–
	Heuristic Weight	2	–
	Evaporation Rate	0.05	–
	Velocity Scaling Factor	0.04	–

PSO Parameters	Inertia Weight	0.6	–
	Cognitive Coefficient	1.6	–
	Social Coefficient	1.6	–
	Best Position Update	Enabled	–
ABC Parameters	Fitness Function	1 / (Distance + 1)	–
	Random Velocity Factor	0.4	–
	Goal Attraction Factor	0.04	–
	Selection Method	Fitness Proportional	–
Flight Dynamics	Altitude Disturbance	0.15 sin (0.05t)	Periodic
	Minimum Altitude	Terrain height + 1	Safety limit
	Maximum Altitude	Base + 50	Safety limit
Performance Metrics	Energy Consumption	281.57	Joules
	Network Lifetime	376.78	Seconds
	Packet Delivery Ratio	82.41	Percentage (%)
	Packet Loss Ratio	17.59	Percentage (%)
	Path Optimality	0.922	0-1
	Route Discovery Time	25.43	Seconds
	Route Stability	138.63	Percentage

5. SIMULATION RESULTS AND DISCUSSIONS

This part contains the detailed analysis of the Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Particle Swarm Optimization (PSO) in Flying Ad Hoc Networks at mountain, urban, desert, and ocean settings. The quantitative findings of the several simulation runs are reported in Table 2, and the graphical display of the seven performance metrics is shown in Figures 4 to 10. The parameters of the evaluation that are used in the analysis are Energy Consumption, Network Lifetime, Packet Delivery Ratio, Packet Loss Ratio, Path Optimality, Route Discovery Time, and Route Stability.

5.1 Energy Consumption

Energy consumption is used to show the overall energy used by the UAVs in navigation and communication. As indicated in Table 2 and Figure 4, the energy consumption of ACO in all terrains is the lowest, with a value between 41 and 44 units.

This is because of its pheromone-directed movement, which encourages comparatively inhalant routes.

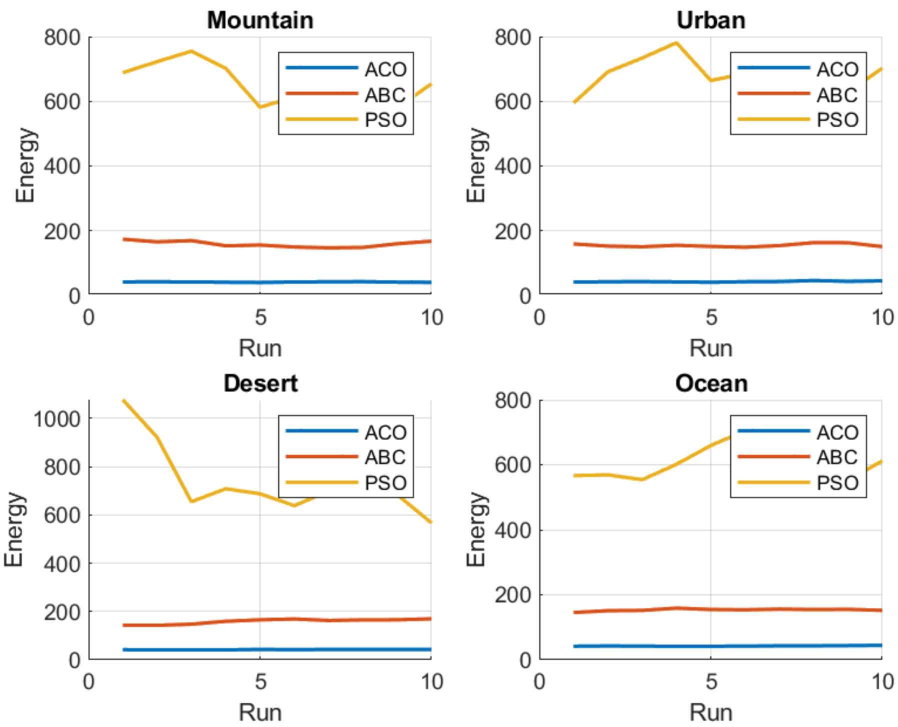

Figure 4. Energy Consumption

ABC exhibits a moderate energy usage, where its values range from 154 to 165 units. Its large-scale exploration and constant alterations of its route are the main reasons for its increased energy consumption. Conversely, PSO has maximum energy consumption, which is more than 580 units in both cases, with maximum consumption of 774 units in urban localities. The phenomenon is caused by aggressive velocity updates and nonstop attraction to the positions that are best worldwide. That is why ACO is the most energy-efficient algorithm, then comes the ABC, but PSO has a large energy overhead.

5.2 Network Lifetime

Network lifetime is used to measure the time interval during which FANET can function before the critical node failures. Based on Table 2 and Figure 5, PSO has the best network lifetime of 387 to 389 iterations. Standard PSO means that it can create a balanced usage of energy among the UAVs.

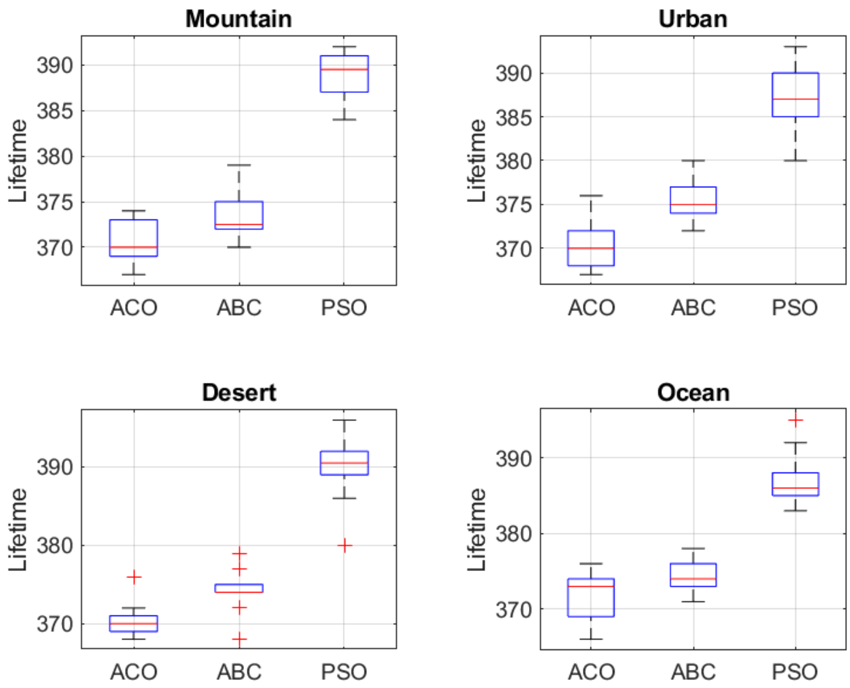

Figure 5. Network Lifetime

The network lifetime of ABC is also high, with a range of 373 to 374 iterations. Its evenly balanced exploitation and exploration process also adds to constant energy dissipation. ACO also depicts relatively fewer lifetime iterations with 368 to 371 iterations, because there is imbalanced energy dissipation along reinforced paths. These findings denote that PSO offers the most prolonged network operation, followed by ABC and ACO records relatively shorter lifetimes.

5.3 Packet Delivery Ratio

Packet Delivery Ratio is used to determine the stability of data transfer in the network. As demonstrated in Table 2 and Figure 6, ACO obtains moderate values of PDR of 0.493 to 0.507, which means that communication is not very reliable.

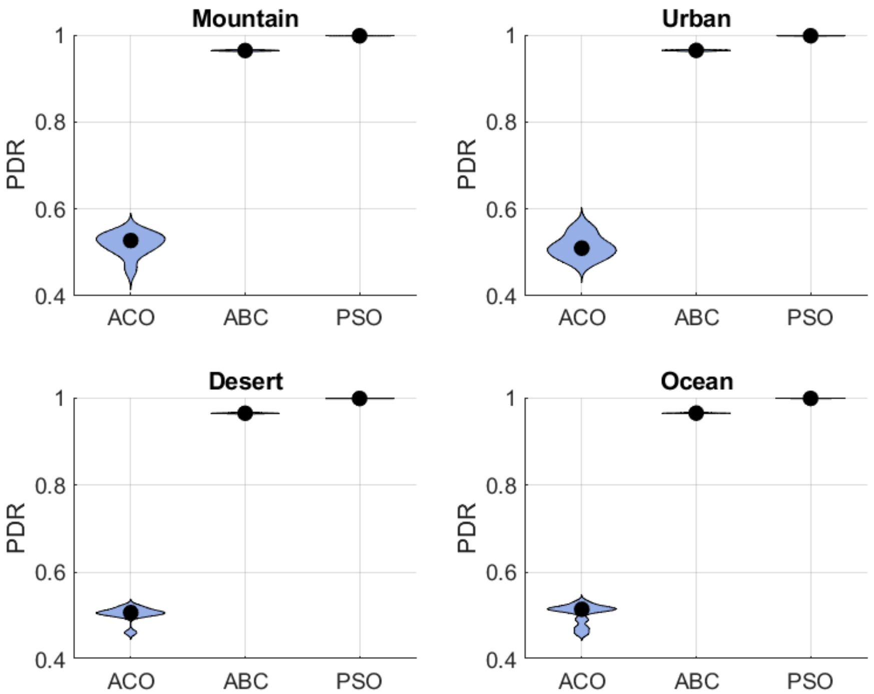

Figure 6. Packet Delivery Ratio

ABC is an important method that helps to overcome the issue of packet delivery and keep the value of PDR near 0.965 in any terrain. This is an indication of its dynamism in choosing the stable and reliable routes. PSO is the best in comparison with ACO and ABC in terms of PDR values near 0.998.

Therefore, PSO has greater reliability in terms of communication, followed by ABC, and ACO has a relatively low performance.

5.4 Packet Loss Ratio

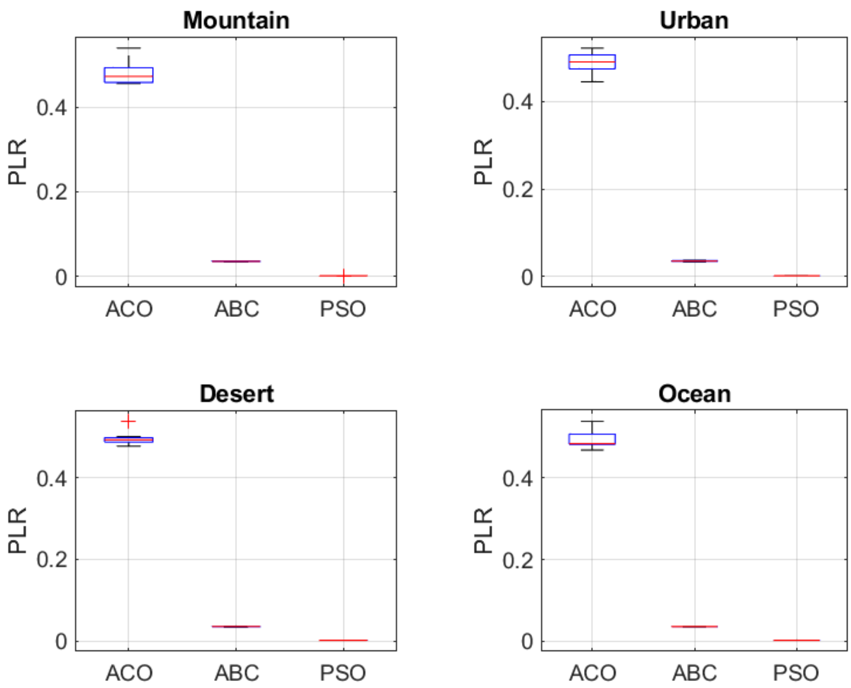

Figure 7. Packet Loss Ratio

Packet Loss Ratio is the percentage of packets that are sent but do not reach the destination. Based on Table 2 and Figure 7, ACO has high values of PLR with a range of 0.493 to 0.507, which means that packet loss is common because of the instability of links. ABC minimizes the loss of packets and keeps the PLR values in the range of 0.035. The way this is enhanced is by adaptive route selection. PSO has the least PLR at about 0.002, which implies that there are few transmission failures. These findings prove the fact that PSO provides the strongest communication environment, next comes ABC, and ACO is more susceptible to link disruptions.

5.5 Path Optimality

Path optimality analyzes the effectiveness of the chosen paths regarding their distance and deviation from the optimal path. Table 2 and Figure 8 indicate that ACO demonstrates the highest values of path optimality, namely between 2.656 and 2.961, which is an indication that UAVs are often associated with the use of longer and less efficient routes.

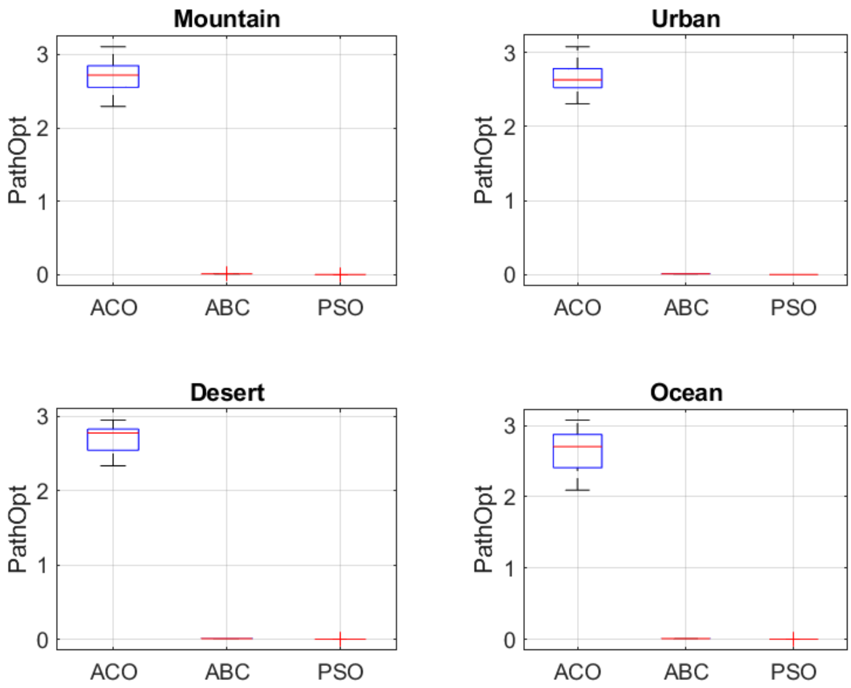

Figure 8. Path Optimality

ABC shows much better performance, and the values are approximately 0.010. This implies that there is a good balance of exploration and exploitation. PSO performs best with an extremely low set of values of order of 10-4, which is near optimal routing behavior. Therefore, PSO produces the most efficient paths, and then ABC comes, and ACO presents minimal efficiency in routing.

5.6 Route Discovery Time

The time of route discovery is taken as the number of cycles that one has to go through to form a valid path of communication. Table 2 and Figure 9 indicate that ACO takes the longest time to discover, with the number of iterations being from 35 to 63. The pheromone reinforcement mechanism is gradual, and it decelerates convergence.

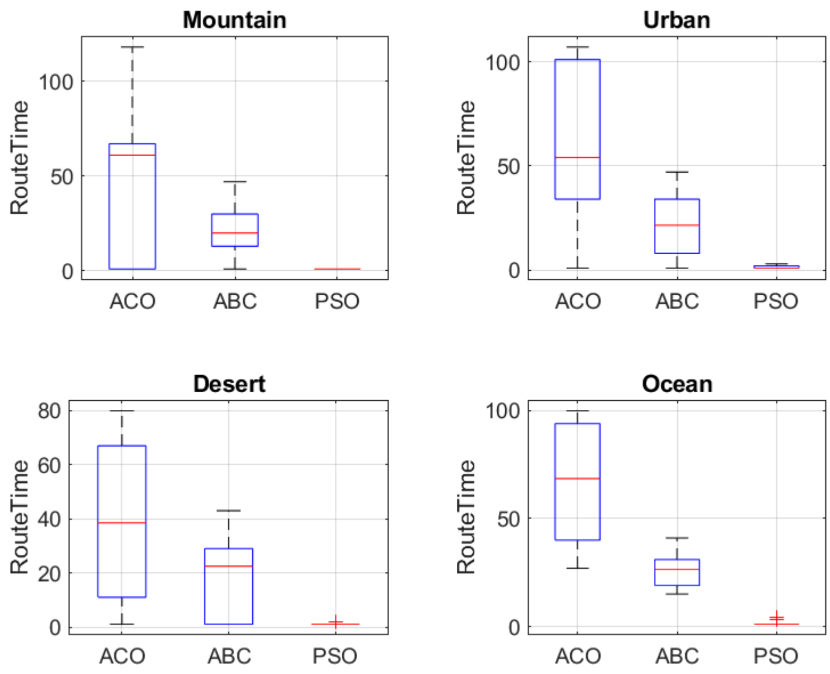

Figure 9. Route Discovery Time

ABC converges moderately, with discovery times ranging between 22 and 27 iterations. PSO always converges the quickest and normally in a single to two iterations, with its global best-guided search mechanism.

Thus, PSO has quick route formation, then the ABC, and the ACO has delayed convergence in complicated environments.

5.7 Route Stability

The route stability implies the continuity of the communication connection through time. Table 2 and Figure 10 indicate that ACO is moderately stable with values of 135 to 136, which means that it has frequent changes of routes.

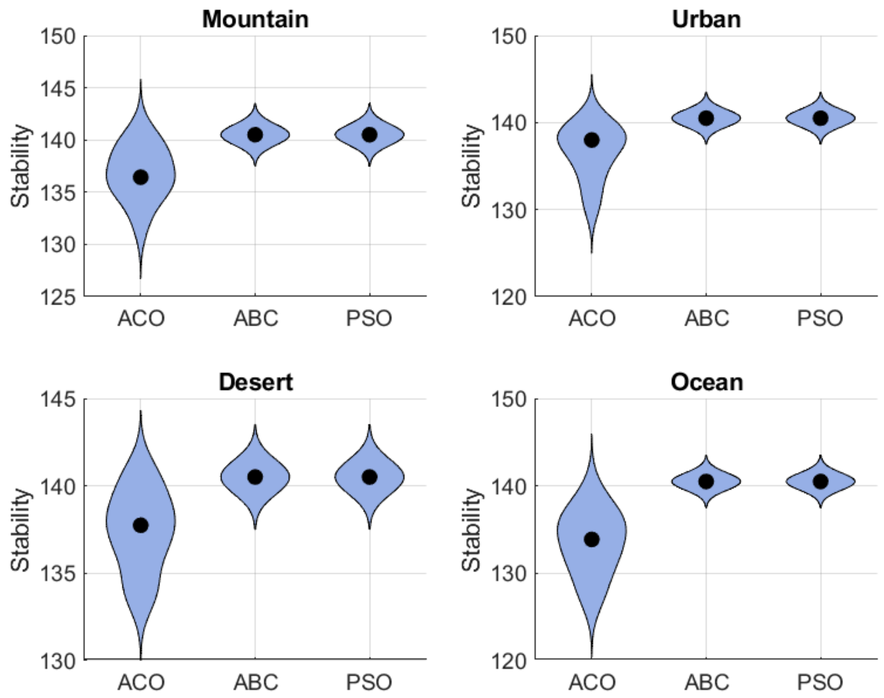

Figure 10. Route Stability

ABC has an average of 140.50 stability in all terrains, and this indicates stable and predictable connections. PSO also has the highest stability values that are near 140.50, showing that the network structures are very stable.

Both ABC and PSO have a high level of route stability, whereas ACO has a relatively lower route stability as it has an exploratory nature.

5.8 Overall Discussion

Using the summarized results of Table 2 and plotted in Figures 4 to 10, some performance peculiarities are observed in the three bio-inspired algorithms. ACO is very energy-saving and less reliable and slower in convergence. ABC offers performance that is balanced, high packet delivery, moderate energy usage, and fair stability. PSO has always shown superior performance to the other algorithms in terms of reliability, speed of convergence, optimality of the path, and network lifetime at the expense of consuming more energy.

These results suggest that PSO is the most suitable to use when high-speed convergence and high reliability are needed, that ABC is suitable when a dynamic environment is required, and that ACO is more suitable under energy-constrained conditions.

Table – 2. Simulation Results

Terrain	Algorithm	Energy	Lifetime	PDR	PLR	Path Optimality	Route Time	Stability
Mountain	ACO	42.58	370.5	0.504	0.496	2.734	53.5	136.15
	ABC	165.49	373.2	0.965	0.035	0.010	22.8	140.50
	PSO	668.74	387.5	0.998	0.002	0.00012	1.4	140.50
Urban	ACO	43.66	371.5	0.504	0.496	2.656	58.7	136.31
	ABC	154.73	374.1	0.965	0.035	0.010	22.6	140.50
	PSO	774.20	388.0	0.998	0.002	0.00011	1.4	140.50
Desert	ACO	42.75	370.8	0.507	0.493	2.690	62.7	135.12
	ABC	155.53	374.3	0.965	0.035	0.010	24.9	140.50
	PSO	581.55	387.4	0.998	0.002	0.00014	1.0	140.50
Ocean	ACO	41.24	368.6	0.493	0.507	2.961	35.4	136.06
	ABC	155.64	374.0	0.965	0.035	0.011	27.1	140.50
	PSO	644.70	388.6	0.998	0.002	0.00012	1.6	140.50

6. CONCLUSION

This paper has provided a comparison of three bio-inspired optimization algorithm Ant Colony Optimization, Particle Swarm Optimization, and Artificial Bee Colony, in Flying Ad Hoc Networks in detail. The hybrid MATLAB-based simulation model was designed to examine the behavior of a swarm of UAVs when different conditions are present in the terrain.

The paper confirms that PSO is better in terms of convergence velocity, stability during formation, and efficiency. The global and local learning processes in its operations allow it to optimize trajectories quickly and have high network connectivity. Nonetheless, PSO can have premature convergence in complex environments.

ACO offers an effective and stable path optimization with the pheromone-based learning. It is flexible to barriers and dynamic transformations of networks. ACO is also stable and reliable in the long term despite its slower convergence and route reliability.

ABC focuses on experimentation and flexibility. The scout mechanism facilitates UAVs to avoid local optima and venture into other paths. It means that ABC is suitable in unpredictable environments, but with increased energy usage and slower convergence.

In general, the findings confirm that bio-inspired algorithms are useful in FANET coordination and routing. There are some specific advantages of each algorithm that can be utilized based on mission goals.

Future studies will be on hybrid optimization methods, which build on the merits of more than one algorithm. It will also be considered to be integrated with machine learning and reinforcement learning to be able to automatically tune the parameters and make intelligent decisions. Also, flight experiments and hardware-based validation in the real world would be done in order to check the simulation results.

The findings of the study are useful in designing next-generation UAVs using the FANET systems that are robust, scalable, and intelligent.

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