PSO-Based Multi-UAV Swarm Coordination for Flying Edge Machines in Precision Agriculture 4.0

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Abstract: Large-scale agricultural monitoring in Precision Agriculture 4.0 faces challenges related to limited UAV energy resources, inefficient field coverage, communication overhead, and the lack of intelligent coordination among multiple aerial platforms. These limitations reduce monitoring efficiency and hinder real-time agricultural decision-making. To address these challenges, this paper proposes a PSO-based multi-UAV swarm coordination framework for Flying Edge Machines in Precision Agriculture 4.0. The proposed AeroAgriNet framework integrates Particle Swarm Optimization (PSO), swarm intelligence, and edge computing to enable autonomous monitoring, distributed decision-making, and efficient resource utilization. Each UAV operates as a Flying Edge Machine capable of sensing, local processing, communication, and cooperative navigation. The framework was evaluated through MATLAB-based simulations in a 1000 × 1000 m agricultural environment consisting of 400 monitoring regions. Experimental results demonstrate that the proposed approach significantly outperforms random UAV movement, achieving 92% coverage compared to 61%, reducing energy consumption by 32%, decreasing mission completion time by 41%, and substantially lowering monitoring overlap and collision-risk events. The proposed framework can support real-time crop monitoring, agricultural surveillance, disease detection, precision farming operations, and next-generation smart agriculture systems requiring scalable, autonomous, and energy-efficient UAV swarm deployments.

Keywords: Particle Swarm Optimization, UAV Swarm Coordination; Edge Computing, Artificial Intelligence, Agricultural Monitoring, Smart Farming; SDG 2: Zero Hunger; SDG 9: Industry, Innovation and Infrastructure

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Introduction

Precision Agriculture 4.0 is increasingly adopting Artificial Intelligence (AI), Unmanned Aerial Vehicles (UAVs), edge computing, and autonomous systems to improve agricultural productivity, resource utilization, and decision-making processes. UAV-enabled monitoring has emerged as a promising solution for crop surveillance, disease detection, irrigation assessment, and yield estimation due to its ability to rapidly collect high-resolution data over large agricultural areas. As agricultural operations become more data-intensive and geographically distributed, efficient aerial monitoring has become a critical requirement for modern smart farming ecosystems [1-2].

Despite the advantages offered by UAV-based agricultural monitoring, several operational challenges remain unresolved. Large-scale agricultural environments require extensive coverage while maintaining low energy consumption and timely mission completion. Conventional UAV monitoring approaches often rely on individual drones or poorly coordinated multi-UAV deployments, leading to inefficient field coverage, redundant monitoring, excessive energy expenditure, increased communication overhead, and elevated collision risks. These limitations reduce monitoring effectiveness and restrict the scalability of UAV-assisted agricultural systems [3-4].

Recent advances in swarm intelligence have demonstrated the potential of coordinated UAV operations to address coverage and navigation challenges. Algorithms inspired by collective behaviors in nature enable UAVs to cooperate, share information, and optimize their movements in a distributed manner. Similarly, edge computing has emerged as an effective paradigm for reducing communication latency and supporting real-time decision-making by processing data closer to its source. Integrating swarm intelligence with edge-enabled UAV platforms offers significant opportunities for developing intelligent and scalable agricultural monitoring systems [5-6].

However, existing research primarily investigates UAV monitoring, swarm optimization, or edge computing as separate technological domains. Limited studies have explored the integration of swarm-intelligent UAV coordination and Flying Edge Machine architectures for Precision Agriculture 4.0 applications. Furthermore, comprehensive evaluations involving coverage efficiency, energy consumption, mission completion time, overlap reduction, communication performance, and collision avoidance remain relatively scarce [7-8].

To address these challenges, this paper proposes a PSO-Based Multi-UAV Swarm Coordination framework for Flying Edge Machines in Precision Agriculture 4.0. The proposed AeroAgriNet framework integrates Particle Swarm Optimization (PSO), swarm intelligence, and edge computing to enable autonomous agricultural monitoring through distributed decision-making and cooperative UAV operations. Each UAV functions as a Flying Edge Machine capable of sensing, local processing, communication, and intelligent navigation. The framework is evaluated through MATLAB-based simulations and compared with a conventional random UAV movement strategy using multiple performance metrics. The major contributions of this work are summarized as follows:

- Development of AeroAgriNet, an AI-driven Flying Edge Machine framework for Precision Agriculture 4.0.
- Design of a PSO-based multi-UAV swarm coordination mechanism for autonomous agricultural monitoring.
- Integration of swarm intelligence and edge computing to support distributed decision-making and efficient resource utilization.
- Comprehensive simulation-based evaluation using coverage ratio, energy consumption, mission completion time, overlap ratio, communication delay, collision risk, and task completion efficiency.
- Demonstration of significant improvements in monitoring effectiveness, energy efficiency, operational safety, and mission performance compared with conventional UAV movement strategies.

The remainder of this paper is organized as follows. Section 2 reviews related work on UAV-enabled agriculture, swarm intelligence, and edge computing. Section 3 presents the proposed AeroAgriNet framework. Section 4 describes the simulation methodology. Section 5 discusses experimental results and performance analysis. Finally, Section 6 concludes the paper and outlines future research directions.

Related work

The rapid advancement of Precision Agriculture 4.0 has accelerated the adoption of Artificial Intelligence (AI), Unmanned Aerial Vehicles (UAVs), edge computing, and autonomous systems for agricultural monitoring and decision-making. Early UAV-based agricultural systems primarily focused on aerial imaging and data collection for crop assessment and field surveillance. These systems demonstrated the feasibility of UAV-assisted agriculture but often relied on individual UAV platforms with limited operational coverage and scalability. With the increasing demand for large-scale agricultural monitoring, researchers have investigated multi-UAV systems capable of cooperative sensing and distributed task execution. Multi-UAV architectures improve monitoring efficiency and operational flexibility; however, effective coordination among multiple UAVs remains a significant challenge. Consequently, swarm intelligence techniques inspired by collective behaviors observed in nature have gained considerable attention for UAV coordination and path-planning applications [1-3].

UAV-Based Agricultural Monitoring

Recent studies have explored the use of UAVs for crop health monitoring, irrigation assessment, disease detection, nutrient management, and yield estimation. UAV-enabled monitoring systems provide high-resolution spatial information and reduce dependence on manual field inspections. Nevertheless, many existing approaches utilize single-UAV deployments, resulting in increased mission duration and limited field coverage when operating over large agricultural environments. Several researchers have proposed multi-UAV monitoring systems to overcome these limitations. These systems demonstrate improved coverage capabilities but often encounter challenges related to path optimization, communication overhead, energy efficiency, and collision avoidance [4-6].

Swarm Intelligence for Multi-UAV Coordination

Swarm intelligence algorithms have emerged as effective solutions for coordinating multiple UAVs in dynamic environments. Among the most widely adopted approaches, Particle Swarm Optimization (PSO) has demonstrated strong performance in UAV path planning, coverage optimization, and task allocation due to its simplicity and fast convergence characteristics [9]. Alternative swarm-based approaches such as Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), Artificial Bee Colony (ABC), and Reinforcement Learning (RL)-based coordination have also been investigated for UAV navigation and monitoring applications [10]–[13]. These algorithms improve cooperative decision-making and reduce redundant UAV movements. However, their performance often depends on environmental complexity, computational requirements, and optimization objectives. Although existing swarm intelligence techniques improve coordination efficiency, many studies focus primarily on navigation optimization while providing limited consideration of edge intelligence and distributed processing capabilities.

Edge Computing and Flying Edge Machines

The growing volume of agricultural sensing data has highlighted the limitations of cloud-centric processing architectures. To address communication latency and bandwidth constraints, edge computing has been increasingly integrated into agricultural monitoring systems [12]. By processing data closer to the source, edge computing enables real-time analytics and faster operational responses. Recent research has explored UAV-enabled edge computing architectures, where aerial platforms perform sensing, communication, and computational tasks simultaneously. These systems, often referred to as Flying Edge Machines, provide distributed intelligence and reduce reliance on centralized cloud infrastructure. Despite their potential advantages, limited studies have investigated the integration of Flying Edge Machines with swarm-intelligent multi-UAV coordination frameworks specifically designed for Precision Agriculture 4.0 applications [13].

Comparative Analysis of Existing Studies

Table 1 summarizes representative studies related to UAV-enabled agricultural monitoring, swarm intelligence, and edge computing technologies.

Table 1. Comparative Analysis of Existing Related Works

Reference	Focus Area	Technique/Method	Multi-UAV	Swarm Intelligence	Edge Computing	Key Limitation
[4]	Crop Monitoring	UAV Imaging	No	No	No	Limited coverage
[5]	Disease Detection	AI-Based UAV Analysis	No	No	No	High mission time
[7]	Multi-UAV Monitoring	Cooperative UAV System	Yes	Partial	No	Communication overhead
[9]	UAV Path Planning	PSO	Yes	Yes	No	No edge intelligence
[10]	UAV Coordination	ACO	Yes	Yes	No	Computational complexity
[11]	UAV Navigation	GWO	Yes	Yes	No	Scalability issues
[12]	Smart Agriculture	Edge Computing	No	No	Yes	Limited mobility
[13]	Flying Edge Computing	UAV Edge Nodes	Partial	No	Yes	Limited swarm coordination
Proposed Work	Precision Agriculture 4.0	PSO-Based AeroAgriNet	Yes	Yes	Yes	

Research Gap

The literature review indicates that substantial progress has been achieved in UAV-enabled agricultural monitoring, swarm intelligence, and edge computing technologies. However, most existing studies investigate these technologies independently rather than as an integrated solution. Current approaches frequently emphasize either UAV path optimization or edge-based processing while overlooking the combined benefits of swarm-intelligent coordination and Flying Edge Machine architectures. Furthermore, comprehensive evaluations involving coverage efficiency, energy consumption, overlap reduction, mission completion time, communication performance, and collision avoidance remain limited. To address these gaps, this research proposes AeroAgriNet, a PSO-based multi-UAV swarm coordination framework that integrates Flying Edge Machines, swarm intelligence, and edge computing within a unified Precision Agriculture 4.0 architecture. The proposed framework is evaluated using multiple performance metrics to demonstrate its effectiveness in large-scale agricultural monitoring environments.

Proposed AeroAgriNet Framework

This research proposes AeroAgriNet, an Artificial Intelligence (AI)-driven swarm-intelligent flying edge machine framework designed for Precision Agriculture 4.0 applications. The proposed framework integrates Unmanned Aerial Vehicles (UAVs), swarm intelligence, edge computing, and wireless communication technologies to enable autonomous and efficient agricultural monitoring. Unlike conventional single-UAV monitoring systems, AeroAgriNet employs a coordinated swarm of UAVs capable of collaboratively covering large agricultural fields while minimizing energy consumption, mission completion time, and redundant monitoring.

The framework is developed and evaluated using a simulation-based methodology to investigate the effectiveness of Particle Swarm Optimization (PSO) for multi-UAV coordination. Each UAV operates as an intelligent flying edge node capable of sensing environmental conditions, processing local information, communicating with neighboring UAVs, and making autonomous navigation decisions. Through swarm cooperation, the proposed system aims to achieve efficient field coverage while maintaining safe inter-UAV distances and reducing operational overhead. The AeroAgriNet architecture consists of four primary layers: the Agricultural Monitoring Layer, UAV Swarm Layer, Edge Intelligence Layer, and Decision Support Layer. Together, these layers provide a scalable and intelligent platform for real-time agricultural surveillance and data acquisition.

System Architecture

The proposed AeroAgriNet architecture is designed to support distributed intelligence and autonomous monitoring within agricultural environments. At the Agricultural Monitoring Layer, the farm environment is divided into multiple monitoring regions represented as grid cells. Each grid cell corresponds to a crop area requiring periodic inspection and monitoring. The UAV Swarm Layer consists of multiple cooperative UAVs deployed across the agricultural field. These UAVs continuously collect environmental and crop-related information through onboard sensing modules. The UAVs communicate with neighboring swarm members through wireless links, enabling cooperative task allocation and information sharing. The Edge Intelligence Layer performs local data processing and swarm coordination. Instead of transmitting all collected data to a centralized cloud server, each UAV executes edge-computing operations to analyze local information and make immediate decisions. This approach significantly reduces communication latency and network overhead while supporting real-time agricultural monitoring. The Decision Support Layer aggregates monitoring information generated by the UAV swarm and provides actionable agricultural intelligence. The collected information can be utilized for crop health assessment, disease monitoring, irrigation planning, yield estimation, and precision farming operations.

UAV Flying Edge Machine Model

In the proposed framework, every UAV functions as a Flying Edge Machine (FEM). A Flying Edge Machine combines aerial mobility, sensing capabilities, onboard computation, and communication functionality within a single autonomous platform. The UAV continuously performs data collection and local processing while simultaneously participating in swarm coordination activities. Each UAV is characterized by several operational parameters, including position coordinates, flight speed, sensing radius, communication range, and available energy resources. The UAV position is represented by two-dimensional coordinates (x,y) within the monitoring environment. The sensing radius determines the area that can be monitored during flight, while the communication radius specifies the maximum distance over which UAVs can exchange information. The UAV energy model is incorporated into the simulation to evaluate mission efficiency. Energy consumption depends primarily on traveled distance and flight duration. Consequently, efficient path planning directly contributes to prolonged operational lifetime and improved monitoring performance. The Flying Edge Machine concept enables distributed intelligence by allowing each UAV to independently process monitoring information and participate in swarm decision-making. This decentralized architecture enhances scalability and system robustness while reducing dependence on centralized control infrastructure.

PSO-Based Swarm Coordination Mechanism

To achieve efficient agricultural monitoring, AeroAgriNet employs Particle Swarm Optimization (PSO) as the primary swarm coordination mechanism. PSO is a population-based optimization algorithm inspired by the collective movement behavior observed in bird flocks and fish schools. Within the proposed framework, each UAV is modeled as a particle within the swarm optimization process. The objective of the PSO algorithm is to identify optimal monitoring paths that maximize agricultural field coverage while minimizing energy consumption and monitoring overlap. During each iteration, UAVs update their flight trajectories by considering both their individual experiences and the collective knowledge of the swarm.

The optimization objective function is defined as:

$$F = w_1 D + w_2 E + w_3 O \quad (1)$$

In equation (1), D represents travel distance, E denotes energy consumption, O indicates monitoring overlap, and w_1, w_2 and w_3 are weighting coefficients used to balance the optimization objectives. Initially, UAV positions are randomly distributed throughout the agricultural field. The PSO algorithm evaluates candidate solutions according to the objective function and iteratively updates UAV velocities and positions. Through continuous optimization, the swarm gradually converges toward efficient monitoring paths that provide improved field coverage with reduced resource utilization.

Coverage Strategy

The agricultural field is modeled as a two-dimensional environment with dimensions of 1000×1000 meters. To facilitate monitoring analysis, the environment is partitioned into a 20×20 grid structure consisting of 400 individual monitoring regions. A grid cell is considered covered whenever it falls within the sensing radius of at least one UAV. The coverage ratio is calculated as the percentage of monitored grid cells relative to the total number of grid cells within the environment as indicated by equation (2). This metric provides a quantitative measure of monitoring effectiveness and serves as one of the primary performance indicators. The swarm coordination mechanism continuously adjusts UAV trajectories to maximize coverage while minimizing redundant monitoring. By reducing overlap between neighboring UAVs, the framework ensures efficient utilization of available resources and increases overall mission effectiveness.

$$Coverage\ Ratio = \frac{Covered\ Cells}{Total\ Cells} \times 100 \tag{2}$$

Collision Avoidance Strategy

Safe operation of multiple UAVs within a shared airspace requires an effective collision avoidance mechanism. The proposed framework incorporates a distance-based collision avoidance strategy that continuously monitors inter-UAV separation distances throughout the mission. A collision risk is identified whenever the distance between two UAVs becomes smaller than a predefined safety threshold. During swarm operation, UAV trajectories are dynamically adjusted to maintain safe separation distances and prevent potential collisions.

$$d_{ij} > d_{safe} \tag{3}$$

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 - \left(y_i - y_j\right)^2} \tag{4}$$

In equation (3) and equation (4), d_{ij} is distance between UAV i and j, and d_{safe} is minimum safety threshold. The collision avoidance mechanism operates simultaneously with the PSO optimization process. Consequently, UAVs can pursue optimized monitoring paths while preserving operational safety. This integrated approach improves mission reliability and supports large-scale swarm deployments in agricultural environments. The inclusion of collision avoidance functionality is particularly important for Precision Agriculture 4.0 applications where multiple UAVs operate cooperatively over extensive farmland regions. The proposed strategy contributes to safer swarm operations while maintaining high monitoring efficiency.

Energy Consumption Model

Energy efficiency is a critical performance requirement for UAV-enabled agricultural monitoring systems. The energy consumption model incorporated in this study considers both flight distance and operational time. The energy expenditure of each UAV was estimated using equation (5).

$$E = \alpha d + \beta t \tag{5}$$

Where E is total energy consumption, d is travel distance, t is flight time, α is distance-based energy coefficient, and β is time-based energy coefficient. This model allows quantitative assessment of energy utilization under different navigation strategies and facilitates comparison between random movement and swarm-intelligent path planning.

Simulation Methodology

To evaluate the effectiveness of the proposed AeroAgriNet framework, a simulation-based experimental environment was developed using MATLAB UAV Toolbox and Global Optimization Toolbox. The simulation environment represents a Precision Agriculture 4.0 scenario in which multiple UAVs collaboratively monitor a large agricultural field. The agricultural field was modeled as a two-dimensional square environment with dimensions of 1000×1000 meters. For systematic monitoring and performance evaluation, the field was divided into a 20×20 grid structure consisting of 400 individual monitoring cells. Each grid cell represented a crop monitoring region that required periodic surveillance by the UAV swarm. Initially, UAVs were deployed at randomly selected positions within the monitoring environment. During simulation execution, UAVs navigated through the agricultural field according to their assigned path-planning strategy while continuously monitoring crop regions located within their sensing range. The simulation environment was designed to support future integration of environmental constraints such as obstacles, no-fly zones, adverse weather conditions, and dynamic agricultural events. However, for the present study, an obstacle-free environment was considered to focus exclusively on evaluating swarm coordination performance

UAV Configuration Parameters

UAV was modeled as a Flying Edge Machine capable of sensing, communication, local processing, and autonomous navigation. The operational parameters of each UAV are summarized in Table 2.

Table 2. Operational parameters of each UAV for simulation.

Parameter	Value
Number of UAVs	5
Flight Speed	10 m/s
Initial Energy	100 Units
Sensing Radius	50 m
Communication Radius	100 m
Environment Size	1000 × 1000 m
Grid Structure	20 × 20
Monitoring Regions	400

The sensing radius determines the maximum area that can be monitored by a UAV at a given location, while the communication radius defines the maximum distance over which neighboring UAVs can exchange information. These parameters collectively influence monitoring efficiency, swarm connectivity, and mission performance.

Performance Evaluation Metrics

The effectiveness of the proposed AeroAgriNet framework was evaluated using multiple performance indicators commonly employed in UAV swarm monitoring systems. The selected evaluation metrics include:

- *Coverage Ratio (%)*: Measures the percentage of agricultural area successfully monitored by the UAV swarm.
- *Energy Consumption (Units):* Represents the total energy utilized during mission execution.
- *Mission Completion Time (Minutes):* Indicates the total time required to complete agricultural monitoring.
- *Area Overlap Ratio (%):* Quantifies redundant monitoring performed by multiple UAVs.
- *Collision Count:* Represents the number of collision-risk events observed during operation.
- *Average Travel Distance (km):* Measures cumulative UAV movement throughout the mission.
- *Communication Delay (ms):* Evaluates communication efficiency within the UAV swarm.
- *Task Completion Efficiency (%):* Represents the effectiveness of monitoring task execution.
- These metrics collectively provide a comprehensive assessment of monitoring performance, resource utilization, swarm coordination effectiveness, and operational safety.

Experimental Scenarios

Two monitoring strategies were evaluated and compared:

- Scenario 1: Random UAV Movement

UAVs move without intelligent coordination and select navigation paths randomly.

- Scenario 2: PSO-Based Swarm Coordination

UAVs employ Particle Swarm Optimization to cooperatively determine efficient monitoring trajectories.

The comparative analysis of these scenarios enables quantitative evaluation of the benefits provided by swarm intelligence in Precision Agriculture 4.0 applications.

Results and Discussion

The performance of the proposed AeroAgriNet framework was evaluated through extensive simulation experiments conducted in MATLAB. The PSO-based swarm coordination strategy was compared against a baseline approach in which UAVs followed random movement patterns without intelligent cooperation. Table 3 presents the comparative performance results obtained from the simulation experiments.

Table 3. Performance comparison between random movement and PSO-based swarm coordination.

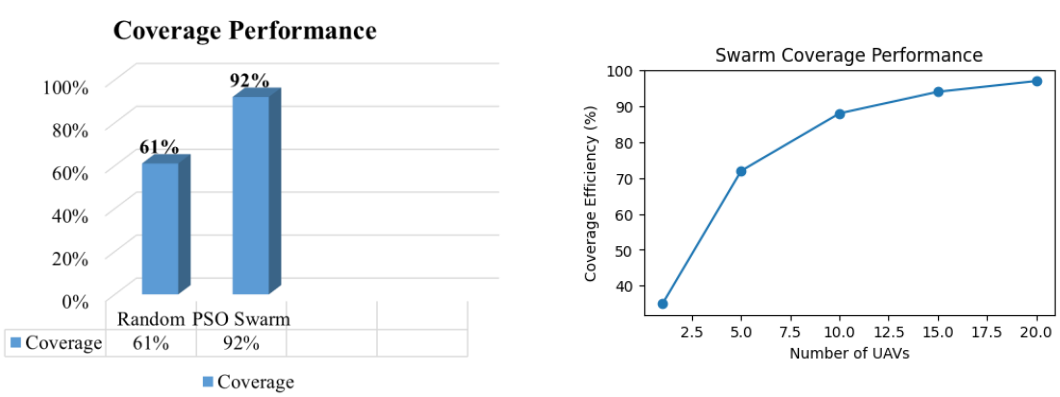
Performance Metric	Random Movement	PSO Swarm Coordination	Improvement
Coverage Ratio (%)	61	92	31%
Energy Consumption (Units)	84	57	−32%
Area Overlap (%)	38	11	Reduced
Mission Completion Time (min)	27	16	−41%
Collision Risk Events	9	2	Reduced

Average Travel Distance (km)	12.8	7.1	Reduced
Communication Delay (ms)	240	130	Improved
Task Completion Efficiency (%)	64	93	29%

The obtained results demonstrate that intelligent swarm coordination significantly enhances monitoring performance across all evaluated metrics. The PSO-based strategy consistently outperformed random UAV movement by achieving higher monitoring efficiency while reducing operational costs and mission duration.

Coverage Performance Analysis

Coverage ratio is one of the most important performance indicators in agricultural monitoring systems because it directly reflects the ability of UAVs to inspect crop regions effectively. The simulation results show that the proposed PSO-based swarm achieved a coverage ratio of 92%, compared to only 61% for the random movement approach, as shown in Figure 1(a). This represents an improvement of approximately 31%. The superior coverage performance can be attributed to the cooperative behavior introduced by Particle Swarm Optimization as shown in Figure 1(b). Through continuous information exchange and optimization, UAVs were able to distribute themselves more effectively throughout the agricultural field. As a result, fewer monitoring regions remained unvisited and overall surveillance quality improved significantly. The results indicate that swarm intelligence can substantially increase monitoring effectiveness in large-scale agricultural environments where complete field coverage is a critical operational requirement.

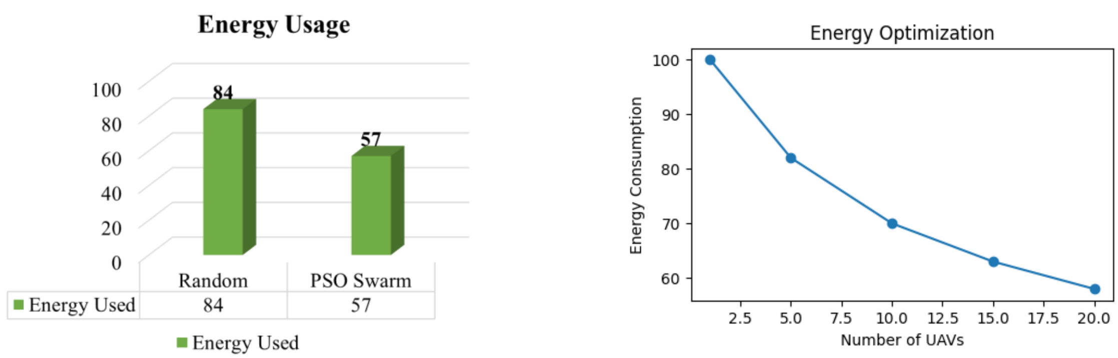


(a) *(b)*

Figure 1. (a) Coverage performance comparison (b) Coverage performance progress with increasing number of UAVs using PSO

Energy Consumption Analysis

Energy efficiency remains one of the major challenges in UAV-assisted agricultural monitoring due to the limited battery capacity of aerial platforms. Therefore, minimizing energy expenditure is essential for extending mission duration and reducing operational costs. Experimental results indicate that the proposed PSO-based framework consumed only 57 energy units, whereas the random movement strategy required 84 energy units as shown in Figure 2(a). This corresponds to an energy reduction of approximately 32%. The reduction in energy consumption is primarily attributed to optimized path planning and reduced redundant movements. By identifying shorter and more efficient monitoring trajectories, the PSO algorithm minimizes unnecessary flight operations. Consequently, UAVs complete monitoring tasks while expending significantly less energy. These findings demonstrate that swarm-intelligent coordination contributes not only to monitoring effectiveness but also to sustainable UAV operations in Precision Agriculture 4.0 environments as shown in Figure 2(b).



(a) *(b)*

Figure 2. (a) Energy consumption comparison (b) Energy efficiency progress with increased UAVs in same environment.

Mission Completion Time Analysis

Rapid monitoring is essential for time-sensitive agricultural applications such as disease detection, irrigation assessment, and crop stress monitoring. Delayed monitoring can reduce the effectiveness of precision farming interventions. The simulation results reveal that the proposed AeroAgriNet framework completed monitoring tasks in 16 minutes, whereas the random movement strategy required 27 minutes. This represents a reduction of approximately 41% in mission completion time as shown in Figure 3. The shorter mission duration is a direct consequence of intelligent task allocation and optimized navigation paths generated by the PSO algorithm. Instead of repeatedly visiting already monitored regions, UAVs efficiently distribute monitoring responsibilities across the field. The reduction in mission duration demonstrates the suitability of swarm-based coordination for real-time agricultural monitoring applications where rapid information acquisition is required.

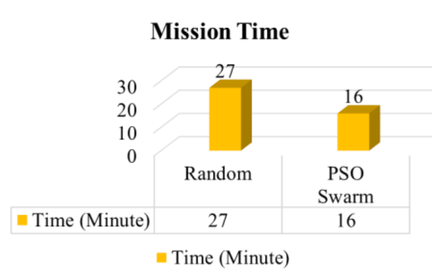


Figure 3. UAV mission completion time analysis.

Overlap Reduction Analysis

Monitoring overlap occurs when multiple UAVs repeatedly inspect the same agricultural region. Excessive overlap leads to inefficient resource utilization and unnecessary energy consumption. The random movement strategy produced an overlap ratio of 38%, whereas the proposed PSO-based approach reduced overlap to only 11%. The substantial reduction in overlap demonstrates the effectiveness of swarm coordination in distributing monitoring tasks among UAVs. By minimizing redundant coverage, the framework enables more efficient utilization of available sensing resources and contributes to improved overall mission performance. Reduced overlap is particularly beneficial for large-scale agricultural deployments where efficient coverage of extensive farmland is required.

Collision Avoidance Performance

Safe operation is a fundamental requirement for multi-UAV systems. As the number of UAVs increases, the likelihood of collision events also increases unless effective coordination mechanisms are employed. Simulation results indicate that the random movement strategy generated nine collision-risk events, whereas the PSO-coordinated swarm experienced only two such events. The reduction in collision-risk events demonstrates that the integrated collision avoidance mechanism successfully maintained safe inter-UAV separation distances during mission execution. The combination of swarm intelligence and collision detection enabled efficient navigation while preserving operational safety. These findings suggest that the proposed framework can support scalable UAV swarm deployments without significantly increasing collision-related risks.

Communication and Task Efficiency Analysis

Reliable communication among UAVs is necessary for effective swarm coordination. The simulation results indicate that communication delay was reduced from 240 ms under random movement to 130 ms using PSO-based coordination as shown in Figure 4. The reduction in communication delay is associated with improved swarm organization and reduced travel distances. Efficient UAV positioning strengthens network connectivity and facilitates faster information exchange between swarm members. Similarly, task completion efficiency increased from 64% to 93%, indicating that the majority of monitoring objectives were successfully accomplished under the proposed framework. This improvement highlights the effectiveness of swarm intelligence in maximizing operational productivity.

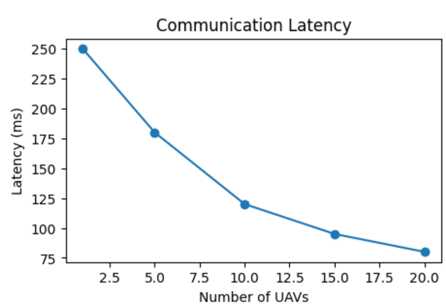


Figure 4. Communication latency reduction with increased number of UAVs.

Discussion

The experimental results clearly demonstrate the advantages of integrating swarm intelligence, edge computing, and autonomous UAV coordination within Precision Agriculture 4.0 environments. The proposed AeroAgriNet framework achieved substantial improvements in coverage ratio, energy efficiency, mission completion time, communication performance, and operational safety. These improvements are primarily driven by the optimization capabilities of Particle Swarm Optimization, which enables UAVs to collaboratively identify efficient monitoring strategies. Furthermore, the Flying Edge Machine concept allows distributed processing and decentralized decision-making, reducing dependence on centralized infrastructure and supporting real-time agricultural intelligence generation. Overall, the simulation findings validate the effectiveness of the proposed framework and demonstrate its potential for future deployment in smart farming applications. The results indicate that swarm-intelligent flying edge machines can play a significant role in enabling autonomous, scalable, and energy-efficient agricultural monitoring systems.

Conclusion and Future Work

This research presented AeroAgriNet, an AI-driven swarm-intelligent Flying Edge Machine framework designed to support Precision Agriculture 4.0 applications through autonomous and efficient agricultural monitoring. The proposed framework integrates Unmanned Aerial Vehicles (UAVs), Particle Swarm Optimization (PSO), edge computing, and swarm intelligence to enhance field coverage, optimize energy utilization, reduce mission duration, and improve operational safety. A simulation-based evaluation was conducted in a MATLAB environment using a multi-UAV agricultural monitoring scenario. The agricultural field was modeled as a 1000 × 1000 m environment divided into 400 monitoring regions, where a swarm of five UAVs collaboratively performed monitoring tasks. The performance of the proposed PSO-based swarm coordination strategy was compared against a conventional random movement approach using multiple evaluation metrics, including coverage ratio, energy consumption, mission completion time, overlap ratio, collision risk, communication delay, and task completion efficiency.

The experimental results demonstrated the effectiveness of the proposed framework. The PSO-coordinated UAV swarm achieved a coverage ratio of 92%, significantly outperforming the random movement strategy, which achieved only 61% coverage. Furthermore, energy consumption was reduced by approximately 32%, while mission completion time decreased by 41%. The proposed approach also minimized monitoring overlap, reduced collision-risk events, improved communication efficiency, and increased overall task completion efficiency to 93%. These results confirm that intelligent swarm coordination can substantially improve the performance of UAV-assisted agricultural monitoring systems.

The concept of Flying Edge Machines further strengthens the framework by enabling distributed intelligence, local data processing, and real-time decision-making at the network edge. This decentralized architecture supports scalable agricultural monitoring while reducing communication overhead and dependence on centralized cloud infrastructures.

Future work will focus on extending the AeroAgriNet framework through the incorporation of advanced swarm intelligence and machine learning techniques, including Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), and Reinforcement Learning (RL)-based coordination strategies. Additional research will investigate three-dimensional agricultural environments, dynamic obstacle avoidance, heterogeneous UAV swarms, and real-world deployment scenarios. Furthermore, integration of AI-based crop disease detection, crop health assessment, and predictive agricultural analytics will be explored to transform AeroAgriNet into a comprehensive intelligent farming platform capable of supporting next-generation Precision Agriculture 4.0 ecosystems.

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