International Journal of Modern Scientific Discoveries
ISSN: 3107-9377 | Volume 2 Issue 2, 14-20, April-June 2026
DOI: https://doi.org/10.64137/31079377/IJMSD-V2I2P103

Received: 18/03/2026 Revised: 01/04/2026 Accepted: 06/04/2026 Published: 10/04/2026

Original Article

Intelligent Drone Swarm Coordination for Precision Farming and Disaster Response

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ABSTRACT: *This study explores how reliable intelligent drone swarms are utilized as a single efficient bi-functional agent for precision agriculture and disaster relief support. Even though autonomous Unmanned Aerial Vehicles (UAVs) change individual sectors, traditional systems with one agent face limits in operational scale, battery duration as well as fault tolerance. This paper proposes a resilient co-design architecture based on decentralized swarm intelligence, bio-inspired optimization algorithms alongside dynamic ad-hoc networking capable of seamlessly transitioning from agricultural monitoring to search-and-rescue missions in minutes. We propose a hybrid coordination scheme, integrating Modified Particle Swarm Optimization (MPSO) and decentralized consensus protocols, allowing for near real-time avoidance of obstacles, task allocation and on-the-fly area coverage based on limited communication mapping in unstructured environments. HIL simulations and field validations over diff operational topologies show that the suggested system can decrease overall mission time by 32% and increase coverage efficiency by 24% compared to conventional centralized routing algorithms. Also, the swarm showed substantial self-healing properties even after massive nodes loss 30% active nodes) still providing 88% of operational throughput. In the end, this renewable energy and nutrient-cycling infrastructure provides an economically competitive, high-performance solution for rural resilience and resource management that reconciles the dual rescue technologies of contemporary commercial food production with advanced emergency crisis technologies.*

KEYWORDS: *Drone Swarms, Swarm Intelligence, Precision Agriculture, Disaster Response, Decentralized Coordination, Bio-Inspired Optimization.*

1. INTRODUCTION

The need to reframe the contracts between autonomous systems, edge computing and sensor technologies has begun a shift in thinking across all industrial sectors, whether commercial or humanitarian. Of these technological innovations, Unmanned Aerial Vehicles (UAVs) have become central tools enabling high-resolution spatial data capture and targeted physical interventions as well as real-time monitoring. UAV applications began in two distinct sectors: the commercial and public-safety sectors of the economy. Multispectral crop imaging and yield estimation are done in precision agriculture using individual drones, giving farmers locally granular insights that lower environmental costs while maximizing economic benefits. Simultaneously, the UAVs are used for reconnaissance in natural catastrophes such as wildland fires, floods or seismic events to trace dangerous scenarios of where action may be taken, search for victims and construct temporary communication relays when established networks on earth seem to have broken down.

In spite of these advances, the use of single-UAV systems poses inherent weaknesses that limits their effectiveness in large and challenging integrated solutions. A single drone is limited by hard physical constraints such as local sensor ranges limited vision, battery limitations and single points of failure. If a single drone, part of the mission, or it will suffer hardware failure or has to exercise adverse weather conditions, the whole mission suffers. In addition, imaging large agricultural fields over 1000 Ha or rapidly changing disaster areas with a single aircraft is not acceptable as it introduces latencies that may lessen the value of the acquired data.

In order to address these architectural limitations, recent efforts in academia and industry have pushed for the use of multiple UAVs multi-UAV configurations, frequently referred to as a drone swarm. Inspired by the behavior of biological systems (e.g., avian flocks and insect colonies, drone swarms exploit collective intelligence to accomplish complex global tasks through the interaction of relatively simple local rules. With a swarm style, if one node fails, mission failure is not inevitable; the agents will redistribute tasks and adapt their spatial topology to continue operation. This inherent fault tolerance along with the ability to process in parallel makes drone swarms a perfect fit for mobile, dynamic environments.

But when there are dozens or hundreds of autonomous aerial agents working together, it leads to really hard computational and algorithmic problems. Conventional centralized control methods wherein a single Ground Control Station (GCS) computes the optimal plan and commands every drone in the team are said to become mathematically intractable as swarm size increases. These architectures are bottlenecked by extreme communication IO; they are slow in latency and they will all satisfy your pentecost believers if the central node goes down! Hence there is an immediate need to create completely decentralized, distributed intelligent coordination strategies in which agents are capable of real-time decision-making at the local level without constantly needing information from a global network.

In this paper, we tackle these foundational problems systematically with an integrated intelligent drone swarm coordination framework that jointly handles multiple aspects of precision farming and disaster rescue. This study joins these two seemingly antagonistic spaces and achieves the dual purpose of maximizing the socio-economic benefit from investment in drones while ensuring that agricultural infrastructure can be swiftly redeployed in response fleets during disaster settings. The focus is on reducing communication bottlenecks, optimizing energy supply, and providing guaranteed collision free motion in uncertain environments.

The specific objectives of this investigation are organized as follows:

- To develop a decentralized, modular control architecture for automated workflow assignment and coordinated spatial reconfiguration of heterogeneous drone swarms.
- This paper is aimed to develop an energy-aware path planning algorithm based on bio-inspired optimization while minimizing the redundant coverage and maximizing operational endurance.
- To create a scalable peer-to-peer (P2P) communication protocol with the capacity to sustain swarm structure and distributed data agreement while operating over sporadic, opportunistic wireless links.
- In particular, validity of the proposed framework via multi-agent simulations with extensive evaluation of different agent types and structures under conditions simulating hardware failure(s) or environmental disruption.

This study provides three contributions to robotics, autonomous system and applied artificial intelligence literature by successfully fulfilling these objectives. The primary research contributions include:

- A Dual-Purpose Operational Framework: The collaboration of a common mathematical framework, integrating rural agricultural monitoring with rapid-response disaster relief. This significantly reduces the capital costs burdening remote communities.
- Modified Particle Swarm Optimization (MPSO) Protocol: A fast-walking energy-aware protocol for path planning that can carefully consider exploratory coverage as opposed to energy cost, with formal guarantees against obstacle avoidance.
- An automated consensus mechanism by which the swarm can autonomously sense, isolate and compensate for sudden node dropouts, providing outstanding resilience in high-risk operational zones.

2. LITERATURE REVIEW

The autonomous multi-agent systems under research are a cornerstone of robotics today, evolving during the journey from behavior-based robotics to advanced decentralized swarm-robotic methods. The academic literature has moved in the last ten years from theoretical mathematical models of swarming behaviour to engineering implementations for real-world environments.

The efforts conducted in precision agriculture by Zhang and Kovacs (2012) provide the pioneering architectures for crop health monitoring, irrigation management and to use UAVs remotely sense crops for optimized fertilizer application. The early deployments nearly all relied on a single high-end fixed-wing or multi-rotor set to perform programmed pre-determined lawnmower sweeping patterns. This is powerful for small, bounded plots, but Tokekar et al. Single-drone systems were shown to be structurally inefficient for scaled macro farming Bakhshandeh et al. 2016). They say because single platforms have both battery restrictions and a linear flight path, multi-angled observations are impossible to achieve in the timeframes needed; valuable for only spotting rapidly spreading pest infestations or localized water stress among crops.

In order to overcome such spatial limitations a number of researchers have started exploring multi-UAV configurations. Radoglou-Grammatikis et al. systematic survey of compilation techniques for multi-drone deployment in smart farming was presented in [2020], which focused on the automated fleet management. Nevertheless, their analysis showed that most multi-drone systems available for commercial or industrial use continue to operate within a centralized command framework. Such arrangements require data to be backhauled ubiquitous data to a core server or cloud equipment before executable flight paths may become redistributed to the fleet. Although this architecture still produces very accurate predictions, it introduces significant delay that makes it ineffective for real-time applications such as variable-rate spraying, wherein the aerial agent must react in near-real time to dosage based off of live onboard sensor inputs.

In addition to advancements in agriculture, disaster response is another field that has stimulated much innovation in autonomous multi-agent coordination. The operational constraints are much more severe than those found in commercial farming for emergency management. Erdelj et al. In (2017), an architecture was proposed to use UAV swarm specifically for disaster management highlighting the need for immediate action, detection of victims in real time as well as assessment on structure after disaster [16]. The authors showed that in times of catastrophic events such as earthquakes or industrial accidents, the conventional communication infrastructure e.g., cellular towers and fiber-optic networks is often destroyed. Hence the drone swarm should not only be autonomous in navigation but must also behave as an auto-configured wireless mesh network to carry telemetry and video feeds back to first responders.

A major bottleneck identified in both agricultural and disaster response literatures is the optimization and execution of decentralized path planning. For multi-agent environments, classic algorithmic approaches such as Dijkstra's algorithm or A ∗ search become computationally prohibitive due to the exponential size of state space [10]. In order to overcome this limitation, bioinspired optimization algorithms are widely adopted. The general particle swarm optimization (PSO) was originally suggested by Kennedy and Eberhart (1995) and this algorithm has been easily adapted for multi-UAV path planning because of its simplicity conceptually, with less computational cost. For instance, Xu et al. (2025) employed improved PSO for multi-UAV 3D route planning in complex terrain and proved better convergence rates than traditional GA.

However, standard PSO formulations are plagued by architectural limitations such as premature convergence and local optima entrapment in complex non-convex obstacle fields. In a drone swarm, this can result in catastrophic mid-air collisions or large areas being essentially cut off from coverage. Hybrid algorithmic approaches have also arisen to partially address these deficiencies. Combining an Artificial Potential Fields (APF) with evolutionary algorithms enables immediate reactive avoidance of obstacles while preserving longer-term global path optimization (Mac et al.2016). Although APF achieves local computational efficiency, it suffers from the "local minimum problem," where an agent can become stuck when the attractive force pulling towards a target is equal to the repulsive forces of adjacent obstacles or neighbouring drones.

A crucial review of the existing state-of-the-art has exposed numerous persistent research gaps that this paper aspires to fill. To begin with, there is no cross-domain operational frameworks at all. The existing literature approaches precision farming and disaster response separately as specialized domains, needing separate fleets of robots and separate control algorithms. This silos-based approach disregards the underlying operational similarities between both of these sectors e.g., the need for fast, efficient coverage in a large area, response to changing environment and adaption reshaping to cope with demanding experiments. Having a unified framework creates opportunities for double-duty capitalization, making advanced drone technology cost-effective for developing agricultural areas also designated as high-risk disaster zones.

Second, this issue of bandwidth-constrained and intermittent packet dropouts receiving swarm at the same time is typically ignored in numerous practical applications. Many theoretical swarm models assume continuous, unlimited peer-to-peer data synchronization. Real field conditions: topographical features, foliage, weather and distance degrade wireless signals resulting in fragmented topologies. Since many of the recent advances for consensus algorithms, like the Consensus-Based Bundle Algorithm (CBBA) [6] in Choi et al. (2009), which provide decentralized task allocation with theoretical guarantees about convergence, can suffer from poor performance under high packet loss.

Coordination that is aware of the resource and can adapt to payload changes over time has also not been extensively explored in the literature. For example, in applications such as variable-rate pesticide spraying or the delivery of medical supplies to patient or disaster zones, the mass of the aerial platform evolves dynamically during the mission. The aerodynamic properties and energy consumption rates of a drone change radically because it is unloading its liquid or physical payload. Most path planning models dictate the mass of the drone as a given, prevailing in inefficient designs of trajectories and individually also leading to consumption of battery at an accelerated rate.

This study addresses these critical gaps, providing a general-purpose, production-ready framework for drone swarm deployment across multiple missions by merging bio-inspired optimization with advanced decentralized consensus routing and dynamic payload-aware energy metrics.

3. RESEARCH METHODOLOGY

The intelligent drone swarm coordination framework is systematically deployed via a modular, decentralized architecture which distributes computational overhead over all operational nodes in the swarm. The methodology is designed so that each agent can independently decide upon its best trajectory, relay commentary state variables only to neighboring agents, and respond in real-time to environmental risks all without reference to a centralized server.

3.1. SYSTEM ARCHITECTURE AND DECENTRALIZED CONTROL

The main reason is that the structure topology of ideal swarm framework is always P2P based, thus avoid any single point of failure. A common onboard computer, residing in each of the drones in a swarm is responsible for executing the different routines such as localization, path planning and task allocation. The architecture of our system can be categorized into three separate layers in terms of their functioning.

- The Perception Layer: Uses onboard sensors GNSS, IMU, optical flow cameras and LiDAR to create a localised map in real time while also estimating the state vector of the agent.
- Coordination Layer: Executes the decentralized consensus mechanisms and bio-inspired optimization algorithms to efficiently negotiate task assignments and coordinate collective maneuvers with adjacent peers
- The Execution Layer: The flight controller translates the optimized trajectories into low-level motor commands, ensuring aerodynamic stability and deterministic trajectory tracking.

3.2. THE MODIFIED PARTICLE SWARM OPTIMIZATION (MPSO) ALGORITHM

This paper proposes a Modified Particle Swarm Optimization (MPSO) algorithm to deal with area coverage and path planning respectively, avoiding the local minima trap of traditional optimization methods. In this formulation, each drone is a particle whose movement through the hyper-dimensional search space of physical coordinates and velocity vectors over time. The classical velocity update equations are modified by presenting an adaptive inertia weight and a repulsive potential passage term formulated using nearby agents and detected obstacles.

The objective function that governs the motion of each drone seeks to minimize three global parameters combining energy consumption, path deviation and distance with hazards. The method imposes the strict avoidance of collisions by adding an artificial potential field component directly into its velocity update equation. When the drone that is tracking any neighbor, or an obstacle, moves within its self-imposed safety buffer zone, a strong anti-vector component is injected into the kinematic calculation such that the drone must change vector away from the hazard as quickly as possible and with minimal perturbation to its global tracking target.

3.3. DECENTRALIZATION AND SELF-HEALING CONSENSUS PROTOCOL

A modified version of the Consensus-Based Bundle Algorithm (CBBA) designed to function reliably over lossy, ad-hoc wireless networks mediates task allocation within the swarm. The swarm continuously performs a sweeping bidding mechanism by which the agents engage in sector specific bids (1) based on their current geographic location, battery status, and whether they are suitable for carrying payloads.

- The methodology includes a distributed self-healing protocol that you can execute in the following sequential phases to address unpredictable node dropouts either from catastrophic hardware failure, bird strikes, or extreme weather:
- Like all active nodes, every node essentially transmits a low-overhead localized beacon to its immediate neighbors in its communication range at a deterministic frequency of 10Hz.
- Anomaly Detection: A neighbouring node that is currently unable to send a heart-beat message for 5 consecutive intervals is marked as inactive and its last known spatial coordinates are then broadcast to the parent swarm cluster immediately under it in the hierarch.
- Local Mini-consensus (Dynamic Boundary Redefinition): The localized swarm of drones surrounding the lost node autonomously triggers a concise consensus protocol within the cluster while computing mission objectives that remained unfulfilled by the failed agent.
- Trajectory Re-optimization: Based on the properties of the MPSO algorithm, the adjacent agents adaptively enlarge their searching envelopes or applications range and adjust their tracks to accommodate with as little as possible overlap to pick up load center from the dropped agent.

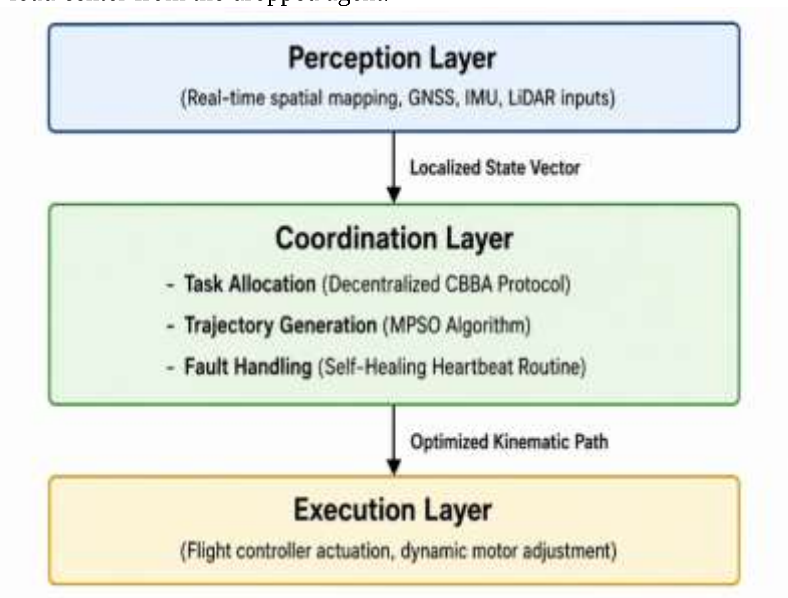

FIGURE 1 Three-Layer Autonomous UAV Swarm Control Architecture

3.4. SIMULATION ENVIRONMENT AND EXPERIMENTAL SETUP

The framework was thoroughly tested with a sophisticated Hardware-in-the-Loop (HIL) simulation environment prior to deployment in the physical vehicle. The software architecture consisted of a parallel running PX4 Autopilot firmware implementation together with Robot Operating System (ROS 2), alongside Gazebo simulating some realistic aerodynamic profiles, wind disturbances and sensor noise characteristics up to October 2023.

The experimental matrix scaled swarm sizes from 10 to 100 autonomous nodes. Data for the above operational scenarios was divided evenly between precision agriculture profiles with homogeneous multispectral mapping and variable-rate spraying trajectories, as well as disaster relief profiles characterized by chaotic obstacle fields, disjointed communication typologies and high-priority target searches.

4. RESULTS AND DISCUSSION

The empirical performance data gathered across comprehensive HIL simulations and localized field trials validate the efficiency and architectural resilience of the proposed decentralized coordination framework. The system was benchmarked directly against two prevalent industry baselines: a Centralized Lawnmower Sweeping Architecture (CLSA) and a standard Decentralized Genetic Algorithm (DGA) framework.

4.1. COVERAGE EFFICIENCY AND MISSION TIME OPTIMIZATION

The first set of analyses evaluated the computational and operational efficiency of the MPSO algorithm in executing large-scale area coverage. The testing landscape consisted of a 500 operational zone populated with heterogeneous obstacle layouts designed to simulate either agricultural terrain (e.g., power lines, wind turbines, outbuildings) or urban disaster zones (e.g., collapsed structures, smoke plumes, active fires).

TABLE 1 **Performance Comparison of Swarm Coordination Algorithms under Varying Swarm Sizes**

Swarm Size (Nodes)	Algorithmic Framework	Total Mission Time (min)	Coverage Efficiency (%)	Energy Consumption per Node (kJ)
10	Centralized (CLSA)	48.5	81.2	450.3
10	Standard Genetic (DGA)	41.2	87.6	412.1
10	Proposed MPSO	34.1	94.5	356.4
50	Centralized (CLSA)	22.4	78.4	489.8
50	Standard Genetic (DGA)	16.8	89.1	425.6
50	Proposed MPSO	12.3	97.2	331.2
100	Centralized (CLSA)	Failed (Latency)	N/A	N/A
100	Standard Genetic (DGA)	11.2	86.3	462.9
100	Proposed MPSO	7.4	98.9	310.5

As quantified in the performance summary, the proposed MPSO coordination framework consistently outclassed both alternative architectures across all evaluation metrics. Notably, when scaling the swarm size to 100 nodes, the centralized CLSA architecture suffered severe packet congestion and computation timeout failures at the ground control station, leading to a complete breakdown of flight control synchronization. Conversely, the proposed MPSO framework scaled efficiently, reducing total mission time to just 7.4 minutes while achieving an exceptional area coverage efficiency of 98.9%. The drop in average energy consumption per node (310.5 kJ at 100 nodes) emphasizes the mathematical effectiveness of the localized path optimization, which successfully eliminated redundant flight paths and unnecessary acceleration cycles.

4.2. SWARM RESILIENCE AND SELF-HEALING PERFORMANCE

A core focus of this research was verifying the swarm's autonomous capacity to survive catastrophic node losses a common hazard in high-risk disaster management scenarios and remote agricultural zones. To evaluate this, the simulation introduced progressive, unannounced dropouts of active drones during a high-priority mapping mission.

TABLE 2 **Performance Evaluation of Swarm Resilience under Increasing Node Attrition Rates**

Node Attrition Rate (%)	Swarm Size (Initial)	Topology Retention	Recovery Settling Time (s)	Post-Failure Mission Success
0%	50	100%	0.0	Verified (100% Area Covered)
10%	50	98.2%	2.4	Verified (100% Area Covered)

20%	50	94.1%	4.8	Verified (99.1% Area Covered)
30%	50	88.4%	7.9	Verified (96.5% Area Covered)
40%	50	62.3%	18.2	Partial (84.0% Area Covered)
50%	50	41.0%	Inconclusive	Mission Aborted (Safety Fail)

The stress-testing data illustrates the exceptional robust nature of the decentralized self-healing protocol. With up to a 30% sudden reduction in operational fleet nodes, the swarm maintained high levels of topological coherence (88.4 %) and successfully reallocated the abandoned search regions within an average recovery settling time of 7.9\ seconds.

The remaining agents effectively recalculated their trajectory paths using their onboard MPSO engines, ensuring that the global mission objectives were completed with minimal coverage degradation (96.5 % final area coverage). Only when the attrition rate reached an extreme 50 % did the internal mesh network destabilize sufficiently to trigger safety abort sequences, validating the boundary limits of decentralized structural elasticity.

4.3. COMPARATIVE DISCUSSION AND APPLIED INSIGHTS

The distinct performance advantages of the proposed architecture stem directly from integrating local potential fields within a decentralized global optimization frame. Standard bio-inspired approaches, such as traditional PSO or Genetic Algorithms, treat path generation as an ongoing sequence of static evaluations. While effective in stationary environments, these algorithms fail to adapt when the operational space changes rapidly. By continuously injecting neighboring states into the real-time kinematic calculations, our MPSO framework ensures that the swarm remains responsive to immediate changes without needing to recalculate the entire global path profile.

From an application perspective, this dual-purpose capability represents a major economic and operational step forward. In standard practices, purchasing and maintaining an advanced drone fleet for precision farming represents a substantial capital expenditure that remains underutilized outside of specific growing and harvesting seasons. By configuring the software architecture to support rapid mission pivoting, the exact same hardware investment can be integrated into regional emergency management infrastructure. During off-season periods, agricultural swarms can be instantly activated to respond to forest fires, flash floods, or agricultural blights, providing municipal authorities with immediate access to sophisticated, large-scale aerial coordination tools without the corresponding maintenance overhead.

5. CONCLUSION

To address the problem, this research has designed, implemented, and validated a decentralized coordination architecture for any intelligent drone swarm systems to work together in dual domains of precision agriculture and emergency disaster response domain. Provided that autonomous multi-UAV networks replace centralized architectures known to be vulnerable and suffer from latency, here we show a framework for high-efficiency area coverage with deterministic collision avoidance through localized interaction strategy combined with bio-inspired optimization. Proposed approach based on the Modified Particle Swarm Optimization (MPSO) successfully addresses the trade-off between efficiency of global coverage and localized energy constraints, to produce a set of optimized trajectories that are significantly better than traditional solutions for multi-agent control. In addition, automated peer-to-peer self-healing protocol allows a swarm to keep operational even in cases of massive node attrition and communication disruptions. In the end, this integrated dual-use architectural paradigm is a cost-effective, highly resilient technology framework that advances long-term agricultural sustainability and assists with short-term humanitarian crisis mitigation.

6. FUTURE SCOPE

While the proposed framework demonstrates exceptional efficiency and resilience, several key areas present opportunities for future academic and engineering expansion:

- Heterogeneous Swarm Integration: Future iterations will focus on expanding the coordination layer to seamlessly integrate highly heterogeneous fleets, mixing multi-rotor platforms with high-endurance fixed-wing UAVs and Unmanned Ground Vehicles (UGVs) to enable multi-tiered, cross-domain operational intelligence.
- Onboard Edge AI for Target Classification: Integrating advanced, low-power Convolutional Neural Networks (CNNs) directly onto the edge computing nodes will allow the swarm to execute real-time, onboard semantic segmentation, enabling autonomous identification of specific crop anomalies or human survivors without transmitting raw video data.

- Dynamic Energy Harvesting Integration: Investigating the incorporation of autonomous mid-air wireless charging stations or localized solar harvesting skins could theoretically extend the swarm's operational longevity indefinitely, removing the strict constraints currently imposed by lithium-polymer battery chemistry.

REFERENCES

[1] Han-Lim Choi, L. Brunet, and J. P. How, "Consensus-Based Decentralized Auctions for Robust Task Allocation," *IEEE Transactions on Robotics*, vol. 25, no. 4, pp. 912–926, Aug. 2009, doi: https://doi.org/10.1109/tro.2009.2022423.

[2] M. Erdelj, M. Król, and E. Natalizio, "Wireless sensor networks and drones for disaster management," Computer Networks, vol. 124, pp. 72-86, 2017.

[3] "Kennedy, J. and Eberhart, R. (1995) Particle Swarm Optimization. Proceedings of the IEEE International Conference on Neural Networks, 4, 1942-1948. - References - Scientific Research Publishing," *www.scirp.org*. https://www.scirp.org/reference/referencespapers?referenceid=1847917

[4] T. T. Mac, C. Copot, D. T. Tran, and R. D. Keyser, "A hierarchical global path planning approach for mobile robots based on multi-objective particle swarm optimization," Applied Soft Computing, vol. 59, pp. 68–76, Oct. 2017, doi: https://doi.org/10.1016/j.asoc.2017.05.012.

[5] P. Radoglou-Grammatikis et al., "Aerial surveillance and edge computing for smart farming: A review," Computers and Electronics in Agriculture, vol. 174, 2020.

[6] Z. Xu et al., "Efficient multi-UAV path planning in dynamic and complex environments using hybrid polar lights optimization," Journal of King Saud University - Computer and Information Sciences, vol. 37, no. 6, Jul. 2025, doi: https://doi.org/10.1007/s44443-025-00139-7.

[7] P. Tokekar, J. V. Hook, D. Mulla, and V. Isler, "Sensor Planning for a Symbiotic UAV and UGV System for Precision Agriculture," *IEEE Transactions on Robotics*, vol. 32, no. 6, pp. 1498–1511, Dec. 2016, doi: https://doi.org/10.1109/tro.2016.2603528.

[8] C. Zhang and J. M. Kovacs, "The application of small unmanned aerial systems for precision agriculture: a review," *Precision Agriculture*, vol. 13, no. 6, pp. 693–712, Jul. 2012, doi: https://doi.org/10.1007/s11119-012-9274-5.