

Review

Application Analysis of Swarm Control Technology in Orchard Agricultural Production

Zixuan Zhang ^{1,2,3,4} , Huawei Yang ^{1,2,3,4,*} , Peng Qi ^{1,2,3,4} , Xiaojie Shi ^{1,2,3,4}, Xinbing Ding ^{1,2,3,4}, Shaowei Wang ^{1,2,3,4} , Shucheng Wang ^{1,2,3,4}, Lu Xun ⁵, Supakorn Wongsuk ⁶ and Liyang Su ⁷ 

¹ Shandong Academy of Agricultural Machinery Sciences (SAAMS), Jinan 250100, China; qi-peng@139.com (P.Q.)

² Centre for Agricultural Robotics Innovation (CARI), Shandong Academy of Agricultural Machinery Sciences, Jinan 250100, China

³ Shandong Key Laboratory of Intelligent Agricultural Equipment in Hilly and Mountainous Areas, Jinan 250100, China

⁴ Huang Huai Hai Laboratory of Modern Agricultural Equipment, Ministry of Agriculture and Rural Affairs, Jinan 250100, China

⁵ College of Mechanical & Electrical Engineering, Henan Agricultural University, Zhengzhou 450002, China

⁶ Faculty of Agriculture, Chiang Mai University, Chiang Mai 50200, Thailand

⁷ College of Agricultural Unmanned System (CAUS), China Agricultural University, Yuanmingyuan West Road No.2, Haidian District, Beijing 100193, China

* Correspondence: yhw105@163.com

Abstract

Swarm control technology, leveraging artificial intelligence algorithms to coordinate multiple devices, offers an effective solution for developing precision and intelligent operation systems in orchard management. This paper focuses on the core technologies underpinning swarm coordination and reviews the current state of research on collaborative communication, path planning, task allocation, and formation control, with reference to both domestic and international studies. Based on the full growth cycle of fruit trees, encompassing monitoring, precision management, and harvesting, the paper summarizes the applications and research progress of swarm control technology at each stage. Furthermore, it identifies key challenges in applying swarm technology to orchard environments, including low efficiency in heterogeneous system coordination, delayed responses to dynamic conditions, resource constraints in large-scale swarm systems, and limited adaptability to agricultural contexts, and offers strategic recommendations to address these limitations.

Keywords: swarm control technology; orchard agriculture; collaborative communication; path planning; heterogeneous systems; agricultural robots



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1. Introduction

As a vital component of specialized agriculture, the fruit industry is characterized by pronounced seasonality, high dependence on manual labor, complex production management, and diverse operating environments. The high-quality development of China's fruit industry is currently constrained by several prominent challenges as follows: a mechanization rate below 30% in core orchard operations, structural labor shortages, and a low degree of operational standardization [1]. These issues underscore the urgent need for industrial upgrading through technological innovation. Breakthroughs in agricultural robotics and unmanned aerial vehicle (UAV) technologies have introduced new momentum for the transformation of traditional agriculture. Agricultural robots, through the integration of

artificial intelligence and big data, have demonstrated relatively mature applications in fertilization, crop protection, and harvesting [2]. UAVs, as critical enablers of precision agriculture, are now widely adopted across major agricultural nations [3]. However, single-agent systems present several limitations in orchard environments. For example, UAVs often face operational inefficiencies due to battery life and resupply constraints, while heavy-load robots may cause soil compaction.

The concept of biological swarming was first introduced in 1959 by French biologist Grassé [4], who observed termites rebuilding their nests, laying the groundwork for subsequent research in swarm technology. Swarm technology, leveraging artificial intelligence algorithms, enables the scientific configuration and efficient coordination of multiple intelligent agents. Based on functional differentiation, swarm systems can be categorized as homogeneous or heterogeneous. In homogeneous swarms, agents share identical mechanical structures and controllers, each with a single function. In contrast, heterogeneous swarms consist of agents with diverse hardware architectures and control mechanisms, enabling multiple functions. By utilizing distributed collaboration mechanisms to optimize system performance, swarm systems have emerged as a promising research direction for advancing agricultural intelligence [5]. The swarm robot system has the following four core advantages: flexibility, enabling it to adapt to new situations; scalability, allowing normal operation when robots are added or removed; robustness, ensuring continuous operation despite exceptions or errors; and sustainability, offering significant resource and operational benefits. According to the research of Tziolas et al. [6], due to the reduction in fossil fuel consumption and the improvement in the efficiency of collaborative robots, the swarm system reduces greenhouse gas emissions per kilogram of grapes by 43–48% and energy consumption by 40–43% compared with traditional manual and tractor operations. These systems have demonstrated distinct advantages in applications such as mobile network coverage [7] and complex environment rescue missions [8]. In particular, heterogeneous swarms for air–ground coordination [9] have shown significant improvements in task efficiency through cross-domain platform integration.

At present, swarm control technology has become mature in field environments, but a systematic review of swarm control technology throughout the entire orchard production process remains a gap. The perennial characteristics, complex canopy structure and diverse varieties of orchards pose unique challenges to collaborative communication, path planning and task allocation. For this reason, this paper systematically sorts out the application status and research progress of swarm control technology around the three stages of orchard monitoring, precise management and harvesting. By deconstructing the job characteristics and technical requirements of each stage, the adaptability of swarm control technology is explored. Finally, this paper summarizes the key issues and development suggestions of orchard swarm collaboration to provide theoretical support and technical references for the construction of smart orchards.

2. Materials and Methods

This study adopted a narrative review approach with a predefined retrieval and screening protocol, aiming to synthesize recent advances in swarm control technologies applied to orchard operations, including harvesting, spraying, irrigation, monitoring, and pruning from 2015 to 2026.

2.1. Information Sources and Search Dates

The following three major bibliographic databases were searched: the Web of Science Core Collection, the IEEE Xplore Digital Library, and the China National Knowledge Infrastructure (CNKI). The final search was conducted on 23 July 2026. The publication

period was restricted to 2015–2026, with a particular emphasis on studies published in or after 2018.

2.2. Search Strategy

Search keywords were organized into the following three thematic groups: (1) swarm control: “swarm”, “multi-robot”, “formation control”, “task allocation”; (2) agricultural scenes: “orchard”, “fruit”, “vineyard”, “precision agriculture”; and (3) operation processes: “harvesting”, “spraying”, “irrigation”, “monitoring”, “pruning”. Keywords were translated into Chinese for CNKI and retained in English for Web of Science and IEEE Xplore. Searches were performed across the “Title”, “Abstract”, “Keywords”, and “Subject” fields, depending on database capabilities. Records were refined by publication years 2015–2026 and languages English or Chinese.

2.3. Inclusion and Exclusion Criteria

Inclusion criteria: studies focusing on the application of swarm or multi-robot control technologies in orchard or agricultural scenarios; peer-reviewed journal articles or conference proceedings; publications in English or Chinese. Exclusion criteria: purely theoretical studies lacking experimental or simulation validation; duplicate publication: when a conference paper and its extended journal version coexist, only the more comprehensive version should be retained; publications in languages other than English or Chinese.

2.4. Selection Process

All retrieved records were imported into EndNote 20 (Version 20.4.1, Clarivate Analytics) for management. Deduplication was performed in the following two stages: automatic duplicate detection using EndNote’s Find Duplicates function based on title, author, year, and DOI, followed by manual verification to resolve near-duplicate entries. Two reviewers independently screened titles and abstracts against the eligibility criteria. Full texts of potentially eligible studies were then retrieved and independently assessed for final inclusion. Disagreements at any stage were resolved through discussion or consultation with a third reviewer.

2.5. Search Results

The initial search across all databases yielded 350 records. After removing 45 duplicates, 305 records remained for title and abstract screening, of which 180 were excluded. The full texts of the remaining 125 reports were sought, with 116 successfully retrieved and assessed for eligibility. Ten full-text articles were excluded due to inappropriate study design, insufficient data, or language mismatch. Ultimately, 106 studies met the inclusion criteria and were included in this review. Among them, 95 were published in English and 11 in Chinese; 95 were journal articles and 11 were conference papers.

3. Key Technologies in Swarm Coordination

Swarm systems can be classified according to their organizational architecture into centralized, distributed, and hybrid structures. In centralized architecture, agents are organized in a master–slave configuration, where the master robot holds full control and is responsible for system-level coordination. In contrast, distributed architectures are non-hierarchical, with agents operating autonomously and achieving coordination through mutual interaction or communication. Hybrid architectures, essentially hierarchical in nature, involve dynamically generated leader agents at the upper level who exercise partial control over subordinate agents. While this approach offers a balance between centralized and distributed models, it also introduces higher system complexity and implementation challenges. Current research in swarm coordination predominantly focuses on central-

ized and distributed architectures. Scholars have conducted extensive reviews on control methods for UAV swarms, taxonomies of swarm control strategies [10,11], swarm communication and obstacle avoidance in precision agriculture [12], and coordination of aerial robotic collectives [13]. This section centers on the following four critical components of swarm coordination: task allocation, path planning, cooperative communication, and formation control. By analyzing the current state of research in each area, this paper aims to clarify technological trends and establish a theoretical foundation for applying swarm coordination technologies in orchard operations.

3.1. Cooperative Communication

Communication in swarm systems involves not only interactions between mobile agents and a central control unit but also peer-to-peer communication among multiple agents. Continuous communication is fundamental to the stable operation of a swarm, serving as the foundation for effective path planning, task allocation, and formation control. It ensures real-time information sharing and coordinated behavior among agents. Communication between agents and the control center typically relies on remote-control links, while inter-agent communication is primarily facilitated through wireless technologies such as Wi-Fi, Zigbee, and Bluetooth. Each of these methods has inherent limitations. For example, traditional radio frequency (RF) communication suffers from bandwidth constraints; Wi-Fi and Zigbee are vulnerable to electromagnetic interference. In practice, Wi-Fi and Bluetooth are more commonly used in agricultural tillage, while Zigbee is frequently applied in orchard monitoring and weeding tasks. Selecting an appropriate communication method tailored to the specific operational environment remains a pressing issue in current research. Although the single-node power consumption of Wi-Fi and ZigBee is relatively low, when the swarm scale expands, the cumulative energy consumption will increase linearly. The lifespan of electronic components (3 to 5 years) is shorter than that of mechanical bodies, resulting in hidden operation and maintenance costs. Large-scale deployment of nodes will also increase electronic waste. Future designs should adopt a low-power wide area network hierarchical architecture, component-level maintenance, and software-defined radio to reduce energy consumption and waste at the architectural level [14].

In precision agriculture applications, the integration of digital compasses, GPS receivers, and Wi-Fi transmission enables wireless propagation of spatiotemporal data for robot-to-robot (R2R) communication [15]. Within the dense canopy environment of peach orchards, communication reliability can be further enhanced using an improved Ad Hoc On-Demand Distance Vector routing protocol (AODV-SP) based on Wi-Fi signals [16]. Regarding UAV swarm communication, optical communication schemes utilizing specific divergence angles maintain a 100 Mbps transmission rate at designated angles, proving suitable for both air-to-ground and air-to-air scenarios [17]. To mitigate performance degradation during network reconfiguration, smooth switching functions have been proven effective in preventing transient velocity fluctuations, energy waste, and actuator damage caused by topological changes [18].

In scenarios lacking global communication and positioning capabilities, agents must rely solely on short-range communication, basic motion control, and obstacle avoidance to collaboratively search for specific targets. In optical signal-based artificial multi-pheromone systems, robots dynamically release pheromones based on their position, and color sensors detect these signals to achieve cooperative target search [19]. Furthermore, a novel target search method based on a robot-chain model and an elimination mechanism has been proposed. This approach is entirely distributed, accomplishing search tasks relying only on local communication and ranging [20]. Finally, addressing secure communication in heterogeneous robotic swarms, existing research has proposed a decentralized communica-

tion scheme inspired by blockchain technology. This work established a reliable network topology model, completed the design of data storage and communication protocols, and verified the scheme's effectiveness from multiple perspectives [21].

3.2. Path Planning

In multi-agent operations, the environment is often complex and dynamic. To ensure that swarm robots can navigate safely, reliably, and efficiently through obstacle-rich environments, path planning is a critical capability. Existing path planning approaches for robotic swarms are generally categorized into centralized and distributed frameworks. In centralized path planning, the swarm is treated as a unified system. All degrees of freedom across individual agents are consolidated, and a single planning algorithm is applied to generate a global solution. In contrast, distributed path planning involves independently planning a path for each agent, followed by coordination mechanisms to handle inter-agent collisions, ultimately integrating these individual plans into a cohesive swarm-wide strategy. Path planning methods for single-agent systems are typically divided into traditional algorithms and swarm intelligence-based algorithms. Representative traditional approaches include Dijkstra's algorithm, the A* algorithm, probabilistic roadmaps (PRMs), and sampling-based rapidly exploring random trees (RRTs). On the other hand, genetic algorithms (GAs) and ant colony optimization (ACO) are common swarm intelligence techniques, and their application in path planning shares similar principles with those used in task allocation. The general structure of path planning methods is summarized in Figure 1.

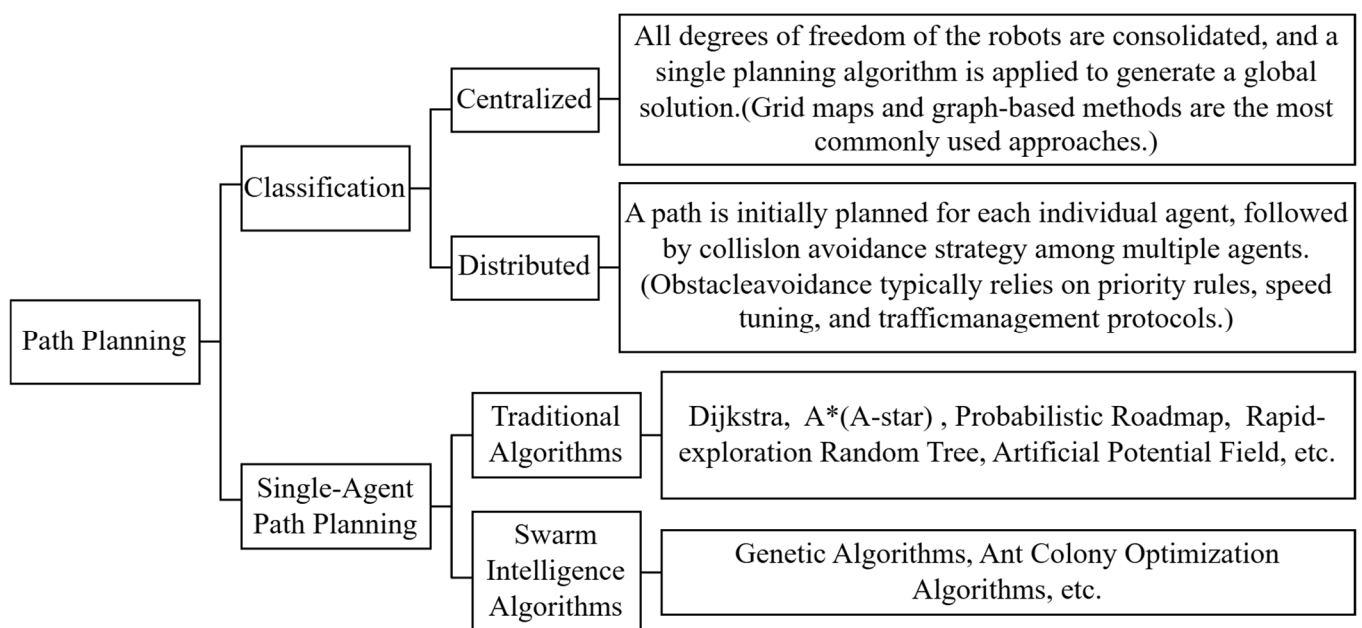


Figure 1. Fundamental structure of path planning.

In the domain of general path planning, the Tube-RRT* method, an improved rapidly exploring random tree algorithm, efficiently computes homotopic paths within an optimal virtual tube. By balancing gap volume and path length, it enables swarm robots to traverse obstacle-rich environments swiftly and smoothly [22]. Addressing multi-robot path planning in unknown environments, introducing a probabilistic window mechanism into the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm allows for the allocation of probability distributions over reachable positions by combining current sensor inputs with prior knowledge, facilitating the selection of more optimal paths [23]. Artificial intelligence provides effective solutions for swarm path planning, with current mainstream

approaches categorized into the following four types: reinforcement learning, evolutionary computation, swarm intelligence, and graph neural networks [24].

For dynamic path planning scenarios involving micro-robot swarms, the Enhanced Bidirectional Rapidly Exploring Random Tree (EB-RRT*) algorithm, supported by an image-guided motion controller comprising a direction controller and a speed controller, enables mobile target tracking. Additionally, a target-pulse algorithm has been developed to meet the demands of high-speed target tracking [25]. To address the issue of incomplete model representation in heterogeneous UAV swarm systems, multi-objective evolutionary algorithms incorporating specialized mating and reproduction strategies can generate more efficient swarm routes by comprehensively considering flight distance, flight time, and energy consumption [26]. In agricultural production scenarios, addressing crop health data sampling tasks requires path generation centered on regions of interest and the construction of an enhanced planning space that ensures uniform sampling to improve sensor data collection density [27]. Furthermore, in farmlands characterized by complex topological structures, efficient operations necessitate the cooperative deployment of ground robots and UAV swarms. Current studies have explored path optimization across diverse farm layouts by applying various algorithms [28].

3.3. Task Allocation

Task allocation in swarm coordination serves as the foundation for autonomous control and mission execution in swarm systems. It manages the scheduling of complex tasks by determining the number, type, and operational scope of agents based on real-time requirements, while simultaneously considering multiple constraints such as task specifications, agent capabilities, and payload limitations. Task allocation algorithms are generally categorized into two types based on control architecture. Table 1 compares the usage conditions, characteristics and typical algorithms of centralized and distributed task allocation strategies.

Table 1. Task allocation strategies in swarm systems.

Category	Conditions	Characteristics	Representative Algorithms	Applicable Scenarios
Centralized	Static; known task space; small-scale	Easy to control and capable of achieving globally optimal decisions. Lacks real-time responsiveness and robustness due to limited information exchange between the allocation terminal and agents.	Mixed-Integer Programming (e.g., Branch and Bound): formulates task allocation as an optimization problem using objective functions and constraints.	Orchard spraying, weeding; logistics and transport scheduling.
			Heuristic Algorithms: genetic algorithms, particle swarm optimization, ant colony optimization, reinforcement learning.	
Distributed	Dynamic; mostly unknown task space; large-scale	Higher communication burdens; good real-time responsiveness and robustness.	Motivation-Driven Behavior Models	Orchard monitoring, harvesting.
			Market-Based Strategies: contract net protocol, auction algorithms.	
			Bio-Inspired Algorithms Game-Theoretic Approaches	

Table 1 elucidates the relationship between task allocation architectures and specific orchard operational characteristics. Centralized control, which relies on global information to facilitate overarching planning, is well-suited for large-scale operations such as spraying and weeding. These tasks are highly repetitive and executed in relatively predictable environments, imposing lower demands on system robustness and presenting minimal risk from single-point failures. Consequently, centralized strategies can effectively leverage their strengths in global optimization and operational efficiency. In contrast, distributed control operates using only local information, offering superior responsiveness and flexibility. This approach is essential for dynamic scenarios like pest monitoring and harvesting, where dense canopy occlusion and environmental uncertainty necessitate real-time recognition and decision-making under high robustness constraints. By enabling localized information exchange, distributed allocation ensures continuous and stable operations in complex field conditions.

Currently, swarm-based task allocation faces several complex challenges, including dynamic task handling, large-scale task allocation, coordination between heterogeneous aerial-ground systems, algorithmic performance optimization, and adaptability to specific application contexts. Therefore, algorithm design must not only minimize cost metrics such as the distance between agents and task locations but also adapt to task-specific operational demands through dynamic agent grouping and resource-aware coordination, ensuring effective allocation of swarm resources.

In dynamic and unknown environments, addressing the challenges of large-scale task allocation, dynamic task allocation methods based on Optimal Mass Transport (OMT) theory enhance traditional OMT-based allocation through adaptive grouping and load-balancing reassignment. This approach achieves task equilibrium at the individual robot level while ensuring effective large-scale dynamic task distribution [29]. For dynamic task allocation scenarios involving distributed heterogeneous UAV swarms, methods based on an extended contract net protocol enable effective allocation for coordinated reconnaissance-strike missions and multi-target assignments by formulating a dynamic task allocation model under multiple constraints [30]. In agricultural applications, addressing multiple constraints—including supply-demand matching, operation cycles, and machinery capabilities—existing studies have developed a dynamic and static cooperative task allocation model for multiple agricultural machines based on an improved ant colony optimization algorithm, supporting both dynamic and static task allocation [31].

In practical applications of multi-agent systems, task allocation algorithms often require integration with path planning and cooperative communication to achieve optimal performance. At the intersection of task allocation and path planning, current research introduces hierarchical decentralized concepts into task assignment, tightly coupling them with search-based path planning. This approach dynamically adjusts regional robot density and maintains robustness under limited communication conditions and agent failures [32]. Heterogeneous air-ground cooperative multi-target detection models can be constructed based on Mixed-Integer Linear Programming (MILP). By applying a Branch-and-Bound algorithm enhanced by an Improved Genetic Algorithm (IGA-B&B) to solve these models, optimal task allocation and path planning are achieved simultaneously [33]. In the domain of integrating task allocation with communication, inspired by particle swarm optimization, researchers have proposed distributed dynamic task allocation algorithms. Utilizing improved swarm topologies for communication, these algorithms reduce inter-robot message exchange, significantly accelerate convergence rates, and enhance task allocation efficiency [34].

3.4. Formation Control

Swarm formation control is a fundamental component supporting task execution in multi-agent systems. Its core challenges include formation generation, reconfiguration, and maintenance, with formation generation being the most critical step. In complex and unknown environments, constructing a stable and reasonable formation significantly enhances operational efficiency and lays a solid foundation for subsequent tasks. Multi-agent formations vary in structure, including line, V-shaped, and circular formations. Line formation facilitates navigate through narrow passages, V-shaped formations reduce energy consumption and expand the effective coverage area, while circular formations are well-suited for collaborative task execution. Formation control methods are divided into the following two categories: centralized and distributed. Formation control is categorized into centralized and distributed architectures based on control structure. Table 2 compares the typical algorithms and applicable scenarios for these two approaches. Centralized control requires global information and suits scenarios demanding unified coordination, whereas distributed control offers greater flexibility, making it more adaptable to dynamic environments.

Table 2. Formation control strategies in swarm systems.

Category	Representative Algorithms	Applicable Scenarios
Centralized	Leader–follower method, virtual structure method, graph theory methods, model predictive control method	Standardized orchard spraying, transportation
Distributed	Behavior-based strategies, artificial potential field, reinforcement learning	Monitoring of unstructured orchards; multi-task collaboration throughout the entire cycle

Table 2 reveals the corresponding relationship between the formation control architecture and the operational characteristics of the orchard. Centralized control relies on global planning to ensure geometric accuracy: in the leader–follower method, the following vehicles maintain formation based on their relative positions to the leading vehicles, which is suitable for orchard transportation scenarios with fixed row spacing and clear channels. The virtual structure method regards the formation as a rigid body and uniformly defines the formation’s geometric shape, which is suitable for ensuring uniform spray spread in standardized densely planted orchards. Model predictive control adds multiple constraints during the control process and can optimize the control sequence based on feedback correction of real-time information. It is suitable for maintaining configuration stability during precise pesticide application and pruning. In contrast, distributed control enhances system robustness through local interaction as follows: based on behavior and artificial potential field methods, robots can autonomously avoid canopy obstacles while moving and maintain distances, which is highly suitable for monitoring and inspection in unstructured environments. Reinforcement learning can continuously optimize formation strategies through interaction with the environment and is applicable to multi-stage and multi-task orchard formation operations throughout the entire growth cycle.

To address the challenges of controlling large-scale, high-order heterogeneous UAV swarms within dynamic and uncertain systems, distributed formation control methods based on reinforcement learning effectively support heterogeneous multi-rotor UAV swarms in executing optimal formation switching and corresponding flight missions [35]. To overcome the local minima issues prevalent in traditional algorithms, distributed formation control algorithms utilizing neural networks to optimize potential field parameters

significantly enhance capabilities in real-time obstacle avoidance, formation maintenance, and trajectory tracking [36]. Addressing bandwidth constraints in complex operational environments, adaptive formation coordination protocols leverage robust control strategies and local information exclusively to track dynamic targets, thereby substantially reducing bandwidth requirements [37]. To meet the demands of efficient response, formation control technology based on an IoT platform collects and provides feedback on multi-robot trajectories; when integrated with particle swarm optimization-deep learning algorithms, it markedly improves both control accuracy and operational efficiency [38].

Regarding formation transformation and reconstruction, quantitative analyses reveal distinct disparities in reconfiguration costs as follows: transitioning from a triangular lattice to a rhombic structure incurs the lowest cost, whereas the arrow configuration requires the longest reconstruction time, and the linear “snake” formation proves the most expensive, with cluster configuration shown in Figure 2 [39]. To achieve real-time distributed transformation, consensus-based formation maintenance and reconstruction methods integrated with the artificial potential field method facilitate effective obstacle avoidance while preserving structural integrity [40]. Scalability is further enhanced through a stiffness-based self-reconfigurable hierarchical framework, which enables the autonomous merging, splitting, and reconstruction of formations [41]. Complementing these strategies, a self-organizing dynamic ring-shaped formation geometric model allows robots to establish reliable formations using optical signal communication [42]. For heterogeneous ground swarms, dynamic window optimization frameworks that integrate potential field and consensus principles support robust formation generation and reconfiguration [43]. Furthermore, distributed control protocols address the specific challenge of formation encirclement in collaborative robotic systems, offering a viable solution for targeted agricultural weed management [44].

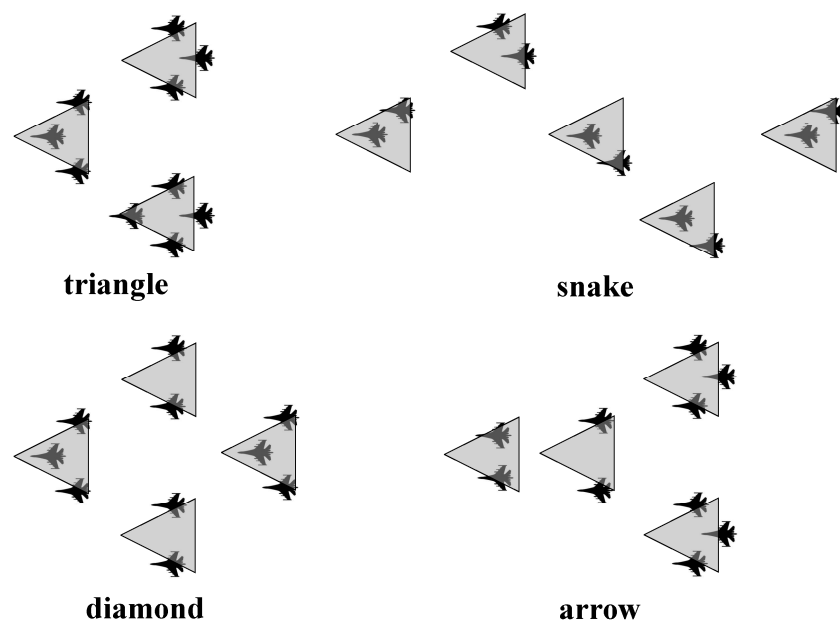


Figure 2. Cluster configuration of 10 UAVs (reproduced from [39]; CC BY 4.0).

Intelligent swarm technology comprehensively integrates core technologies such as cooperative communication, path planning, task allocation, and formation control, significantly enhancing operational efficiency and adaptability. Specifically, cooperative communication ensures real-time information sharing, path planning guarantees the safe and efficient movement of robots, task allocation enables rational resource management, and formation control achieves highly coordinated operations. Meanwhile, swarm technology

continuously improves dynamic response capabilities, promotes algorithm lightweighting under resource-constrained conditions, and deepens integration with artificial intelligence technologies. The collaborative mode of aerial-ground heterogeneous swarms further expands 3D operational capabilities in orchards, enabling efficient and comprehensive management across all dimensions of orchard operations.

4. Swarm Technology in Orchard Operations

In orchard production scenarios, single-machine operations face challenges such as low deployment efficiency for large-scale tasks, unstable network communication performance, and difficulties in coordinating energy consumption and latency [45]. The use of swarm coordination technology can overcome the limitations of individual machines in terms of payload and functionality, representing a crucial direction for future development. At present, research on micro aerial robot swarms [46], multi-robot information collection systems for precision agriculture [47], swarm robot systems for full-cycle agricultural management [48], and integrated multi-robot modules [49] is steadily increasing. This section provides a detailed analysis of the application of swarm coordination technology in orchard monitoring, precision management, and harvesting stages and examines research progress and key technologies at each stage. It is worth noting that, as the application of swarm technology in orchard scenarios is still in the exploratory stage, this study also draws upon mature swarm control technologies from other agricultural settings, such as fields, plantations, and forests, adapting them to develop orchard-specific solutions.

4.1. Application of Swarm Technology in Orchard Monitoring

Orchard monitoring, as a core component of smart orchard management, establishes a comprehensive sensing network for environmental parameters and biological growth characteristics by integrating IoT sensor networks and multi-source remote sensing technologies. This technical system enables rational resource allocation, early warning of pests and diseases, optimized irrigation and fertilization, and precise guidance for harvesting windows. At the same time, it accumulates large-scale production data, enhances the accuracy and efficiency of orchard management, and drives the transformation of orchards toward digitalization and sustainability.

4.1.1. Mapping and Surveying

Orchard mapping and surveying can accurately represent orchard layouts and tree distributions, providing a scientific basis for planning planting zones and allocating resources efficiently. The collected data can be integrated into digital twin platforms, reducing yield estimation errors and offering topographical references for orchard mechanization projects (such as terrace construction on slopes), thereby significantly lowering management costs. Compared with single-drone mapping, drone swarms can simultaneously map from multiple angles, producing clear 3D images.

In the domain of orchard spatial information acquisition, drone swarms driven by information gain can be deployed for crop field monitoring and mapping. This approach enables the adaptive selection of target areas based on anticipated information gain, thereby significantly enhancing monitoring efficiency and accuracy [50]. Addressing the complex orchard planting environments prevalent in southern China, the integration of UAV-collected data with deep learning algorithms facilitates the precise extraction and mapping of cultivated land plots [51]. Regarding innovations in collaborative operational modes, as shown in Figure 3, a tri-drone collaborative mapping and measurement framework utilizes coordinated task allocation algorithms to assign flight missions among multiple UAVs. This provides an efficient data collection and analysis solution for agricultural land monitor-

ing and management [52]. The integration and advancement of these technologies are propelling agricultural spatial perception toward greater intelligence and systematization.

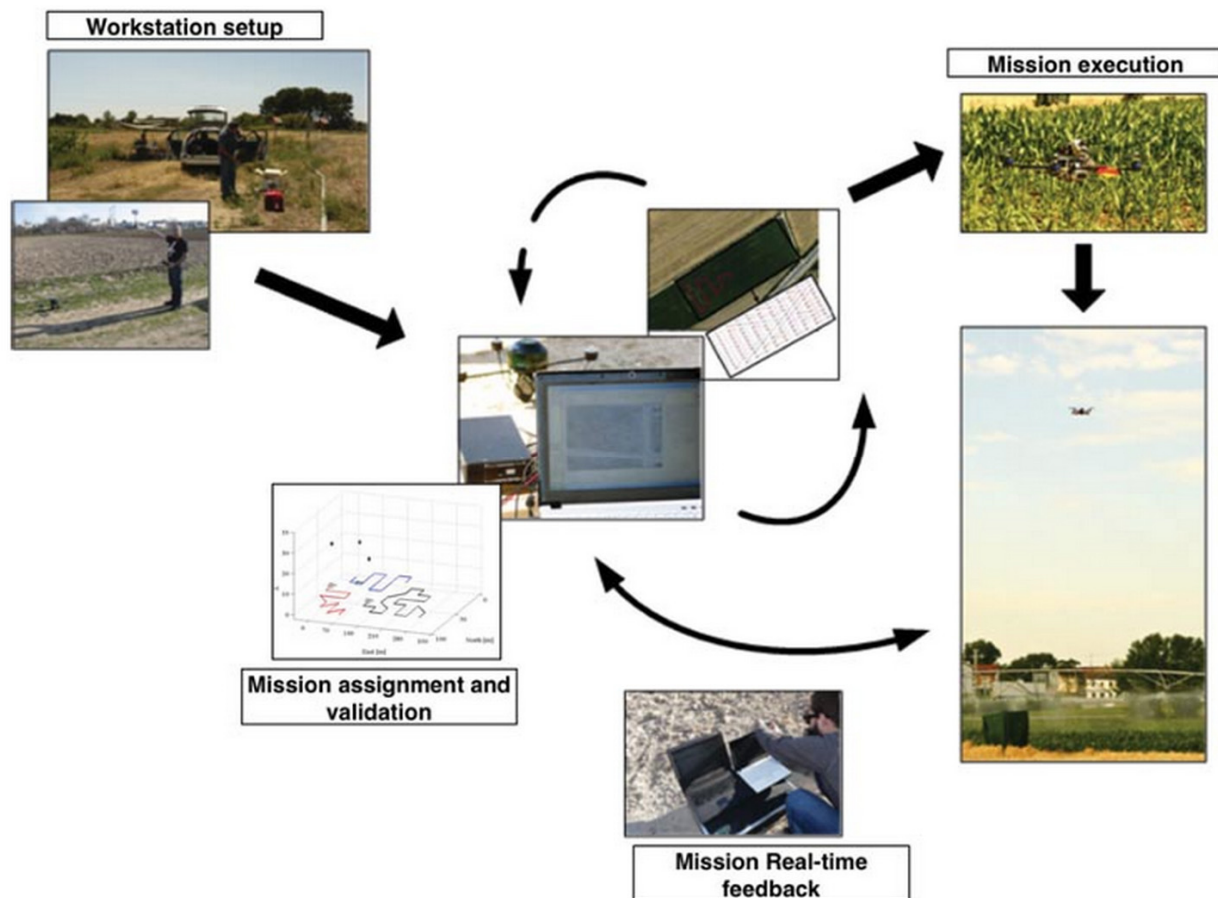


Figure 3. Tri-drone collaborative vineyard data sampling (reproduced from [52] with permission of John Wiley and Sons).

4.1.2. Crop Health Monitoring

Establishing crop detection systems enables real-time assessment of damaged crop conditions and is a key step in advancing digital agriculture. With the increasing maturity of satellite and UAV technologies, crop monitoring based on remote sensing has gradually become an efficient and promising approach to crop information collection, significantly reducing labor and operational costs. The core objective of crop monitoring is to efficiently collect crop growth data across entire fields through UAV aerial surveys. Similar to weed detection and mapping, the introduction of swarm control technology allows for rapid acquisition of growth status data for all crops within a given area, addressing the limitations of single UAVs or robots in terms of payload, task diversity, and robustness.

In the field of crop health detection using UAV swarms, research is breaking through key bottlenecks via multi-dimensional technological collaboration: by optimizing communication modules [53,54], UAV path planning algorithms [55], and flight task scheduling algorithms [56], these systems ensure the timeliness and accuracy of data collection, providing more precise and efficient data support for crop health assessment. Although the application of swarm coordination technology in orchard crop health monitoring remains at an exploratory stage, there have already been innovative practices, such as UAV swarm collaborative monitoring based on soybean defoliation modeling [12], sugarcane sample collection and pest and disease control as shown in Figure 4A [57], and nutritional and pest/disease status monitoring in large hazelnut orchards [58]. Additionally,

Boldrer et al. [59] introduced a distributed algorithm for multi-robot continuous monitoring and target detection; this system can still operate stably in various failure scenarios; eleven unmanned aerial vehicles were used for on-site verification monitoring and target detection as shown in Figure 4B. These works offer valuable reference architectures for crop health monitoring in orchards.



Figure 4. Application of swarm coordination technology in crop health monitoring. (A) Field tests of monitoring tasks in sugarcane fields. (a) robot entering the tunnel; (b) uneven terrain and big crevices; (c) robot passing over crevice, the structure is tilted and struggles to overcome the valley. (reproduced from [57]; CC BY 4.0) (B) Eleven unmanned aerial vehicles were used for on-site verification monitoring and target detection (reproduced from [59]; CC BY 4.0).

The orchard monitoring system leverages machine vision and IoT technologies to achieve comprehensive, multi-dimensional, and wide-coverage information acquisition, utilizing a swarm coordination architecture with minimal interaction requirements. Its core technological breakthroughs lie in high-precision image recognition and multi-source sensor data fusion. Combined with full-coverage path planning and efficient task allocation enabled by intelligent swarm control, this system provides reliable data support for precision orchard management.

4.2. Application of Swarm Technology in Orchard Precision Management

Orchard precision management serves as a fundamental component of modern agriculture's full-chain operation system. It encompasses a wide range of seasonal tasks such as soil preparation and seeding, intelligent irrigation, precision fertilization, weed removal, and artificial pollination. These practices not only improve fruit yield and quality but also contribute to ecological security through soil improvement and integrated pest management. At present, plant protection UAVs and agricultural robots have been rapidly adopted in fruit tree spraying, seeding, fertilizing, and pollination, accelerating the development of swarm coordination technologies in these areas. The literature [60] investigated a distributed control scheme for UAV swarms, enabling speed control, formation control, and obstacle avoidance. The method can be applied to tasks such as seeding, spraying, and crop monitoring. In another study, researchers [61] addressed the path allocation problem for field agricultural machinery fleets, proposing a solution applicable to tillage, weeding, seeding, and fertilization. With the deep integration of intelligent equipment and digital algorithms, orchard management is evolving from single-machine operations to swarm-coordinated systems.

4.2.1. Tillage and Seeding

Tillage and seeding are foundational steps in fruit tree cultivation, playing a critical role in sustainable agricultural development and the improvement of fruit quality. Through soil turning and loosening, tillage improves the structure of the tillage layer, alters key physical and chemical soil properties, and regulates nutrient and organic matter content. These changes enhance soil aeration, water retention, and nutrient-holding capacity, creating favorable conditions for root development. Additionally, tillage helps suppress weed growth, reduces the risk of pest outbreaks, and lowers subsequent management costs [62]. The seeding discussed in this section includes both fruit tree seeding and green manure seeding. Orchard seeding is a fundamental aspect of orchard establishment. Rational seeding strategies optimize resource allocation, improve germination rates and stress resistance, and are directly linked to fruit quality and economic returns. Green manure seeding increases soil organic matter, conserves soil moisture, biologically suppresses weed growth, and reduces herbicide usage, ultimately enhancing fruit yield and quality. Although there are differences between fields and orchards in terms of crop types, row spacing and terrain, both cultivation and sowing, as basic operation links, rely on common procedures such as land leveling, furrow digging and precise seed sowing. The mature experience of fields provides a verified technical framework for orchards, which helps to shorten the research and development cycle of orchard swarm farming systems and avoid repetitive technical detours.

To meet the stringent requirements of precision seeding, the binarization method based on Dynamic Thresholding with Mean-Filtered Differencing (BD-MFD) can be employed to evaluate UAV seeding performance. By extracting seed landing point coordinates, this approach facilitates the optimization of key structural and operational parameters of the UAV seeding system [63]. Extending this application to ecological restoration, customized seed treatment and container fabrication processes significantly enhance post-dispersion germination and growth rates. Concurrently, equipping UAV platforms with centralized fuselages and six-propeller arm configurations ensures flight stability, while dedicated mission planning software enables the precise determination of seed deployment zones [64]. Furthermore, Voronoi diagram-based task allocation for tractor fleets offers a viable strategy to reduce total mission time by assigning workspaces based on individual machine performance, as illustrated in Figure 5a [65]. In experimental validations, UAV-acquired agricultural maps provided the spatial data necessary for computers to assign seeding tasks accurately to three machines.

In the domain of formation control for tillage, multi-tractor systems operating in I-, V-, and W-shaped formations—often utilizing a leader–follower system—present a feasible solution for enhancing operational efficiency [66]. Field trials involving two coordinated tractors demonstrated that leader–follower system improves navigation efficiency by 95.1% [67]. Addressing formation control and path-tracking challenges, the bidirectional weighted constraint approach effectively reduces error propagation within the fleet and mitigates reliance on global communication [68]. Given the uneven spacing of operation lines and dense distribution of peach trees in peach orchards, an adaptive elite differential evolution (AEDE) algorithm is proposed for multi-tractor path optimization to optimize operation paths and improve operation efficiency [69]; task allocation system is as shown in Figure 5b.

4.2.2. Pollination

Pollination is a critical process for ensuring high fruit yield and quality in orchards. Currently, UAV-based intelligent pollination techniques apply pollen powders via aerial spraying. While these methods compensate for the inefficiencies of natural and manual

pollination, they face challenges in complex terrains. Specifically, they struggle to dynamically coordinate spraying range, speed, and terrain matching, which often results in poor atomization uniformity and uneven pollen deposition. These issues are particularly prominent in mountainous orchards, where significant elevation differences between rows and complex canopy structures can create pollination blind spots and lead to resource wastage. UAV swarm pollination offers a promising solution by enabling more uniform pollen coverage, reducing the occurrence of malformed fruits, and improving the marketability of produce.

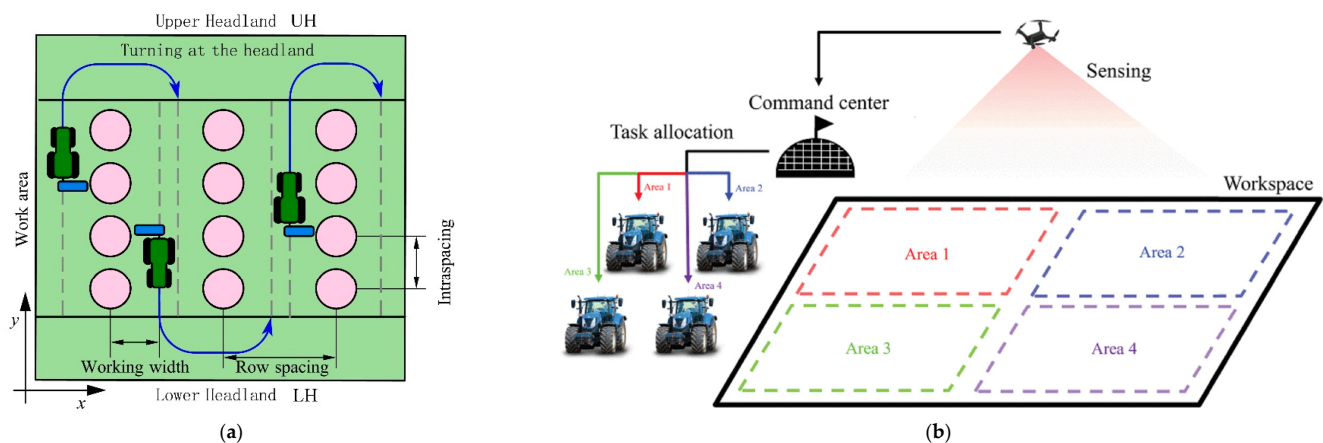


Figure 5. Applications of swarm coordination technology in tillage and seeding. (a) Schematic diagram of multiple tractors working in standard peach orchard (reproduced from [65]; CC BY 4.0). (b) Task allocation system for autonomous tractor fleet: a camera-equipped UAV detects the workspace and calculates and allocates a suitable sub-workspace to each tractor (reproduced from [69]; CC BY 4.0).

Research on UAV swarm pollination technologies for fruit trees remains limited. Jia et al. [70] proposed a multi-rotor UAV swarm system for precision pollination under abnormal climatic conditions during the flowering stage of fruit trees. They developed a method to identify pollination-deficient areas from thermal infrared images of blooming trees and designed a corresponding UAV swarm control strategy. Graph theory methods enable robot swarms to execute both uniform and non-uniform pollination patterns within blueberry fields [71]. Addressing the need for compensatory pollination, Fan et al. [72] proposed a multi-rotor UAV clustering strategy, complemented by bespoke matching and path planning algorithms; this framework was successfully validated through a 16-UAV simulation, trajectory of horizontal formation from three small task cohorts to compensatory precision pollination is shown in Figure 6. Future research trajectories aim to integrate plant life-information perception with 5G-enabled intelligent cluster systems. In the sector of greenhouse vegetable production, two types of drones (search drones and pollination droness) integrate autonomous flight control and pollination mechanisms based on artificial intelligence for flower detection and positioning. They can autonomously search for flowers and pollinate them, enabling UAVs to carry out efficient tomato pollination in greenhouse environments [73].

4.2.3. Weeding

Weed identification and removal play a critical role in reducing competition for nutrients, minimizing pest and disease mediums, and conserving water and fertilizer resources, ultimately improving overall orchard productivity. The use of swarm coordination technologies enables rapid and effective coverage of large areas. Data collected during operation can be processed using intelligent vision algorithms to accurately distinguish between

weeds, crops, and other vegetation. Intelligent spraying systems selectively target only weed-affected zones, thereby reducing agrochemical use, improving weeding efficiency, and promoting sustainable orchard management.

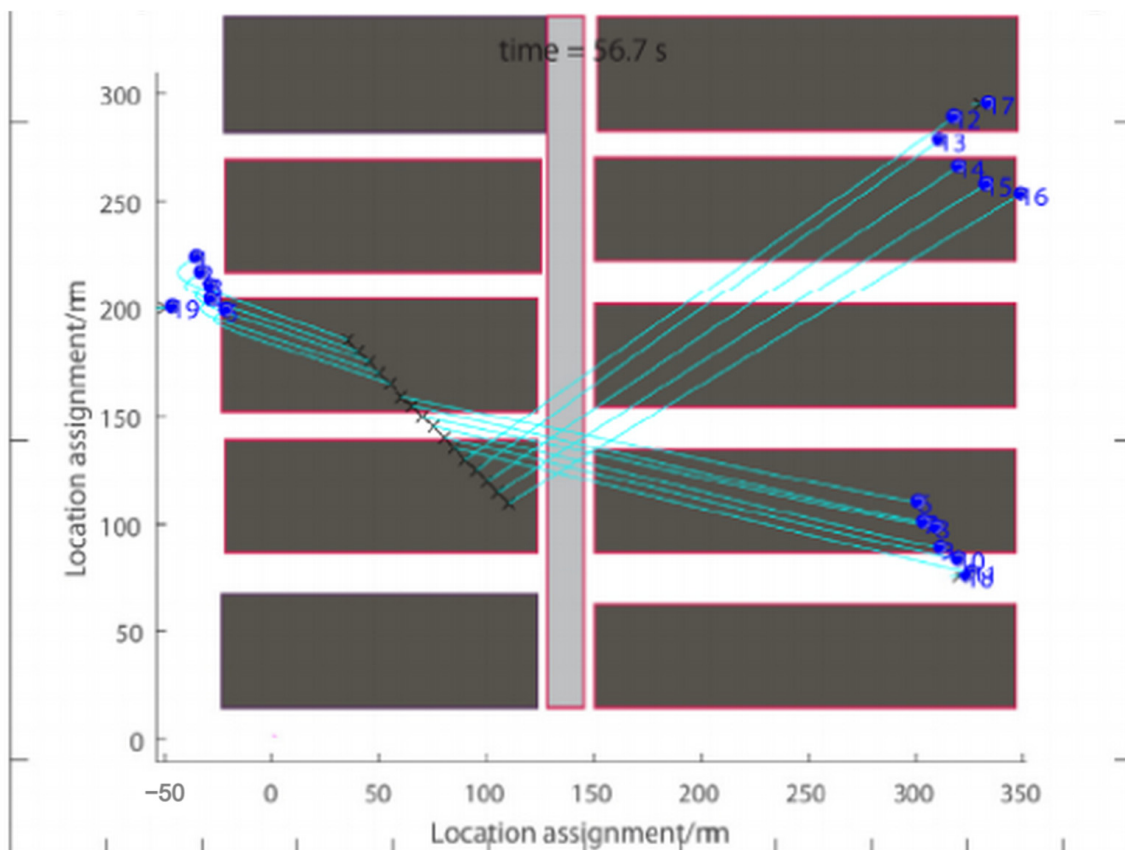


Figure 6. Trajectory of horizontal formation from three small task cohorts to compensatory precision pollination (reproduced from [72]; CC BY 4.0).

At present, corresponding solutions have been developed for various weeding scenarios of different crops. For organic orange orchards, a dual-drone system consisting of a weed detection drone and a weed removal drone has been developed. This system integrates a neural network based on YOLOv10 for weed identification and location and is also equipped with communication and coordination protocols between the drones. The productivity and sustainability of organic agriculture can be enhanced through autonomous detection, localization and removal of invasive weeds [74]. In addition, in the SAGA project, the distributed search strategy for unmanned aerial vehicle (UAV) swarms designed based on weed distribution patterns has achieved remarkable results in the management of low-density weeds: drones were deployed in sugar beet fields to collect data on weeds, diseases and nematodes, while optimizing mission planning to achieve automated and precise weed removal [75,76].

In olive orchards, as shown in Figure 7, a significant technological breakthrough has been achieved in an air–ground heterogeneous cluster system: after the unmanned aerial vehicle swarm completes the large-scale rapid inspection, the weed coordinates are synchronized to the ground spray robot. This collaborative mechanism can achieve precise inter-row weed tracking. While effectively controlling weeds and pests, the pesticide application amount is reduced by 50% [77]. Aiming at the problem of inconsistent slopes in orchards in hilly and mountainous areas, some scholars have considered the influence of slope changes on the energy consumption of weeding robots, established an

energy consumption model for orchard weeding operations, and proposed a task allocation algorithm based on the Golden Kepler Optimization Algorithm (GKOA). The operational efficiency of the multi-robot system has been improved [78].



Figure 7. Detection and removal of weeds and pests in olive orchards (reproduced from [77]; CC BY License).

4.2.4. Precision Application of Water, Fertilizer, and Agrochemicals

Scientific irrigation and fertilization are key measures to ensure fruit quality and the core links of water, fertilizer and pesticide management in orchards. All three face common challenges such as large operation area, high timeliness requirements and uneven spatial distribution. Under the traditional single-machine operation mode, one device needs to traverse all fruit trees in sequence, which takes a long time and is difficult to meet the differentiated demands of different regions. As shown in Figure 8, swarm control technology enables multiple devices to simultaneously cover different plots. Through the coupling of information flow and task flow, it achieves precise and efficient management of water, fertilizer and pesticides.

In orchard fertilization and irrigation, aiming at the problems of multi-machine collaborative operation of fertilizer applicators and collaborative distribution of fertilizer vehicles under different fertility conditions, a task allocation model based on the Chaotic Cauchy Fireworks Algorithm (CCFWA) is proposed. The experimental results show that this algorithm effectively avoids local optima while maintaining a relatively fast convergence speed [79]. To address the challenge of dynamic path planning for unmanned aerial vehicle (UAV) swarm in real-time monitoring and fertilization tasks, an improved distributed ant colony optimization (ACO) algorithm has been proposed. Compared with the traditional zigzag algorithm, the improved ant colony algorithm significantly enhances the operational efficiency [80]. In addition, a multi-UAV collaborative remote sensing system has been developed and researched, which can be used for real-time water resource management and distributed irrigation control. Researchers have also discussed the technological development of key subsystems, covering embedded multispectral imaging sensors, image stitching algorithms, registration techniques, etc. [81].

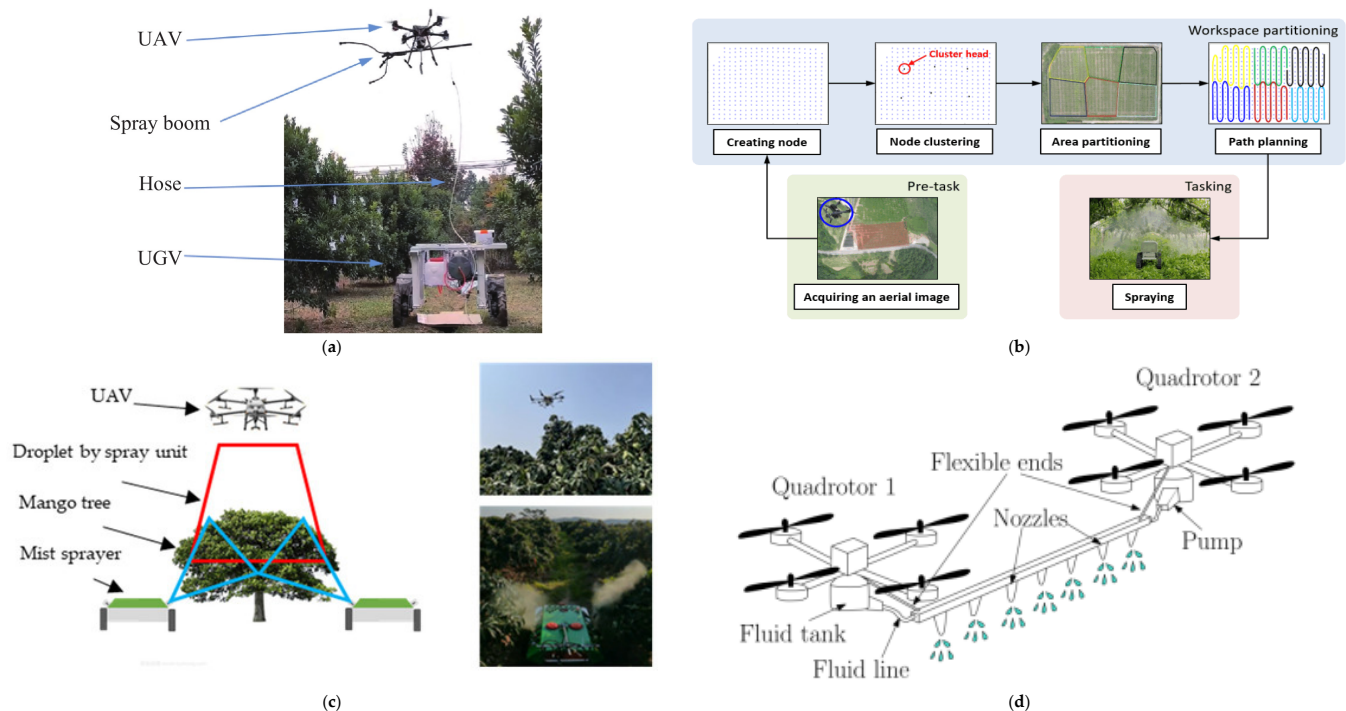


Figure 8. Applications of swarm system technologies in integrated irrigation systems for water, fertilizer, and pesticide delivery. (a) Structure of the UAV-UGV cooperative targeted spraying system for honey pomelo orchard (reproduced from [82]; CC BY 4.0). (b) Multi-robot pesticide spraying system in pear orchards (reproduced from [83]; CC BY 4.0). (c) Air-ground co-operation stereoscopic plant protection system operation diagram (reproduced from [84]; CC BY 4.0). (d) Dual-UAV pesticide spraying in orchards (reproduced from [85], with permission of the corresponding author.).

In orchard spraying operations, as early as 2012, Moorehead et al. [86] pioneered the design of an autonomous multi-tractor system for weeding and spraying in citrus orchards. This system employed remote human supervision for task allocation and used orchard maps to generate fully optimized coverage paths. Over an 18-month deployment period, it accumulated more than 1500 km of operational travel, significantly improving productivity. Using Voronoi diagrams and the k-means clustering algorithm, the orchard area can be divided into clustered nodes, enabling task assignment based on the number of available robots. This approach significantly reduces spraying time [83]. A dual-UAV spraying system has been developed, wherein two drones are simultaneously connected to a pipe with nozzles to achieve synchronized movement. This configuration substantially increases the coverage area and volume of the spray [85]. Task optimization for UAV swarm spraying has been investigated and validated through experiments involving a five-UAV system [87]. Another study designed a UAV-UGV cooperative target spraying system for honey pomelo orchard using the master–slave formation control method. Orchard experiments verified that both the droplet density and deposition value of the system operation were improved, and the spraying effect was more uniform than that of a single unmanned aerial vehicle [82].

An air-ground three-dimensional coordinated pesticide application system, including a six-rotor electric unmanned aerial vehicle and an orchard tracked fog sprayer, significantly increased the droplet coverage in various parts above the mango leaves, but failed to significantly improve the droplet deposition and coverage on the back of the leaves [84]. To address the problem of red palm weevil infestation in palm plantations, a multi-UAV task allocation algorithm for targeted pesticide application has been developed, offering an intelligent solution for pest-specific treatment [88]. Furthermore, small-scale agricultural

robot swarms equipped with herbicides, fungicides, and insecticides deliver precise plant protection and effectively reduce operating costs [89].

Currently, the application of swarm control technologies in the precision management of orchards is primarily concentrated in weed removal and pesticide spraying. Weeding tasks rely on tightly integrated recognition–removal systems and synchronous communication, while pesticide and fertilizer application require precise variable-rate regulation. However, research remains limited in areas such as pollination and tillage. Future development should account for orchard topography and tree distribution and design customized operational platforms adapted to specific fruit varieties and growth stages, thereby improving operational precision.

4.3. Applications of Swarm Technologies in Fruit Harvesting

Swarm control technologies have been increasingly applied across the following three key stages of fruit harvesting in orchards: yield estimation, autonomous picking, and post-harvest transport. In the estimation stage, swarm systems equipped with multi-spectral cameras, thermal infrared sensors, and LiDAR can capture real-time data on crop density, canopy height, and fruit maturity. These data streams support the development of yield estimation models, significantly improving estimation accuracy. For autonomous harvesting, robots equipped with mechanical arms and vision-based recognition systems can accurately identify and locate ripe fruit. Using flexible grippers, these robots perform non-destructive picking, achieving substantially higher efficiency compared to manual labor. In the transportation stage, UAVs and unmanned ground vehicles (UGVs) collaborate to establish low-altitude logistics networks. Through swarm dynamic path planning algorithms, freshly harvested produce is rapidly delivered to sorting centers or cold storage facilities, effectively reducing transit time and improving post-harvest efficiency.

4.3.1. Yield Estimation

Accurate yield estimation in orchards plays a vital economic role. It enables pre-harvest planning, storage logistics, resource optimization, price forecasting, and the formulation of investment and marketing strategies. Traditional yield estimation methods typically rely on manual sampling, which is time-consuming and labor-intensive. The integration of swarm technologies into yield estimation allows for the efficient acquisition of multidimensional orchard data through high-precision multispectral cameras, LiDAR systems, and other onboard sensors.

Various multi-modal perception systems have been developed for different crop types, as shown in Figure 9. All-terrain autonomous ground robots equipped with multiple sensors and visual algorithms can be used to generate spatial yield distribution maps of vineyards [90]. For watermelon yield estimation, the YOLOv8 object detection algorithm can be employed to establish both sampling-based and global-based yield estimation models, with a total yield estimation error of less than 3.00%. When only total number and total weight are required, efficient rapid sampling is adopted; when spatial yield distribution is needed, global estimation is used [91]. In apple orchards, a UGV equipped with a monocular vision system and a general-purpose feature learning algorithm can estimate yields by segmenting images [92]. Although these systems rely on single-robot architectures, they offer valuable insights for swarm-based large-scale deployments. In field crop applications, Xu et al. [93] developed a time-series-based cotton yield estimation model enhanced by deep learning techniques. Field experiments employed two types of UAVs to capture both visible and multispectral imagery, validating the model's estimation performance and feasibility.

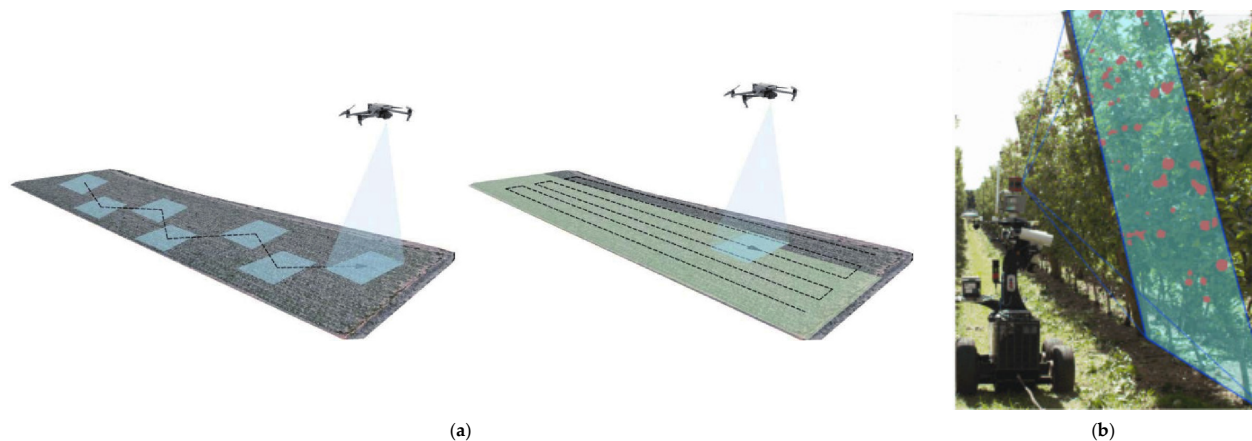


Figure 9. Yield estimation technologies in orchards. (a) Sampling (left) and global scanning (right) for Xisha watermelon yield estimation (reproduced from [91]; CC BY 4.0). (b) Image data acquisition of trees in apple orchards (reproduced from [92] with permission of John Wiley and Sons).

4.3.2. Autonomous Harvesting

Intelligent harvesting technology in orchards can reduce the rate of epidermal damage to crops, improve harvesting efficiency, and while ensuring continuous operation day and night, it can also reduce the demand for seasonal labor. It is the most challenging application scenario of swarm control technology. The maturity of current related research varies significantly and needs to be distinguished into the following three levels: commercial systems, prototype machines, and simulation algorithms.

A large amount of swarm harvesting work is still at the stage of algorithm verification. Previous studies have proposed a collaborative task allocation model for orchard picking based on unmanned aerial vehicle (UAV) swarms, with the shortest moving distance as the core optimization index, which can quickly complete the allocation of multiple picking tasks [94]. For the vegetable harvesting scenario, a distributed control method can be adopted by combining the nearest neighbor sampling information to construct an agricultural multi-robot system for vegetable harvesting [95]. In addition, the improved ant colony algorithm can be applied to the problem of group task allocation in the farmland environment. The results of the farmland harvest experiment show that the improved ant colony algorithm can effectively reduce the path cost [31].

At the prototype level, Hu et al. [96] designed a dual-mechanical arm apple-picking system that integrates machine vision, as shown in Figure 10a, a simplified four-degree-of-freedom operator, and a mobile platform. They evaluated suction, grasping, and hybrid vacuum-driven actuators, but this is still in the experimental stage. Stavridis et al. [97] developed a collaborative system for grape picking, which consists of the following two independent yet collaborative robots: one is responsible for checking and collecting grape maturity data, while the other is in charge of the picking operation. Lytridis et al. [98] studied a heterogeneous robot system for grape harvesting, as shown in Figure 10b, in which the main robot was responsible for the grape harvesting task and the auxiliary robot was responsible for transporting the grapes. In the future, a visual recognition model for grape maturity will also be added to improve the accuracy of harvesting.

At the commercial system level, true multi-machine collaborative harvesting has not yet been implemented on a large scale. At present, commercialized harvesting equipment is still mainly single-machine. The Israeli company Tevel [99] is currently the closest to commercialization. The apple picking system it developed is equipped with multiple flying robots on a ground platform. The fruits picked by the flying robots are placed in on-board boxes, enabling continuous operation around the clock.



Figure 10. Applications of swarm control in orchard harvesting. (a) Structural diagram of the harvesting robot test platform based on dual manipulator (reproduced from [96]; CC BY 4.0). (b) Two robots within a vineyard row while coordinating their motions (reproduced from [98]; CC BY 4.0).

4.3.3. Transportation

Swarm coordination of orchard transport vehicles enables intelligent scheduling and collaborative operations, significantly improving transportation efficiency and enhancing responsiveness to unexpected demands. UAVs hold great potential in agricultural transportation and are well-suited for the postharvest transport of high-yield and high-value fruits, offering a practical solution to terrain-related logistical constraints [100].

A distributed control framework is an effective solution for addressing the problem of motion coordination among agricultural transport vehicle swarms (Vougioukas et al. 2012, [101]). Furthermore, existing research has integrated drones with remotely operated heavy-duty trucks, breaking through the bottlenecks of insufficient UAV payload capacity and limited battery endurance [102]. In cargo transport scenarios, when employing cooperative task allocation for multi-UAV systems, the core objective is to minimize load swing and maintain formation stability during the guidance of suspended payloads to target locations [103].

In orchard harvesting scenarios, yield estimation requires the construction of precise predictive models based on sensor-acquired data. Autonomous picking demands the development of flexible, non-destructive end-effectors and dynamically calibrated vision systems. The transport units necessitate optimized dynamic load allocation models and energy-balancing strategies. These must be integrated with swarm-based task allocation and path planning algorithms to establish an intelligent, end-to-end harvesting platform.

Table 3 systematically reviews and compares the application of swarm technologies across the entire orchard workflow, including monitoring, precision management, and harvesting, from the following four key dimensions: representative studies, core technologies, application advantages, and existing challenges. The results show that swarm technology has accumulated a certain research foundation and orchard trial support in mapping and surveying, weeding, and precision application of water, fertilizer, and agrochemicals. In contrast, pollination, tillage, and harvesting remain largely at the stage of algorithm simulation and laboratory validation. This imbalance stems primarily from the following three factors: first, perception-oriented tasks (e.g., monitoring, weed identification) impose lower demands on operational precision than execution-oriented tasks (e.g., harvesting, pollination). The latter require advanced end-effector and force control technologies, which remain common bottlenecks in robotics. Second, the high-value fresh fruit market sets extremely stringent standards for fruit damage rates, creating a significant gap between market expectations and the actual damage rates achieved by current robotic harvesting systems. Third, the biodiversity of fruit tree species limits technological generalizability. Apple, citrus, grape, and kiwifruit differ markedly in fruit attachment mechanisms, canopy

structures, and flower morphologies. A single end-effector or vision model can hardly be reused across species, which constrains the promotion and deployment of the technology.

Table 3. Technical characteristics and application status of swarm technology across the full chain of orchard operations.

Application Stage	Specific Activity	Representative Studies	Key Technologies	Advantages	Challenges
Orchard Monitoring	Mapping and surveying	Vineyard [3]; complex farmland environment [4]	Machine vision; high-precision image recognition; multispectral remote sensing	Multi-angle simultaneous surveying; high 3D reconstruction accuracy; adaptive target area selection	Signal occlusion on slopes and terraces affects coordination efficiency; mostly applied to farmland and field mapping, orchard-specific applications remain limited
	Crop health monitoring	Sugarcane pest detection [5]; hazelnut orchard plant status monitoring [6]	IoT technology; multi-source sensor data fusion	Rapid large-area coverage; comprehensive analysis of damaged crop conditions via multi-source data fusion	Canopy occlusion affects understory data collection; orchard research still at exploratory stage
Orchard Precision Management	Tillage and seeding	Forestry ecological restoration [7]; large-area tillage [8]	Image recognition; precise positioning	Multi-machine collaboration significantly improves efficiency; extensive research on large-field cluster tillage/seeding, transferable to orchards	Orchard terrain adaptability not yet validated
	Pollination	Fruit tree pollination [9]; blueberry pollination [10]	Infrared image pollination defect identification	Collaborative pollination drones achieve uniform pollen coverage, compensating for efficiency gaps in natural and artificial pollination	Poor pollen sedimentation uniformity under complex canopies; limited orchard pollination research
	Weeding	Orange orchard weeding [11]; olive orchard weeding [12]	YOLOv10 weed identification; precise synchronous communication of detection-removal systems	Rapid large-area weed identification followed by precise targeted removal, reducing pesticide application	Search efficiency needs improvement in low-weed-density scenarios; high real-time communication requirements
	Precision application of water, fertilizer, and agrochemicals	Pear orchard multi-robot spraying system [13]; orchard multi-robot spraying system [14]	Precise variable-rate control of pesticides and fertilizers	Significantly improved spraying efficiency through multi-machine collaboration	Communication attenuation on sloping orchards affects real-time control; limited research targeting orchard scenarios

Table 3. Cont.

Application Stage	Specific Activity	Representative Studies	Key Technologies	Advantages	Challenges
Fruit Harvesting	Yield estimation	Apple orchard yield estimation [15]; cotton yield prediction [16]	Multi-source data fusion to obtain crop density, canopy height, and maturity data; yield prediction model establishment	Replaces manual sampling surveys, improving estimation accuracy and efficiency	Limited reference value for large-area cluster operations (mostly single-robot); model transfer across varieties requires recalibration
	Autonomous harvesting	Apple harvesting system [17]; grape harvesting collaborative system [18]	Flexible non-destructive manipulation mechanisms; dynamically calibrated vision systems	Enables 24/7 operation in principle; multi-arm or multi-machine operation significantly improves efficiency	Currently mostly simulation algorithms and prototypes; not yet validated through multi-season orchard harvesting trials
	Transportation	Agricultural transport vehicles [19]	Optimized dynamic load distribution models; energy balancing strategies	Improves transportation efficiency, reduces logistics costs; drones and trucks complement each other	High transportation costs in mountainous orchards; suitable for post-harvest transport of high-yield, high-value fruits

5. Challenges and Future Directions for Swarm Technologies in Orchards

At present, swarm control technology is developing rapidly. A large amount of research has been carried out around core technologies such as cooperative communication, task allocation, path planning and formation control; many optimization algorithms have been proposed, and some key technical bottlenecks have been overcome. Swarm collaboration technology is expected to become the core driving force for the development of smart orchards, but it still faces core challenges such as “environment, resources, heterogeneity, and verification” and requires systematic collaborative optimization.

5.1. Insufficient Adaptability of the Orchard Environment

Orchard terrain is complex, the working environment is dynamic and unpredictable, and the working scenarios cover multiple height levels. Traditional swarm formation control algorithms have difficulty adapting to this complex working condition, resulting in lagging environmental response and large formation coordination errors.

Existing studies have provided feasible solutions to this problem. The introduction of a stiffness-driven self-reconfiguring hierarchical control framework enables rapid and stable switching of the cluster formation mode according to the operational requirements of the orchard [41]. In addition, by establishing a digital twin database for orchards [104], three-dimensional growth models of multiple tree species and real-time maps of orchards can be constructed to accurately simulate the real working environment. Coupled with the installation of various types of sensors, the environmental perception and real-time positioning capabilities of the cluster in complex dynamic scenarios can be enhanced.

5.2. Large-Scale Swarms Have Limited Resources

The operation areas such as orchard monitoring and picking are extensive and cover a large area, which leads to a sharp increase in the demand for computing resources and communication bandwidth. The traditional centralized communication and computing architecture has problems such as communication bandwidth overload and real-time decision-making delay, making it difficult to process multi-source data in real time and restricting the efficiency and quality of swarm operations.

Existing studies have provided solutions from the two dimensions of communication and computing power. At the communication level, enhancing the local communication capability of the agent can effectively ensure the efficient and precise transmission of information within the cluster [20]. At the computing power level, a distributed computing architecture is built to break down complex computing tasks and allocate them to each agent as needed. Combined with a lightweight deployment model, local decision-making is achieved to reduce the computing power load of the central node [105].

5.3. The Collaborative Efficiency of Heterogeneous Systems Is Relatively Low

In the heterogeneous swarm system of orchards, coordination efficiency has always been the core bottleneck. On the one hand, there is a significant difference in energy consumption between air-ground units. Uneven task distribution can cause some agents to deplete energy prematurely, shortening the system's operating time. On the other hand, the compatibility between heterogeneous communication protocols is poor, which can easily lead to communication failures or delays in information exchange, hindering the smooth progress of collaborative operations.

To address the shortcomings of heterogeneous system collaboration, existing studies have pursued optimization along two directions: energy consumption and communication. By integrating energy-sensing parameters into the task scheduling model and dynamically and reasonably allocating air and ground tasks based on the real-time energy consumption of each unit, energy consumption balance can be achieved [26]. In addition, in the future, a hybrid communication mode can also be developed to fully leverage the advantages of both wireless and direct communication methods, meet the communication requirements of heterogeneous units, and enhance communication stability.

5.4. There Is a Lack of Real-Scene Test Verification

At present, most optimization algorithms are still confined to the simulation experiment stage as described in Section 4.3.2, lacking practical testing and iterative optimization in real orchard scenarios. This leads to insufficient robustness and practicality of the algorithms, making it difficult to support large-scale application in complex engineering scenarios.

To address this issue, on the one hand, in the future, efforts can be made to build more accurate environmental models, integrating knowledge from multiple disciplines and introducing advanced modeling methods to reflect the characteristics of the real environment, thereby constructing more precise real environmental models and enhancing the reliability and validity of simulation results [106]. On the other hand, in the future, the verification and deployment of cluster control algorithms in practical application scenarios should be strengthened. It is necessary to carry out large-scale and multi-scenario field tests and verifications. By collecting data, analyzing problems and optimizing algorithms, the adaptability and robustness of the algorithm can be gradually improved.

6. Conclusions and Future Outlook

This paper focuses on the application of swarm control technologies in orchard agricultural production, examining their potential across the full cycle of orchard production, including pollination, fertilization, weeding, monitoring, harvesting, and transportation. However, due to the unstructured nature of orchard environments and the inherent complexity of swarm coordination technology, current applications remain in the exploratory stage. This study not only reviews the current state of swarm coordination technologies specific to orchard scenarios but also draws on advancements in more mature domains such as open fields, plantations, and forests to propose orchard-specific solutions, offering new perspectives for the intelligent development of orchard operations.

Looking ahead, the application of swarm coordination technologies in orchard operations can be further advanced along two key directions. First, establish a digital twin platform for orchards to provide data support for swarm control; simultaneously build a swarm remote monitoring platform to achieve equipment control and collaborative decision-making; and reduce the usage cost through a regional agricultural machinery swarm sharing platform and design a simple interface to lower the operation difficulty. Secondly, by integrating artificial intelligence algorithms, the swarm system is endowed with autonomous learning capabilities, enabling it to automatically optimize operation strategies. Moreover, technical limitations in production environments such as complex terrain and unstable communication signals are incorporated into the design, promoting the modernization and intelligence of the orchard industry. However, from theoretical design to practical application, especially in small and medium-sized business entities, there are still many practical constraints that need to be given due attention in subsequent research and promotion.

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