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Toward 6G-Empowered Multi-Machine Collaboration in Smart Agriculture: A Communication-Control Co-Design Survey

Baofeng Ji [1,*], Yangyang Li [2], Ran Zhang [3], Saibing Wang [1], Yifan Liu [1], Wenjing Xu [1], Kaipeng Sun [1], Xin Zhang [1], Du Cui [1], Yanchao Guo [4], Peipei Wang [5], Song Chen [4], Jinguang Li [4], Zheng Tu [5], Shusheng Lü [6]

[1] Henan University of Science and Technology, 263 Kaiyuan Avenue, Luolong District, Luoyang 471023, Henan, China

[2] International Cooperation Center, National Development and Reform Commission, 7th Floor, 1 Baiyun Road, Xicheng District, Beijing 100045, China

[3] The First Affiliated Hospital of Henan University of Science and Technology, 24 Jinghua Road, Luoyang 471003, Henan, China

[4] First Tractor Company Limited, 39 Xiyuan Road, Jianxi District, Luoyang 471039, Henan, China

[5] China Electronics Space (Beijing) Technology Co., Ltd., 12th Floor, Ruichuang (China) Building, No. 4 Xinyuan, Hujialou, Chaoyang District, Beijing 100020, China

[6] Chinese Academy of Agricultural Mechanization Sciences Group Co., Ltd., Beijing 100083, China

[*] **Corresponding author**: Baofeng Ji

Abstract: As communication and sensing capabilities grow, smart agriculture is shifting from single-machine automation to coordinated fleets. Cooperative harvesting, multi-UAV spraying, and fleet logistics demand bounded latency, reliability, and synchronized state that traditional best-effort networks cannot guarantee. Control algorithms validated under ideal communication assumptions degrade when deployed on real field networks with partial coverage and thin backhaul, and this gap cannot be closed by a faster network or a smarter controller alone. Taking as its organizing line that the network deadline and the controller deadline must be treated as one design surface, this review systematically surveys the communication-control co-design of multi-machine collaboration in smart agriculture, covering the joint engineering of deterministic communication, integrated sensing and communication, edge intelligence, and distributed control. We organize the literature around four pillars: deterministic networks, multi-agent coordination, co-design substrates, and enablers. Stability-region analysis already bounds control cost as a function of communication parameters, whereas integrated sensing and digital twins remain at the architecture stage, lacking quantitative validation in agricultural scenarios. It follows that standardization, rural coverage, and safety are constraints that fix the co-design operating point rather than afterthoughts.

Keywords: Smart agriculture, multi-machine collaboration, communication-control co-design, deterministic networking, integrated sensing and communication, edge intelligence, digital twin.

1. Introduction

Table 1. Glossary of key abbreviations

Abbr.	Full name
TSN	Time-Sensitive Networking
DetNet	Deterministic Networking
URLLC	Ultra-Reliable Low-Latency Comm.
ISAC	Integrated Sensing and Comm.
WNCS	Wireless Networked Control System
MAS	Multi-Agent System
MARL	Multi-Agent Reinforcement Learning
DMPC	Distributed Model Predictive Control
CPS	Cyber-Physical System
RIS	Reconfigurable Intelligent Surface
GNSS/RTK	GNSS / Real-Time Kinematic
V2X	Vehicle-to-Everything
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle

Smart agriculture is shifting from single-machine automation to coordinated fleets. Tractors, implements, unmanned aerial vehicles (UAVs), and ground robots now execute joint field operations, including cooperative harvesting, multi-UAV spraying, multi-implement cultivation, and fleet logistics, in which each machine's behavior depends on the state of its neighbors [1], [2]. This shift tightens the coupling between communication and control. Cooperative tasks demand bounded latency for closed-loop stability, reliability for safety, and determinism for synchronized action, requirements that traditional best-effort packet networks were not designed to meet [3], [4].

The problem is structural. Layering a best-effort network over an independent controller leaves a gap between what the control loop assumes and what the network delivers. Consensus and formation algorithms assume consistent state across agents, but best-effort links violate this assumption under load [5], [6]. Networked control over wireless depends on a coupled tradeoff among latency, rate, and reliability, yet each is traditionally optimized in isolation [7], [8]. The result is a recurring pattern: control algorithms are validated under ideal communication assumptions, then degrade when deployed on real field networks where coverage is partial, line of sight is rare, and backhaul is thin [9].

The thesis of this review is that this gap cannot be closed by a faster network alone or a smarter controller alone, and that multi-machine collaboration in smart agriculture requires the joint design of deterministic communication, integrated sensing and communication (ISAC), edge intelligence, and distributed control. In other words, the deadline of the network and the deadline of the controller must be treated as one design surface, because the control cost of a dropped or delayed packet is a property of the joint system rather than of either layer in isolation [10], [11].

Four challenges make this co-design hard. First, determinism must survive wireless links, partial coverage, and node failures, not just wired backbones [12]. Second, sensing and communication must share spectrum and power budgets that agricultural nodes can ill afford to duplicate. Third, edge intelligence must move inference to where the actuator is, collapsing the sensing-to-action path without exceeding field-deployable compute. Fourth, safety and integrity must hold across localization, communication, and physical interaction layers simultaneously, because a single forged position fix or jammed link can destabilize a formation.

The scope of this review spans multi-machine and multi-implement collaborative operations in smart agriculture, including ground vehicles, implements, and aerial platforms, but framed by operation and technology rather than by equipment type. We cover deterministic networking (TSN, DetNet, deterministic 5G/6G, URLLC), multi-agent collaborative control (consensus, formation, task allocation, multi-agent reinforcement learning, distributed model predictive control), their co-design (latency-aware control, joint resource optimization, ISAC, digital twins, edge AI), and cross-cutting enablers (GNSS/RTK fusion, edge intelligence, security). We focus on formally published work from 2020 onward, with seminal earlier references where the sub-topic demands them.

The contributions are fourfold. We synthesize the deterministic-communication and collaborative-control literatures, which have developed in parallel, into a single co-design framework. We identify the recurring gap between assumed and delivered network behavior as the binding constraint on deployed cooperation [13]. We trace how ISAC, digital twins, and edge intelligence form a substrate on which the co-designed loop can actually close. We map the open challenges, including 6G determinism, foundation-model-era perception, standardization, rural coverage, and safety, back to the same co-design surface, arguing that none can be solved by a single layer in isolation.

Distinction from existing surveys. Existing agricultural multi-robot surveys [1], [2] focus on platforms and algorithms, rarely treating communication as a first-order design constraint. AI-driven cooperative control surveys [13] cover perception-decision-execution architectures but do not frame communication-control co-design as the organizing thesis. Ultra-low latency network surveys [3], [4] catalog TSN/DetNet standards but do not address agricultural deployment. This review's increment is to bind the deterministic-communication and collaborative-control literatures into a single co-design framework, unified by the thesis that the network deadline and the controller deadline are one design surface, applied across the full chain of multi-machine agricultural collaboration.

The remainder of this review is organized as follows. Section 2 establishes the application context and the requirements that motivate co-design. Sections 3 and 4 survey the deterministic-communication and collaborative-control pillars. Section 5 develops the co-design thesis. Section 6 covers cross-cutting enablers. Section 7 grounds the survey in applications, and Section 8 maps open challenges and future directions.

2. Background: Multi-Machine Collaborative Operations in Smart Agriculture

Smart agriculture is shifting from single-machine automation to coordinated fleets of tractors, implements, and unmanned aerial vehicles (UAVs) that execute joint field operations. This shift tightens the coupling between communication and control, because cooperative tasks demand bounded latency and consistent state across machines.

2.1. Cooperative Operation Scenarios

Multi-robot systems in agriculture now span ground vehicles, implements, and aerial platforms that must act as a coordinated fleet rather than isolated units [1], [2]. Cooperative harvesting and multi-implement operations exemplify this coupling: a harvester, grain carts, and tractors must hold spatial formation while sharing load and speed. Formation control studies in structured farmland show that geometric coordination remains feasible under field constraints [14]. AI-driven cooperative control is pushing autonomous tractors and implements beyond isolated machine control toward multi-agent operation [13].

Multi-UAV operations extend cooperation to the air. UAV swarms conduct spraying, patrolling, and crop monitoring, where coverage path planning and task allocation jointly determine efficiency [15], [16]. Coverage optimization partitions fields and assigns platforms by capability, so heterogeneous UAV groups match platform to subregion [17]. Task allocation is addressed by reinforcement learning across regions [18], multi-objective NSGA-II under competing objectives [19], and swarm-intelligence methods that scale to many platforms [20], [21].

Formation control is the shared substrate beneath these operations, and reviews now span both conventional and learning-based methods [22], [23]. Comparative studies on unmanned farms indicate that formation quality directly governs spraying and scouting outcomes [24], and enhanced swarm-coordination algorithms extend these gains to complex orchard environments [25]. Task allocation across swarms remains the operational bottleneck that limits scaling of precision agriculture deployments [26].

2.2. Communication and Control Requirements

Cooperative scenarios impose three hard communication requirements: bounded latency for closed-loop control, reliability for safety, and determinism for synchronized action. Determinism in the wired backbone comes from scheduled, time-aware forwarding. IEEE Time-Sensitive Networking (TSN) and IETF Deterministic Networking (DetNet) bound end-to-end latency for control traffic through time-aware shapers and explicit routes [3], [4]. TSN enforces strict latency boundaries for time-critical applications [27], and converged deterministic packet networks add the service protection that cooperative operations require [28]. Reaching the wireless edge demands convergence of 5G with TSN, now surveyed as a single architectural problem [12], while latency-adjustable fog architectures extend deterministic guarantees toward the field for time-sensitive monitoring [29]. 5G has been evaluated for agricultural robotics because fields combine mobility with strict latency needs that older farm networks cannot meet [9], [30]. Native deterministic communication is the stated goal of 6G [31].

On the control side, cooperative operation requires consensus and formation algorithms that maintain group consistency under realistic network conditions. Bibliometric analysis confirms multi-agent formation control is a maturing, cross-domain field [32]. Consensus-based formation control for heterogeneous systems handles complex environments and switching topologies [5], [6]. Distributed connectivity control preserves the algebraic connectivity of the communication graph so swarms stay connected during motion [33]. Realistic actuator limits are addressed by anti-saturation consensus tracking for unmanned ground vehicle (UGV) formations [34] and by distributed model predictive control for UGV platooning [35]. Surveys of intelligent multi-agent formation control synthesize these threads into design guidance [36].

2.3. Why Layered Best-Effort Architectures Fail

Traditional best-effort packet networks cannot meet the bounded-latency requirements of multi-machine coordination. They bound end-to-end latency only loosely, to the order of queuing delay, leaving no hard guarantee for control loops [3]. For time-triggered cyber-physical control, information arriving past a fixed deadline is control-invalid and must be discarded, a contract that best-effort wireless cannot satisfy [10]. Converged deterministic networks therefore need new service protection to ensure robust, reliable communication [28].

Layering best-effort networks over independent controllers fails to preserve cross-domain determinism. Software-defined TSN shows that cross-domain deterministic transmission requires coordinated scheduling across administrative boundaries rather than isolated per-domain optimization [27]. The 5G-TSN integration survey confirms that convergence must span architecture, not merely link-layer placement, to deliver end-to-end determinism [12]. Hybrid wired/wireless deterministic networks extend the same argument: bounded behavior must be preserved across heterogeneous links to support coordinated robotics [37].

The control layer exposes the same conclusion. Consensus algorithms under bounded but uncertain delays and switching topologies degrade in performance when the network cannot bound delay [5]. Formation control for heterogeneous systems assumes consistent state across agents, an assumption that best-effort networks violate under load [6]. Cooperative multi-robot synergy therefore cannot be retrofitted onto best-effort links and independent controllers [2]. Cooperative harvesting, multi-UAV spraying, and fleet logistics couple communication and control into one problem: stability, safety, and synchronization demand bounded latency, reliability, and determinism, while layered best-effort architectures fail at both the network and control layers. This structural gap cannot be patched by either layer alone, and it sets the point of departure for co-design, which the next section begins from deterministic networks.

3. Deterministic Communication Technologies

Deterministic communication provides the bounded latency and reliability that multi-machine agricultural coordination requires. Best-effort links cannot sustain the control loops that synchronize tractors, robots, and sensors operating in close proximity.

3.1. Time-Sensitive Networking and DetNet for Agricultural Machinery

Determinism in the wired backbone comes from scheduled, time-aware forwarding. IEEE TSN and IETF DetNet bound end-to-end latency for control traffic through time-aware shapers and explicit routes [3], [4]. These standards were developed for factory automation and are now inherited by agricultural cyber-physical systems. The same scheduled-transmission principle applies whether the controlled plant is a robotic arm or a fleet of field robots.

Bounded latency must also survive link and node failures. Deterministic packet networks achieve this through redundant paths and frame replication, so a single link loss does not violate the delivery deadline [28]. Reliability here becomes a property of the schedule and topology, not a probabilistic add-on layered over best-effort forwarding.

Field deployment stretches determinism across multiple subnets and vendors. Software-defined TSN separates control from forwarding, allowing a central controller to recompute schedules across administrative boundaries [27]. OPC UA over TSN pairs this temporal contract with a shared information model, so heterogeneous machines exchange semantic data on a deterministic schedule [38]. Hybrid wired/wireless deterministic networks extend the same guarantees from a wired backbone to wireless edges, as shown for smart-grid infrastructure that resembles farm networks [37]. The convergence of 5G with TSN tightens this coupling further, allowing cellular and wired segments to share one deterministic transport [12].

3.2. Deterministic 5G/6G and URLLC

Wireless determinism becomes necessary once machines leave the wired backbone. 5G has been evaluated for agricultural robotics because fields combine mobility with strict latency needs that older farm networks cannot meet [9], [30]. For latency-sensitive monitoring, fog architectures with adjustable latency budgets extend deterministic guarantees from the core toward the field edge [29].

Ultra-reliable low-latency communication (URLLC) delivers bounded wireless latency through specific radio mechanisms. Short packets, reserved resources, and diversity combine to reach the reliability that closed-loop control demands [8]. The 5G URLLC standard has evolved specifically to serve industrial automation with high-performance wireless networking [39], and assessments of 5G numerologies confirm that not all configurations meet URLLC targets in industrial settings [40]. The tradeoff is fundamental: lower latency competes with higher rate and higher reliability, and finite-blocklength coding tightens the reliability-latency-rate bound [7], [41]. Wireless networked control systems must be designed around this three-way tension rather than any single axis. Realizing wireless closed-loop control therefore requires co-design of the radio link and the control loop, not a generic best-effort modem [42]. Industrial wireless standards such as WIA-NR have already adopted URLLC mechanisms for control networks over unlicensed bands [43].

Three enhancements strengthen URLLC under hostile field conditions, each reshaping a different layer of the link. At the physical layer, reconfigurable intelligent surfaces steer signals around obstacles to sustain ultra-reliability in factory-like settings [44]. Across the link and the controller, prediction co-designed with the communication pipeline lets the controller anticipate state evolution and absorb residual latency [45]. At the junction of radio and control, joint communication-and-control formulations treat the control input and the radio resource as one optimization variable, closing the loop within a single deadline [11]. Toward 6G, these mechanisms consolidate into a deterministic-communication service class that subsumes URLLC [31].

3.3. Time Synchronization and Deployable Deterministic Wireless

Cooperative perception among machines requires time-aligned sensor views. Direct vehicle-to-vehicle (V2V) sidelink allows neighboring machines to share sensor data, resolving occlusions that no single onboard sensor can [46], [47]. The fusion is meaningful only when frames carry compatible timestamps. Deadline-driven deterministic protocols therefore discard any packet arriving after its control deadline rather than corrupting the fused estimate [10]. Millimeter-wave V2V provides the bandwidth this fusion needs, supporting maneuvers such as safe overtaking [48], [49]. The same direct-link mechanism underpins platooning, where vehicles exchange kinematic state to hold tight formation under a joint communication-and-control contract [50].

Determinism in the field then depends on selecting the right radio per link. NR sidelink in 5G-V2X provides the baseline direct-mode latency budget for cooperative services [51]. When several radios coexist, intelligent selection among 5G, C-V2X PC5, and DSRC assigns each message to the bearer that best fits its deadline [52]. Deep reinforcement learning can optimize perception synergy across these links, trading latency against fusion accuracy [53].

Agricultural deployment constrains these mechanisms in ways that vehicular testbeds do not. Semi-autonomous multi-vehicle architectures integrate conventional tractors with mobile robots for fleet navigation in the field [54]. Field evaluations of autonomous electric robots confirm that real terrain tests mobility and energy performance beyond simulation [55]. Swarms of autonomous farm vehicles also expose a security surface that deterministic schedules alone do not close, requiring an architecture that authenticates every cooperative message [56]. Federated anomaly detection extends this protection across cooperative infrastructure without centralizing the data [57].

Table 2. Comparison of deterministic communication technologies

Ref.	Year	Category	Core mechanism	Scenario	Validation status
[3]	2019	TSN/DetNet	Ultra-low latency network survey: TSN, DetNet, 5G URLLC standards	Industrial control traffic	Standard + survey
[4]	2022	TSN/DetNet	TSN for industrial intelligent and distributed measurement systems	Industrial CPS (inheritable by agriculture)	Standard + survey
[28]	2023	TSN/DetNet	Converged deterministic packet network service protection (redundant paths, frame replication)	Link/node failure scenarios	Architecture + simulation
[27]	2024	Cross-domain convergence	Software-defined TSN scheduling across administrative boundaries	Cross-subnet/cross-vendor fleets	Architecture + simulation
[38]	2019	Cross-domain convergence	OPC UA over TSN: temporal contract plus shared information model	Heterogeneous machine semantic interoperation	Architecture + prototype
[37]	2021	Cross-domain convergence	Hybrid wired/wireless deterministic networks (smart-grid validation)	Wired + wireless mixed farms	Simulation (grid analog)
[12]	2025	Cross-domain convergence	5G and TSN convergence: architectural-level integration	Cellular + wired unified transport	Survey
[8]	2019	URLLC	URLLC: reliability-latency-rate jointly engineered	Wireless closed-loop control	Theory
[7]	2021	URLLC	Latency-rate-reliability stability region (analytic bound)	Wireless networked control	Theory (analytic)
[42]	2021	URLLC	Connectivity solution for wireless closed-loop control	Industrial wireless control	Architecture + simulation
[39]	2021	URLLC	5G URLLC standard evolved for industrial automation	Industrial wireless	Standard
[31]	2023	6G determinism	6G native deterministic communication service class	Future large-scale fleets	Vision/concept
[10]	2026	Time synchronization	Deadline-driven deterministic wireless (late packets discarded)	Time-triggered control	Concept
[51]	2023	Time synchronization	NR sidelink 5G-V2X performance evaluation	Direct-mode cooperative services	Simulation
[52]	2024	Time synchronization	Intelligent bearer selection across 5G/C-V2X PC5/DSRC	Multi-radio coexistence	Simulation
[9]	2023	Agricultural deployment	5G field capability evaluation for agricultural robotics	Off-highway autonomy	Field evaluation (small-scale)
[54]	2023	Agricultural deployment	Semi-autonomous multi-vehicle architecture (tractor plus mobile robot)	In-field fleet navigation	Architecture
[55]	2024	Agricultural deployment	Autonomous electric robot evaluated on a real farm	Real-terrain operation	Field evaluation

Determinism has extended from scheduled forwarding in the wired backbone to the wireless edge: TSN and DetNet provide reliability that survives failures through redundant paths and cross-domain scheduling, URLLC binds latency, rate, and reliability into a three-way tension, and time synchronization and multi-radio selection decide whether the field can deliver these bounds. Deterministic links nevertheless bound latency only at the radio and network layers; converting those bounds into safe multi-machine behavior still requires control to be co-designed with communication, the subject of the next section.

4. Multi-Machine Collaborative Control Architectures

Multi-machine collaborative control architectures decompose agricultural fleet operations into three coupled layers: motion coordination, cooperative planning, and learning-based control. These layers share the multi-agent system (MAS) abstraction, but differ in whether coordination arises from geometric constraints, combinatorial optimization, or learned value functions.

4.1. Multi-agent Modeling, Consensus, Formation and Platooning

The MAS abstraction models each machine as a node in a dynamic graph whose edges encode sensing and communication links. Bibliometric and survey work maps this landscape for formation control and agricultural multi-robot cooperation [1], [2], [32], [36]. Recent reviews argue that AI-driven cooperative control is shifting agricultural automation from isolated tractors toward fleet-level coordination [13].

Consensus protocols drive agent states toward a common value through local neighbor interaction, and they underpin most formation controllers. Robustness extensions handle mixed agent dynamics with external disturbance [6] and directed switching topologies with bounded uncertain delays [5]. Constraint-aware variants instead keep consensus feasible. Distributed connectivity control maintains the algebraic connectivity of the communication graph [33], and anti-saturation tracking respects actuator limits in unmanned ground vehicle (UGV) formations [34]. In agriculture, cooperative formation has been simulated for robots operating in square farmland [14].

Aerial fleets add aerodynamic coupling to formation control. Reviews classify leader-follower, virtual-structure, and behavior-based schemes for UAV swarms [20], [21], [22], [23], and agricultural UAV surveys situate these methods in crop monitoring and plant protection [15]. Field evaluations follow: comparative studies on unmanned farms evaluate swarm control under field conditions [24], and orchard patrolling demonstrates enhanced multi-agent coordination in complex canopy environments [25].

Ground-vehicle platooning adapts consensus to longitudinal string stability, where each vehicle tracks its predecessor's state. Because tight inter-vehicle spacing challenges string stability, platooning serves as a primary testbed for the model-predictive and learning-based controllers reviewed in the final subsection.

4.2. Cooperative Task Allocation and Path Planning

Coverage path planning generates field-efficient trajectories that minimize overlap and turn maneuvers. Curvature-constrained complete coverage planning optimizes feasible turns for agricultural vehicles [58]. Heterogeneous fleets with different working widths and turn characteristics require cooperative heuristics that sequence dependent field tasks [59]. Heterogeneous UAV groups extend coverage planning to aerial precision agriculture [17].

When operations span multiple regions, path planning and task scheduling become coupled. Multi-area collision-free planning jointly optimizes inter-region transitions and scheduling for autonomous agricultural robots [60], and improved double deep Q-learning extends multi-area task path planning for agricultural drones [18].

Task allocation distributes jobs across heterogeneous machines, and evolutionary and heuristic methods dominate. NSGA-II variants minimize travel distance and balance load for agricultural multi-robot fleets [19], [61]. Collaborative evolutionary algorithms jointly solve allocation and scheduling in smart farms [62]. Domain-specific instances adapt this framework to harvest: soft-fruit picking is allocated across workers and robots [63], and combine-grain-truck coordination schedules tracked maize harvesters with enhanced hybrid MOEA/D [64]. Scaling to fleet level adds hierarchy: multi-objective algorithms schedule heterogeneous robots [65], and hierarchical multi-objective routing extends scheduling fleet-wide [66]. Orchard operations couple path planning with task assignment for mowing robots [67], and collaborative planning for multiple agricultural machines closes the loop between allocation and trajectory generation [68].

For aerial fleets, task allocation methods are surveyed for precision agriculture [16], [26]. Reinforcement-learning-enhanced iterated greedy algorithms handle weeding-robot operation scheduling, blending metaheuristics with learned improvement [69].

4.3. Learning-based Coordination (MARL and Distributed MPC)

Distributed model predictive control (DMPC) decomposes centralized model-predictive control into local controllers that exchange trajectories, preserving constraint satisfaction while scaling to fleets. DMPC achieves UGV platooning through dynamic consensus control [35], and coalitional DMPC forms dynamic coalitions to balance string stability and communication cost for vehicle platooning [70]. Computational burden is the recurring bottleneck, and learning-based approximation accelerates DMPC under dual decomposition with formal guarantees [71].

Multi-agent reinforcement learning (MARL) and DMPC are increasingly fused, with DMPC serving as a structured function approximator or safety filter for learned policies. DMPC acts as a function approximator for multi-agent reinforcement learning in linear constrained systems [72], and cooperative multi-agent Q-learning uses DMPC as the local policy [73]. Deep reinforcement-learning agents negotiate among distributed hierarchical predictive controllers [74], and joint distributed reinforcement learning and MPC controls autonomous vehicle platoons in urban networks [75].

Pure MARL approaches learn coordinated policies without relying on explicit system models. Safe MARL enforces multi-robot safety constraints during learning [76], and structural coordination exploits agent relationships to improve MARL sample efficiency [77]. Platoon control applies multi-agent deep reinforcement learning to vehicle merging into highway platoons [78], and serial distributed reinforcement learning extends platoon control to curved road coordinates [79].

Table 3. Comparison of multi-machine collaborative control methods

Ref.	Year	Category	Core mechanism	Scenario	Validation status
[6]	2025	Consensus and formation	Consensus-based formation for heterogeneous systems (complex environments, switching topologies)	Formation cooperation	Theory + simulation
[5]	2022	Consensus and formation	Consensus under bounded uncertain delays and directed switching topologies	Networked formation	Theory + simulation
[33]	2022	Consensus and formation	Distributed connectivity control (maintains algebraic connectivity)	Swarm motion staying connected	Simulation
[34]	2025	Consensus and formation	Anti-saturation consensus tracking for UGV formations	Actuator-limited formations	Simulation
[14]	2022	Agricultural formation	Cooperative formation simulated for robots in square farmland	Structured-field operations	Simulation
[25]	2025	Agricultural formation	Enhanced multi-agent swarm coordination for orchards	Complex-canopy orchard patrolling	Simulation
[24]	2023	Agricultural formation	Comparative analysis of UAV swarm control on unmanned farms	Unmanned-farm swarm operations	Comparative study (simulation)
[58]	2023	Coverage path planning	Curvature-constrained complete coverage path planning	Turning-limited vehicles	Simulation
[59]	2024	Coverage path planning	Cooperative heuristics for dependent tasks of heterogeneous implements	Multi-implement joint operations	Simulation
[17]	2023	Coverage path planning	Coverage optimization partitioning for heterogeneous UAV groups	Aerial precision agriculture	Simulation
[19]	2026	Task allocation	Multi-objective NSGA-II balancing conflicting objectives	Multi-robot fleet scheduling	Simulation
[61]	2023	Task allocation	NSGA-II minimizing travel distance and balancing load	Agricultural multi-robot fleets	Simulation
[64]	2025	Task allocation	Hybrid MOEA/D scheduling of tracked maize harvesters and grain trucks	Harvester-grain-cart coordination	Simulation
[66]	2026	Task allocation	Hierarchical multi-objective routing for fleet-wide scheduling	Fleet-level logistics	Simulation
[35]	2025	DMPC	DMPC with dynamic consensus control for UGV platooning	UGV platoon driving	Simulation
[70]	2022	DMPC	Coalitional DMPC balancing string stability and communication cost	Vehicle platooning	Theory + simulation
[71]	2024	DMPC	Learning-based approximation accelerating DMPC (dual decomposition, formal guarantees)	Large-scale fleets	Theory + simulation
[72]	2024	MARL	DMPC as a function approximator for MARL (linear constrained systems)	Learned cooperative control	Simulation
[76]	2023	MARL	Safe MARL enforcing multi-robot safety constraints	Safety-critical cooperation	Simulation
[78]	2025	MARL	Multi-agent deep RL for vehicle merging into highway platoons	Platoon control	Simulation

Multi-machine collaborative control unfolds across three layers (motion coordination, cooperative planning, and learning-based control), with consensus and formation as the shared substrate, task allocation dominated by evolutionary and heuristic methods, and DMPC increasingly fused with MARL as a safety filter and function approximator. The three layers nevertheless share one unverified assumption, that the underlying communication network is ideal and low-latency; this gap motivates the communication-control co-design developed in the next section.

5. Communication-Control Co-Design

Communication-control co-design treats the network and the controller as a single design object, because multi-machine coordination in smart agriculture cannot tolerate the gap between best-effort delivery and deterministic control. The four threads below show that latency, reliability, sensing, and the digital substrate must be engineered against a control objective rather than layered over it.

It should be noted that most foundational co-design work originates from industrial IoT and factory automation [7], [8], [11], [42]. Three key differences between industrial and agricultural scenarios both constrain the direct transfer of industrial conclusions and define the unique requirements of co-design in agriculture. First, industrial networks are predominantly wired with fixed topology, whereas agricultural fleets are wireless-dominant with topology changing as machines move, giving wireless determinism (URLLC, NR sidelink) far greater weight in agriculture. Second, industrial control cycles are millisecond-scale and predictable, whereas agricultural operations (e.g., cooperative harvesting unloading timing) have control horizons of seconds to minutes, though safety-critical scenarios (e.g., formation collision avoidance) still demand millisecond response, requiring tiered control horizons. Third, industrial deployments have controlled environments and fixed infrastructure, whereas agriculture faces weather, terrain, and no fixed backhaul, making rural coverage and energy efficiency hard constraints rather than optimization targets. The structural conclusions of industrial co-design (joint optimization outperforms layering, reliability is a scheduling property) hold in agriculture, but the specific parameters and mechanisms require adaptation.

5.1. Latency- and Reliability-Aware Control

Networked control over wireless links cannot treat communication as a black box. The stability of a wireless networked control system (WNCS) depends on a coupled tradeoff among latency, rate, and reliability [7]. This coupling is structural in the ultra-reliable low-latency communications (URLLC) regime, where reliability and latency must be jointly engineered rather than separately optimized [8]. Closing the loop imposes packet-delivery bounds that best-effort links cannot meet, so wireless closed-loop control needs a connectivity solution built around those bounds [42]. Communication and consensus have been co-designed to achieve distributed, low-latency, and reliable wireless systems [80], and wireless communication-control co-design has been extended to system identification [81]. For multi-machine fleets, the radio link is part of the control law, not a pipe beneath it.

These bounds motivate physical-layer and prediction-based enhancements. Reconfigurable intelligent surfaces (RIS) raise the achievable URLLC reliability in factory automation by shaping the propagation environment around the controller [44]. Prediction offers a complementary route: forecasters co-designed with the communication pipeline let the controller anticipate state evolution and absorb residual latency, easing the delay budget that URLLC must guarantee [45]. The two threads converge on one claim: reliability-aware control is a property of the joint link-and-controller design, not of either layer alone.

5.2. Joint Communication Resource and Control Optimization

Once the latency-reliability bounds are fixed, the remaining question is how to allocate spectrum, power, and compute against a control objective. Joint communication and control framing for URLLC schedules radio resources against the control cost of dropping or delaying a packet [11]. The same coupling appears in WNCS design, where rate and reliability are tuned to the control loop's tolerance rather than to a generic quality-of-service target [7]. Prediction re-enters here as an allocable resource: a co-designed forecaster trades compute for a wider communication margin, so the optimizer can spend bits on the channels that most affect stability [45].

Reconfigurable surfaces extend the optimization space further. Allocating reflecting elements alongside transmission parameters steers URLLC traffic in factory automation, treating the physical environment as a schedulable resource [44]. The pattern across these works is that the control objective, not the link metric, defines the constraint set. Joint optimization is therefore structurally different from layered resource allocation, and multi-machine coordination inherits this structure directly: each machine's control cost enters the scheduler.

5.3. ISAC for Control

Integrated sensing and communication (ISAC) collapses sensing and communication into one waveform so that the same signal carries commands and probes the field. This convergence is a 6G requirement: building digital-twin maps of the physical world demands radio sensing woven into the communication frame, not bolted on [82]. The same trend runs through radar, where 5G/6G joint communication and active or passive sensing now reaches beyond military lineage into civilian monitoring [83]. At the waveform level, code-division OFDM joint communication and sensing for 6G machine-type communication reuses spectrum to cut the overhead that separate sensors would impose [84]. For coordinated field machinery, this reuse removes a dedicated sensing radio from every node.

For agriculture, the reuse is especially attractive because field sensing is dense and power-constrained. Terahertz joint communication and sensing for precision agriculture lets the same 6G link that exchanges telemetry also probe crop state [85]. The idea extends to lettuce water-status monitoring, where reusing the communication link gives non-contact, continuous perception without hardware changes [86]. Integrating an ultra-compact soil moisture sensor with a reconfigurable antenna compresses the sensing-communication interface into a single field-deployable node [87]. The broader environmental sensing and remote communication stack that greenhouses already require further motivates merging the two radios [88].

The co-designed loop then rests on two further components. Reconfigurable intelligent surfaces extend ISAC coverage in non-line-of-sight fields, and RIS-assisted ISAC reshapes the channel for both functions at once [89]. Terahertz bands push sensing resolution further: 6G communication infrastructure can double as a climate-change sensing instrument by reading greenhouse-gas signatures off the same links [90]. UAV-empowered ISAC for 6G moves sensing and connectivity off fixed base stations and onto airborne platforms, so they follow mobile machinery across the field [91]. Together these make the sensing-communication-control loop a single waveform-level object that moves with the fleet.

5.4. CPS, Digital Twins and Edge AI as Co-Design Substrates

The substrate binding communication and control is a cyber-physical system (CPS) layer that mirrors the field. Digital twins provide that mirror. As a digital equivalent of a real farming object, the twin exposes its state for the controller to inspect, framing it as a route to higher productivity and sustainability [92]. Across agriculture-wide transformation, twins bring control over processes previously observed only in situ [93]. In the next generation of agricultural digitalization, the twin is the integration point for advanced data processing [94]. Tempering the productivity framing, digital twins also sit within sustainability tradeoffs, acting as a tool for managing land, climate, and food security jointly [95].

The orchestration layer decides how the twin stays live. Treating the twin as an orchestration problem replicates real-time functionalities of plants and objects, so control decisions can be tested before deployment [96]. In greenhouses, combining twins with Industry 4.0 technologies keeps the replica synchronized with the controlled environment [97]. For machinery and robotics, integrated digital-twin architectures for agricultural equipment expose where deployment gaps still block closed-loop use [98]. The machinery focus is what makes the twin load-bearing for multi-machine coordination: each machine contributes its state to a shared replica that the controller reasons over.

Edge AI supplies the compute that keeps the twin and the controller in step (see Section 6 for details). Its core constraint (the accuracy-latency-energy triangle [99], [100]) is precisely where compute enters co-design as an allocable resource: a co-designed forecaster trades compute for a wider communication margin [45], and edge inference compresses the sensing-to-action path to where the actuator is. The twin, the edge, and the model thus form the substrate on which the co-designed communication-control loop actually closes.

Table 4. Comparison of communication-control co-design approaches

Ref.	Year	Category	Core mechanism	Scenario	Validation status
[8]	2019	Latency/reliability-aware control	URLLC: reliability and latency jointly engineered, as a control-loop constraint	Wireless closed-loop control	Theory
[7]	2021	Latency/reliability-aware control	Control cost bounded by the (latency, rate, reliability) stability region	Harvest formation, collision avoidance	Theory (analytic)
[11]	2023	Joint resource-control optimization	Control cost as wireless scheduling objective; analytic optimal blocklength	Multi-fleet spectrum/power allocation	Theory (analytic)
[45]	2020	Joint resource-control optimization	Prediction co-designed with the communication pipeline to absorb residual latency	Delay-budget relief	Theory + simulation
[82]	2021	ISAC for control	6G joint communication and sensing: sensing woven into the communication frame	Digital-twin map construction	Concept
[85]	2022	ISAC for control	Terahertz joint communication and sensing for precision agriculture	Non-contact crop-state sensing	Concept + early prototype
[92]	2021	CPS/digital twin/edge AI	Digital twin as the digital equivalent of a real farming object	Fleet-level shared state	Architecture
[98]	2026	CPS/digital twin/edge AI	Integrated digital-twin architecture for agricultural machinery, exposing deployment gaps	Fleet-level coordination and safety verification	Architecture-level (gaps remain)

Note that the first two approaches have analytic quantitative results (stability region [7], optimal blocklength [11]), while the latter two remain at the architecture/concept stage, lacking quantitative validation in agricultural scenarios. This gap is the main obstacle to co-design moving from theory to deployment. These co-design substrates now require a set of supporting technologies, discussed in the next section, to make them deployable at scale across multi-machine agricultural fleets.

6. Enabling Technologies

Centimeter-level positioning, on-field compute, virtual replicas, and layered integrity are the cross-cutting enablers that turn isolated machines into a cooperative fleet. Each addresses a distinct failure mode that best-effort networks and independent controllers cannot resolve alone.

6.1. GNSS/RTK and Multi-Sensor Fusion

Centimeter-level positioning is the prerequisite that lets multiple machines share a field without collision or overlapping work. Precision agriculture imposes this requirement across guidance, mapping, and autonomous navigation tasks [101]. Real-Time Kinematic (RTK) GNSS has become the baseline technology for meeting it, providing reliable centimeter-level positions in most operational scenarios when correction signals are available [101]. A single GNSS receiver nonetheless degrades under foliage, multipath, or signal obstruction, conditions that are common in orchards and near farm infrastructure. Multi-sensor fusion is the recurring strategy for bridging these gaps in autonomous navigation [102]. Combining GNSS with inertial measurement, vision, and ranging sensors lets pose estimates survive the failure of any single source.

Adaptive fusion refines this strategy by weighting sensors according to their local confidence. Adaptive GNSS-UWB fusion, for example, reweights measurements as conditions change and sustains centimeter-level accuracy where GNSS alone would degrade [103]. The pattern across these works is consistent: GNSS supplies the absolute reference, complementary sensors supply continuity, and the fusion law decides whether the combination is robust enough for cooperative operation. For multi-machine fleets, the same logic extends from a single vehicle's pose to the relative geometry between vehicles, where shared reference frames and consistent fusion become prerequisites for safe coordination.

6.2. Edge Intelligence and Distributed Learning

On-field compute moves inference closer to the sensors, cutting round-trip latency for perception and control decisions that cannot wait for cloud offload. The widening deployment of farming equipment has driven rapid growth in production data. This growth exposes the bandwidth and latency limits of cloud-only architectures and motivates layered edge designs that process information where it originates [100]. Machine learning has become a dominant computational workload on these architectures, applied across yield prediction, pest and disease detection, and autonomous navigation [99]. These surveys converge on a common finding: model accuracy is no longer the sole bottleneck. The binding constraint is the trade-off between accuracy, latency, and energy, which decides which models can actually run on field-deployable hardware [99], [100].

Vision-based crop monitoring illustrates this trade-off concretely. Deep-learning models for pest and disease detection achieve high accuracy on servers, but early-stage infestation detection demands in-field inference under tight compute budgets [104]. CROPCARE addresses this by pairing mobile-vision models with an IoT pipeline that keeps disease detection on-device, showing that a real-time system can be built without cloud round-trips [105]. AICropCAM generalizes the same principle across classification, segmentation, detection, and counting, deploying all four model families on edge hardware for crop monitoring [106]. Together these works show edge intelligence maturing from architecture-level proposals into deployable perception stacks, which multi-machine fleets require to sense crop state and each other with bounded latency.

6.3. Digital Twins for Cooperative Machinery

A digital twin is a real-time virtual replica of a physical asset that mirrors its state and behavior. It provides the orchestration layer that cooperative fleets need to coordinate rather than merely coexist. The concept offers finer-grained control over farming processes by linking each physical entity to a continuously updated digital counterpart [92], [93]. In smart farming this means each machine, field, and crop exposes its current state to a shared model that planning and control loops can query [92]. The value is not the replica itself but the closed loop it creates. Sensing updates the twin, the twin informs decisions, and the decisions act back on the physical system [94].

For cooperative machinery, the twin becomes the integration point where sensing, communication, and control converge. Digital twins are, above all, an orchestration problem: heterogeneous devices, data streams, and models must be coordinated to keep the replica faithful in real time [96]. A systematic review of integrated digital twins for agricultural machinery and robotics finds that architectures are maturing but quantified impacts and deployment gaps remain uneven across the field [98]. This positions the twin as the natural substrate for multi-machine coordination. Relative positions from fused localization, intentions from edge inference, and safety constraints can all be resolved against a shared virtual state rather than negotiated pairwise between machines.

Applications span controlled and open environments. Greenhouse operators have demonstrated digital twins built on Industry 4.0 technologies to replicate climate, crop, and equipment state for control and optimization [97]. At a broader scale, digital twins are argued to support environmental sustainability by exposing resource flows and inefficiencies that single-instrument monitoring misses [95]. The common thread is that the twin turns disparate data into an actionable shared state, which is what multi-machine cooperation requires to scale beyond isolated vehicles.

6.4. Security and Data Integrity

Cooperative fleets inherit the attack surface of every machine in the fleet, so integrity must be enforced at the localization, communication, and physical-safety layers together. GNSS spoofing is among the most severe threats to localization, because a forged position fix can drive a machine off its intended path without triggering obvious alarms. Detection schemes therefore couple GNSS with independent sensors. Visual-inertial-GNSS integration exposes spoofing through cross-checks between camera, IMU, and satellite measurements [107], [108]. Broader sensor-fusion frameworks generalize this idea to autonomous vehicles by treating inconsistency between modalities as the spoofing signature [109]. A complementary line recovers the true position after detection, using the inherent sparsity and inconsistency of spoofing signals to separate them from authentic ones and reconstruct a trusted fix [110]. The shared principle is that no single sensor is trustworthy enough for cooperative operation; integrity comes from disagreement.

Beyond localization, the cyber attack surface widens as fleets add UAVs and connected machinery. Drone-assisted agriculture is particularly exposed, since UAVs relay telemetry and imagery over wireless links that an adversary can jam, intercept, or manipulate [111]. The security literature for this setting emphasizes layered measures spanning device authentication, link protection, and anomaly detection, while noting that adoption in agricultural deployments remains uneven [111]. For multi-machine fleets the implication is direct: every wireless exchange, whether a position broadcast or a cooperative maneuver command, must be authenticated and integrity-protected end to end.

Physical safety is the integrity constraint that cannot be delegated to cryptography, because a positioning or control failure becomes a human-injury risk when people share the work zone. The emerging field of human-robot interaction in agriculture treats safety and ergonomics as joint design problems, since synergistic operation depends on machines behaving predictably near workers [112]. A systematic review of automated agricultural machinery safety finds that safe operation is now a primary condition for commercialization rather than an afterthought [113]. Practical sensing for this constraint is maturing. Low-cost thermal infrared arrays can detect human presence around highly autonomous machinery even when cameras fail, providing a last-line safety perception layer [114]. Together these threads show that cooperative fleets require integrity in three senses at once: correct localization, authentic communication, and safe physical interaction.

Four enablers address four distinct failure modes: collision, latency, state sharing, and attack. GNSS/RTK with multi-sensor fusion secures a shared reference frame, edge intelligence compresses the sensing-to-action path under accuracy-latency-energy constraints, digital twins expose a queryable shared state, and security enforces integrity across the localization, communication, and physical-interaction layers. Their value is realized only when composed into concrete multi-machine applications, which the next section examines.

7. Applications and Case Studies

Multi-machine applications make the abstract requirements of determinism, sensing, and reliability concrete. Each operation type couples a control problem to a communication problem, and the coupling differs enough across scenarios to motivate separate treatment.

7.1. Cooperative Harvesting

Cooperative harvesting pairs a combine with one or more grain carts so that unloading occurs while both machines move. The rendezvous must coincide with bunker fill state, so scheduling and path planning are tightly coupled.

The shared mechanism is joint scheduling of harvesters and transport under sequential coupling. Hybrid metaheuristic scheduling of tracked maize harvesters and grain trucks reduces idle time and operation duration [64], and multi-agent task-allocation formulations extend this aim to fair task distribution across machines in settings such as soft-fruit farms [63]. The sequential coupling becomes explicit in coverage planning that accounts for differing working widths and turn characteristics, where one machine's trajectory constrains the next [59]. The same coupling recurs in general collaborative path planning and task allocation across multiple agricultural machines [68].

The communication demand follows from the control structure. A moving rendezvous needs bounded-latency exchange of position, speed, and fill-state updates between combine and cart. Best-effort links force the scheduler to widen time margins, which lengthens idle periods and reduces throughput. Deterministic channels such as TSN or URLLC, combined with edge-hosted scheduling, would let the controller tighten operating margins while bounding the risk of missed handovers.

This demand is supported by quantitative evidence. Stability region analysis of wireless networked control systems shows [7] that the control cost is bounded if and only if the (latency, rate, reliability) tuple lies in a specific region, meaning that under best-effort links the scheduler must leave a conservative margin, while a deterministic channel can tighten the margin to within the region's boundary. Joint communication-and-control formulation further yields an optimal control blocklength that minimizes control latency [11]. In the cooperative harvesting scenario, this means the combine-grain-cart rendezvous can transmit control commands at the optimal blocklength over a deterministic channel, narrowing the probability of a missed handover from the probabilistic tail of best-effort links to within a deterministic bound.

7.2. Multi-UAV Swarm Spraying and Mapping

UAV swarms for spraying and mapping couple dense, parallel coverage with formation keeping. The aircraft must hold relative positions while executing coverage paths, and the mesh topology reconfigures as aircraft turn.

Coverage path planning is the shared entry point. Methods optimize field coverage for heterogeneous UAV groups [17] and extend to discontinuous task regions via improved double deep Q-learning [18]. The methodological breadth is reflected in surveys of swarm intelligence and open problems [20], [21], formation control for UAV swarms [22], [23], and UAVs in agriculture broadly [15]. Comparative evaluations of control strategies on unmanned farms [24] and field reports from smart-agriculture deployments [16] catalog how simulation assumptions diverge from operation.

Task allocation governs which UAV covers which region. Multi-objective NSGA-II variants balance conflicting objectives across agricultural scenarios [19], and reviews position swarm task allocation as a path forward for precision agriculture [26]. Obstruction-prone canopies, as in durian orchards, change both sensing and communication and motivate enhanced multi-agent swarm control [25].

The communication-control co-design here is distinctive. Formation keeping needs periodic consensus on relative states with bounded jitter, because spray drift and overlap grow with synchronization error. Mapping missions, in contrast, need higher-bandwidth uplinks for imagery but tolerate more latency. Integrated sensing and communication may help because the same links can carry both telemetry and radar-aided obstacle sensing, but only the durian-orchard result begins to confront the obstruction-prone environment that real orchards present [25].

7.3. Multi-implement Coordinated Operations

Tractors pulling coordinated implements, and ground robots working in formation, require consensus under changing topologies. The control literature has matured, but the communication assumptions are often implicit.

Several reviews map this landscape. Recent surveys trace the shift from isolated to multi-agent operation under AI-driven cooperative control for tractors and implements [13], building on earlier reviews of multirobot systems in agriculture [1] and their enabling technologies [2]. A bibliometric analysis tracks the field's growth [32], and general surveys catalog the algorithmic families [36]. Consensus is the recurring mechanism. Consensus-based formation control targets heterogeneous systems in complex environments [6], and the consensus problem for heterogeneous multi-agent systems with switching topologies and bounded delays directly couples control convergence to communication-graph properties [5]. Distributed connectivity control maintains algebraic connectivity as agents move [33], while anti-saturation consensus tracking for multi-UGV formations addresses actuator limits that otherwise destabilize tight formations [34].

Coverage and orchard-specific results round out the picture. Curvature-constrained coverage path planning addresses skip and overlap for vehicles with limited turning ability [58], and multi-area collision-free planning jointly schedules tasks across regions [60]. Formation control has also been studied for smallholding geometries such as Indonesian square farmland [14], and collaborative path planning for mowing robots extends multi-machine methods to standard orchards [67]. The co-design demand is most visible in the consensus results. Switching topologies [5] and connectivity maintenance [33] are communication-graph problems framed as control problems. Deterministic wireless links that hold a stable topology, or report topology changes within a known bound, let consensus converge at the rates these algorithms assume. Without that determinism, the formation controller must degrade gracefully, which the cited results do not yet demonstrate.

7.4. Fleet Logistics and Scheduling

Fleet logistics concerns routing and scheduling across a farm's machines and tasks. The control horizon is longer than in harvesting or spraying, so the communication requirement shifts from bounded latency to reliable task dissemination and update propagation.

Scheduling methods dominate this scenario. Evolutionary collaboration algorithms target smart farms [62], improved NSGA-II variants minimize total movement distance [61], and multi-objective automated schedulers handle heterogeneous robot fleets [65]. Reinforcement learning enhances iterated greedy scheduling for weeding robots [69], while multi-objective hierarchical approaches treat routing and scheduling jointly [66]. On the movement side, dynamic consensus control with distributed model predictive control targets UGV platooning [35]. The co-design here splits into two layers. The scheduling layer needs reliable, eventually-consistent dissemination of task assignments, which edge intelligence can host. The platoon layer, by contrast, needs the same bounded-latency consensus as formation control, because string stability degrades when inter-vehicle message jitter grows. The platooning result [35] inherits the same communication assumptions as the formation-control work and faces the same gap between simulated and deployed network behavior. Cooperative harvesting, multi-UAV spraying, multi-implement operations, and fleet logistics each couple a different communication demand: the rendezvous needs bounded latency, formation keeping needs periodic consensus, multi-implement work needs topology maintenance, and logistics needs reliable dissemination. Across these scenarios, the shared gap is that control algorithms assume communication-graph properties they rarely enforce, which points to the future directions that follow.

8. Open Challenges and Future Directions

The co-design thesis reframes every open problem below. None of these five directions can be solved by a single layer in isolation. We trace them from the physical layer upward, keeping communication and control on one design surface throughout.

8.1. 6G and ISAC Evolution for Agricultural Machinery

Integrated sensing and communication (ISAC) is emerging as a central 6G waveform strategy, with agriculture appearing as an early use case rather than an afterthought. Terahertz joint communication and sensing was proposed as a 6G use-case for precision agriculture [85]. The same terahertz infrastructure is now recast as a climate-sensing fabric that monitors farms while serving the network [90]. The shared mechanism is waveform reuse: one signal carries bits and probes the channel at once. That dual role is what multi-machine formations need for situational awareness. Radar's migration from military bands into 5G and 6G joint communication and sensing accelerates this convergence [83]. The 6G digital-twin vision of layered environment maps depends on radio sensing being co-designed with the communication frame from the start [82]. Waveform-level designs already target the spectrum efficiency and load savings that dense fleets will require, as in code-division OFDM joint communication and sensing for machine-type communication [84].

A second thread specializes ISAC to the agricultural channel, where the sensed object is a plant or a soil column rather than a generic scatterer. Non-contact, continuous crop water-status monitoring has been demonstrated by reusing the communication link without hardware changes [86]. An ultra-compact soil-moisture sensor integrated with a reconfigurable antenna shows how joint sensing and communication can be packed onto one agricultural node [87]. Reconfigurable intelligent surfaces extend these links beyond line of sight and reshape the rural propagation environment that defeats best-effort networks [89]. UAV-based ISAC brings the same dual-use waveform to aerial swarms that must sense, relay, and coordinate under one power budget [91].

These two threads converge on one co-design implication. When sensing becomes a by-product of the communication waveform, the perception loop and the control loop share one deadline budget. ISAC then stops being a radio enhancement and becomes a control substrate, which is the step this survey argues for.

8.2. Foundation-Model-Era Edge Perception and Fleet Collaboration

The foundation-model era enters agriculture first through edge-deployed perception, not through artificial general intelligence (AGI). Edge computing architectures for smart agriculture are being formalized around the bottleneck that farming equipment faces: an exponential surge in on-field data that cannot round-trip to the cloud [100]. Surveys of machine learning in smart agriculture converge on the same pattern of distributed inference across heterogeneous devices [99]. Within that pattern, crop disease and pest detection has become a dominant real-time workload. Mobile-vision systems target sustainable field deployment of crop disease detection [105]; reviews of deep-learning detectors cover IoT-based pest and disease identification [104]; and edge-native pipelines push classification, segmentation, detection, and counting onto the device [106]. The shared direction is inference moved to where the actuator is, which collapses the sensing-to-action path that multi-machine coordination depends on.

Digital twins supply the system substrate that these perception models and the fleet must share. Digital twins in smart farming were framed early as the route to new levels of productivity and sustainability [92]. Their introduction into agriculture has been driven by the promise of control over physical processes that earlier architectures could not deliver [93]. The next generation of agricultural digitalization treats the digital twin as the unifying paradigm across equipment and fields [94], with environmental sustainability as both motivation and a constraint on twin fidelity [95]. Recent work stresses real-time orchestration of these replicas [96] and Industry 4.0 integration for controlled environments such as greenhouses [97]. A systematic review of integrated digital twins for agricultural machinery and robotics quantifies the architectures, impacts, and deployment gaps that remain [98].

The co-design reading is direct. A foundation model that perceives, a digital twin that mirrors, and a fleet that acts cannot be three separate stacks, because their timing and reliability budgets must agree to the millisecond. AGI-era collaboration therefore inherits the same determinism requirement that motivates this survey, only now the controller is a learned policy and the plant is a twin.

8.3. Standardization and Interoperability

Interoperability is the seam at which communication-control co-design either solidifies or fractures, and deterministic networking standards are its load-bearing layer. Ultra-low latency networks were surveyed early as the convergence of IEEE TSN, IETF DetNet, and 5G ultra-low latency research [3]. Reviews of TSN for industrial smart and distributed measurement systems confirm its applicability to the class of cyber-physical control that agricultural fleets instantiate [4]. Robustness and reliability in converged deterministic packet networks, across both TSN and DetNet, are now treated as a single service-protection problem [28]. OPC UA over TSN was proposed as the unifying industrial communication stack that replaces fragmented fieldbus ecosystems [38].

A second thread pushes determinism across wireless and cross-domain boundaries, which is where agricultural deployments actually live. The integration and convergence of 5G and TSN is now reviewed as a single architectural problem for industrial communications [12]. Software-defined TSN extends deterministic guarantees across heterogeneous domains that a single farm network never contains [27]. Hybrid wired and wireless deterministic networks, validated on smart-grid control, show that the bounded latency needed for time-critical robotics can span media [37]. Deadline-driven deterministic wireless communication makes the deadline itself the contract, because information arriving after it is control-invalid and must be discarded [10]. Surveys of deterministic 6G carry this trajectory forward and name the open challenges that still separate 6G from true determinism [31].

The implication for co-design is that standardization is not a paperwork layer added at the end. The choice of TSN profile, DetNet path, or 6G deterministic flow fixes the latency and reliability budget that the cooperative controller must be designed against. The standard and the controller must therefore be selected together.

8.4. Rural Coverage Gaps and Energy Efficiency

Rural coverage remains the most physical of the open gaps, because determinism is meaningless where there is no link. Field evaluations of 5G for agricultural robotics find that coverage, not bandwidth, is the binding constraint on off-highway autonomy [9]. Broader surveys of 5G in agriculture echo the same gap between headline capability and rural reality [30]. Reviews of environmental sensing and remote communication for smart farming document that even greenhouse-scale deployments struggle with reliable monitoring links [88]. That coverage gap sharpens for open-field multi-machine work, where line of sight is rare and backhaul is thin.

Energy efficiency and latency-adjustable compute are the response once coverage is partial. Latency-adjustable cloud and fog architectures for time-sensitive environmental monitoring trade responsiveness against the energy and backhaul cost that rural links cannot absorb [29]. The same edge architectures that relieve the backhaul also lower the energy bill per closed loop [100]. Rural coverage fixes the operating point at which energy, latency, and reliability must be jointly tuned, so an energy-efficient fleet is by necessity a co-designed fleet.

8.5. Safety and Human-Machine Collaboration

Safety converts the determinism and reliability arguments of this survey into a human-facing obligation. Deadline-driven deterministic wireless communication makes the control deadline a hard contract, because information arriving late is not merely stale but control-invalid [10]. The robustness of converged TSN and DetNet networks is the service-protection property that keeps a cooperative maneuver from collapsing when one link fails [28]. Hybrid wired and wireless deterministic networks extend that guarantee across media, which is the precondition for safe operation across a farm's mixed fixed and mobile infrastructure [37].

Digital twins then become the safety verification substrate that field trials cannot provide. Integrated digital twins for agricultural machinery and robotics expose the architectures and quantified impacts that mark safe deployment boundaries [98]. The broader digital-twin literature frames the twin as the means to test control policies against sustainability and operational limits before they touch a real machine [92], [95]. Human-machine collaboration inherits this substrate. Shared autonomy, risk-graded handover, and human-in-the-loop verification each require a synchronized twin, a deterministic link, and a calibrated trust model. None can be added after the fact; each must be co-designed with the communication and control stack that the rest of this survey describes.

Multi-machine collaboration in smart agriculture will therefore be solved not by a faster network on top of smarter machines, but by one co-designed stack in which determinism, sensing, intelligence, and safety share a single deadline.

9. Conclusion

Smart agriculture is shifting from single-machine automation to coordinated fleets. Cooperative harvesting, multi-UAV spraying, and fleet logistics demand bounded latency, reliability, and synchronized state that best-effort networks cannot meet, and control algorithms validated under ideal communication degrade when deployed on real field networks with partial coverage and thin backhaul. This gap cannot be closed by a faster network or a smarter controller alone; the deadline of communication and the deadline of control must be treated as one design surface.

This review first surveys the application scenarios and communication-control requirements of multi-machine collaboration, and argues why layered best-effort architectures fail to support cooperative operations. It then surveys the two pillars of deterministic communication and multi-machine collaborative control, binds them to the main line of communication-control co-design, and discusses cross-cutting enablers including GNSS/RTK fusion, edge intelligence, digital twins, and security. On this basis, we use cooperative harvesting, multi-UAV spraying, and fleet logistics to illustrate the gains of co-design, and close by noting the deployment problems and open challenges.

On the basis of this discussion, we identify the following research directions. First, how 6G native deterministic communication and ISAC can be grounded in the real terrain and wireless-dominant setting of agricultural fleets still requires quantitative validation. Second, foundation-model-era edge perception and fleet decision-making must be redesigned under accuracy-latency-energy constraints. Third, cross-vendor interoperability and standardization are prerequisites for fixing the co-design operating point. Fourth, the rural coverage gap and energy efficiency are hard constraints in the field rather than optimization targets. Fifth, safety and human-machine collaboration require integrity across the localization, communication, and physical-interaction layers simultaneously. This review aims to offer researchers in this cross-disciplinary area an overview of the state of the art and a set of actionable directions.

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