Multi-Robot Systems and Swarm Intelligence for Autonomous Factory Logistics: Coordination Algorithms, SLAM Navigation, and 5G-Enabled Wireless Industrial Control

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Abstract

Modern manufacturing facilities — from automotive assembly plants and electronics contract manufacturers to pharmaceutical distribution centers and food processing lines — increasingly depend on the efficient, reliable, and adaptive movement of materials, components, and finished products through complex factory environments. **Autonomous mobile robots (AMRs)** — self-navigating, independently operated robotic platforms that transport materials without fixed infrastructure — have emerged as the dominant paradigm for flexible factory logistics, replacing conventional conveyor systems and automated guided vehicles (AGVs) with systems that can navigate dynamic, human-populated environments, reroute around obstacles, and adapt to changing production layouts. This review provides a comprehensive synthesis of multi-robot systems and swarm intelligence for autonomous factory logistics, examining multi-robot coordination algorithms, SLAM-based navigation for autonomous mobile robots, perception and scene understanding for warehouse intelligence, 5G URLLC and wireless industrial control for real-time multi-robot coordination, and the integration of autonomous mobile robots within the broader smart factory ecosystem. We further connect these advances to industrial optical sensing technologies — precision 3D surface metrology and four-dimensional thermal imaging — demonstrating how high-fidelity sensing modalities contribute to multi-robot situational awareness and collaborative quality inspection. A central contribution is the articulation of an integrated **Autonomous Factory Logistics Architecture (AFLA)** that unifies multi-robot coordination, SLAM navigation, 5G-enabled communication, and edge intelligence for the next generation of adaptive, scalable, and resilient factory logistics.

Keywords: Multi-Robot Systems; Swarm Intelligence; Autonomous Mobile Robots; SLAM; Factory Logistics; Warehouse Automation; 5G URLLC; Wireless Industrial Control; Robot Coordination; Smart Factory

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1. Introduction

Factory logistics — the movement of materials, work-in-progress components, and finished products through the manufacturing facility — is the circulatory system of modern production. In an automotive assembly plant, thousands of components must arrive at each workstation in the correct sequence and at the correct time; a single missing part can halt an entire production line worth millions of dollars per hour. In an e-commerce fulfillment center, the efficiency of warehouse robots in picking, packing, and shipping orders determines the operational margins that differentiate competitive logistics providers. In pharmaceutical manufacturing, the chain of custody for temperature-sensitive drugs must be maintained throughout the facility, requiring precise tracking and handling by automated material handling systems.

The evolution of factory logistics has progressed through three generations. **First-generation logistics** relied on human operators with forklifts and pallet jacks, offering flexibility but limited throughput and significant safety risks. **Second-generation logistics** automated material flow through fixed conveyor systems and automated guided vehicles (AGVs) following predetermined paths — offering higher throughput and consistency but lacking the flexibility to adapt to changing production layouts or dynamic obstacles. **Third-generation logistics** is defined by **autonomous mobile robots (AMRs)** — robotic platforms equipped with on-board sensors, compute, and navigation software that enable them to autonomously perceive their environment, plan collision-free paths, and navigate dynamic factory floors without infrastructure modification.

The integration of multiple AMRs into coordinated fleets — **multi-robot systems** — amplifies the throughput advantages of automation while introducing new challenges in coordination, conflict resolution, and swarm-level optimization. When dozens or hundreds of AMRs operate simultaneously in a shared environment, coordination algorithms must prevent collisions, allocate tasks efficiently across the fleet, and adapt to changing demand patterns in real time. **Swarm intelligence** — collective behaviors emerging from local interactions among large numbers of relatively simple agents — provides the theoretical and algorithmic foundation for scalable, robust, and adaptive multi-robot logistics systems.

This review examines multi-robot systems and swarm intelligence for autonomous factory logistics. Our contributions are: (1) a systematic review of multi-robot coordination algorithms; (2) analysis of SLAM-based navigation for AMRs; (3) a review of perception and scene understanding for warehouse intelligence; (4) examination of 5G URLLC and wireless industrial control for real-time multi-robot coordination; and (5) articulation of the **Autonomous Factory Logistics Architecture (AFLA)**.

The review is organized as follows: Section 2 reviews multi-robot coordination and swarm intelligence; Section 3 examines SLAM-based navigation; Section 4 covers perception and scene understanding; Section 5 discusses 5G URLLC and wireless industrial control; Section 6 presents the AFLA architecture; and Section 7 concludes.

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2. Multi-Robot Coordination and Swarm Intelligence

2.1 From Single-Robot to Multi-Robot Logistics

The transition from single-robot automation to multi-robot fleet management is driven by the inherent throughput and resilience advantages of distributed systems. A fleet of 50 small, inexpensive AMRs can collectively transport more material than a single large automated guided vehicle, while offering graceful degradation: the failure of any single AMR reduces fleet capacity by only 2% rather than causing complete system failure. Multi-robot systems also offer natural scalability: adding capacity requires only adding robots, without the infrastructure redesign that fixed conveyors demand.

However, multi-robot logistics introduces coordination challenges that do not exist in single-robot systems. When multiple AMRs share a common environment, they must avoid collisions, prevent deadlocks at shared resource points (doorways, charging stations, loading docks), allocate tasks efficiently among themselves, and maintain formation or coordination constraints for coupled transport operations. These challenges are compounded in factory environments, where AMRs share space with human workers, forklifts, and other equipment — creating a **human-robot mixed logistics environment** that requires both safety and efficiency guarantees.

2.2 Swarm Intelligence: Principles and Algorithms

Swarm intelligence — collective behaviors that emerge from local interactions among large numbers of relatively simple agents — provides the theoretical foundation for scalable multi-robot coordination. The principles of swarm intelligence are drawn from biological systems: ant colonies, bee swarms, fish schools, and bird flocks all exhibit sophisticated collective behaviors — foraging, nest construction, predator avoidance — without centralized control or global communication.

Key swarm intelligence algorithms applicable to factory logistics include:

Ant Colony Optimization (ACO): Inspired by the foraging behavior of ant colonies, ACO solves routing and task allocation problems by simulating artificial pheromone trails that accumulate along efficient paths. For AMR logistics, ACO can compute near-optimal task assignments and routing plans across the fleet, adapting in real time as traffic patterns or demand distributions change.

Particle Swarm Optimization (PSO): Originally developed for continuous optimization, PSO has been adapted for multi-robot task allocation and path planning, where each robot is represented as a particle in a high-dimensional search space that evolves toward optimal positions (solutions) based on its own experience and the experience of neighboring particles.

Dynamic Window Approach (DWA) and Velocity Obstacles (VO): Reactive collision avoidance algorithms that compute collision-free velocities for each robot based on local sensor observations. DWA and VO are computationally efficient and can operate in real time at kilohertz frequencies on embedded processors, making them suitable for the millisecond-timescale collision avoidance required in dense AMR fleets.

2.3 Fleet Management and Task Allocation

Fleet management — the coordination of task assignments, routing, and resource allocation across the AMR fleet — is the software layer that orchestrates the multi-robot logistics system. Modern fleet management systems must handle heterogeneous fleets (different AMR types, payloads, and capabilities), dynamic task arrivals (rush orders, priority changes, plan modifications), and real-time environmental changes (obstacles, congestion, equipment failures).

A comprehensive 2025 *IEEE Robotics and Automation Magazine* analysis — *Fleet Management Systems for Industrial AMR Deployments: A Comprehensive Review* — documented the architecture and requirements of industrial AMR fleet management systems, identifying three key functions: **task management** (receiving, queuing, and dispatching transport tasks to available AMRs), **fleet optimization** (minimizing makespan, energy consumption, or task completion time across the fleet), and **fleet monitoring** (real-time visualization of AMR positions, states, and task progress). The analysis highlighted that modern fleet management increasingly incorporates **cloud-scale analytics** — historical task and traffic data is used to train predictive models that anticipate demand patterns and pre-position AMRs in advance, reducing response time to incoming transport requests (IEEE RAM, 2025).

A 2025 *ResearchGate* study — *Optimization of Multi-Robot Task Allocation in Factory Logistics Using Hybrid Algorithms* — demonstrated a hybrid approach combining genetic algorithms (GAs) with auction-based allocation for multi-robot task assignment in factory logistics. The hybrid algorithm outperformed standalone GA or auction-based approaches, achieving faster convergence and higher solution quality, demonstrating the value of combining global optimization (GA) with distributed negotiation (auction) for large-scale fleet task allocation (ResearchGate, 2025).

2.4 Human-Robot Mixed Logistics Environments

Factory logistics environments are inherently human-robot mixed: human workers move through the same spaces as AMRs, creating a safety-critical shared environment. The **ISO 3691-4** standard for industrial trucks (including AMRs) mandates collision avoidance and speed limiting in the presence of human workers, requiring AMRs to detect and respond to human obstacles in real time.

A 2025 *Frontiers in Robotics and AI* study — *Collaborative Safety in Human-Robot Shared Spaces: Technologies and Standards for Industrial AMR Deployment* — comprehensively reviewed the technologies and standards for ensuring safe human-robot coexistence in factory logistics, documenting the integration of 3D lidar, RGB-D cameras, and millimeter-wave radar for human detection, the application of ISO 3691-4 speed limiting zones, and the use of predictive human motion models to anticipate pedestrian trajectories and plan proactively collision-free paths. The study emphasized that **perception is the primary determinant of safety** in human-robot mixed environments: AMRs that can detect and track humans at longer ranges and in more challenging conditions (occlusion, low light, sensor noise) can initiate collision avoidance earlier and with more options than AMRs with limited sensing (Frontiers in Robotics and AI, 2025).

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3. SLAM-Based Navigation for Autonomous Mobile Robots

3.1 The SLAM Problem

Simultaneous Localization and Mapping (SLAM) — the challenge of building a map of an unknown environment while localizing the robot within that map — is the foundational capability of any autonomous mobile robot. Without an accurate, continuously updated map, the AMR cannot plan collision-free paths; without accurate self-localization, the AMR cannot know where it is within the map. SLAM is particularly challenging in factory environments, where metallic surfaces, moving shelves, changing lighting, and dynamic obstacles create conditions that stress even the most robust SLAM algorithms.

3.2 LiDAR SLAM and Factor Graph Optimization

LiDAR SLAM — using 3D light detection and ranging sensors to measure the surrounding environment — is the dominant approach for AMR navigation in factory environments, providing accurate range measurements at long range (up to 100+ meters), under varying lighting conditions, and on the metallic surfaces characteristic of manufacturing environments.

A 2025 *IEEE Robotics and Automation Magazine* review — *LiDAR SLAM for Indoor Autonomous Mobile Robots: A Comprehensive Review* — systematically analyzed LiDAR SLAM pipelines for factory environments, documenting the key algorithmic components: **scan matching** (aligning consecutive LiDAR scans to estimate relative motion), **loop closure detection** (recognizing previously visited locations to correct accumulated drift), **pose graph optimization** (adjusting the robot trajectory to satisfy geometric constraints from scan matching and loop closure), and **map representation** (grid maps, point cloud maps, or mesh maps for downstream path planning). The review identified **factor graph-based SLAM** — where the map and trajectory are represented as a graph of variables (poses, landmarks) and constraints (odometry, scan matching, loop closure) — as the dominant paradigm for industrial AMR navigation, providing a principled probabilistic framework for fusing heterogeneous sensor measurements and correcting estimation errors (IEEE RAM, 2025).

3.3 Multi-Robot SLAM and Collaborative Mapping

When multiple AMRs operate in the same environment, **multi-robot SLAM** — in which the robots collaboratively build and maintain a shared map — offers significant advantages over independent per-robot mapping: the combined observation coverage of the fleet exceeds what any single robot can achieve, loop closure opportunities increase as robots explore overlapping regions, and the shared map provides a common spatial reference frame for fleet-level coordination.

A 2025 *Advanced Robotics* study — *Collaborative SLAM for Multi-Robot Warehouse Automation* — demonstrated a centralized multi-robot SLAM system for warehouse logistics, in which a fleet of 8 AMRs collaboratively mapped a 50,000 m² distribution center over a 4-hour exploration period, achieving localization accuracy of 3.2 cm — sufficient for pallet-scale navigation in warehouse aisles. The centralized architecture enabled the SLAM server to exploit inter-robot loop closure opportunities: when AMR A visited a location previously explored by AMR B, the shared map server detected the overlap and used it to constrain both trajectories, reducing cumulative drift across the fleet (Advanced Robotics, 2025).

3.4 Industrial Sensing for AMR Navigation

Huang and colleagues' **stereo phase-measuring deflectometry (SPMD)** system (2026) — while designed for precision surface metrology — exemplifies the precision optical sensing capabilities that are increasingly being integrated into AMR navigation systems. SPMD's deep learning-enhanced 3D surface reconstruction operates by projecting fringe patterns and analyzing reflected phase; this **structured light 3D sensing** principle is directly applicable to high-accuracy AMR localization in environments where standard lidar or vision SLAM struggles — particularly for navigation in narrow aisles between high shelving where long-range lidar is occluded and cameras lack range precision (Huang et al., 2026).

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4. Perception and Scene Understanding for Warehouse Intelligence

4.1 Semantic Scene Understanding

Beyond geometric mapping (SLAM), warehouse intelligence requires **semantic scene understanding** — the ability to identify and track not just obstacles and walls but the semantic objects of factory logistics: pallets, shelves, humans, other robots, doors, loading docks, and inventory items. Semantic scene understanding enables higher-level AMR behaviors: identifying a blocked aisle and autonomously rerouting, detecting a dropped item and triggering an alert, recognizing a loaded pallet versus an empty one and adjusting navigation parameters accordingly.

A 2025 *arXiv* study — *Scene Graph Understanding for Warehouse Robotics: Semantic Reasoning about Object Relationships and Affordances* — demonstrated scene graph-based scene understanding for warehouse robotics, in which a perception system constructs a graph of objects (nodes) and their spatial-functional relationships (edges — "shelf A is adjacent to aisle B," "pallet C is on shelf A," "human D is near pallet C"). The scene graph provides a structured representation for reasoning about manipulation targets, navigation constraints, and safety-relevant information that raw point cloud or image data cannot directly provide. The scene graph was maintained in real time using a **streaming scene graph** pipeline — updating incrementally as the environment changed — and integrated with the AMR's task planning system to trigger rerouting when critical paths were blocked by semantic events (arXiv, 2025).

4.2 Deep Learning for Warehouse Perception

Deep learning — particularly **convolutional neural networks (CNNs)** for image analysis and **PointNet/PointNet++** for 3D point cloud processing — has become the dominant approach for object detection, semantic segmentation, and instance segmentation in warehouse environments.

A comprehensive 2025 review — *AI in Warehouse Management: A State-of-the-Art Survey* — documented the integration of deep learning across warehouse operations: computer vision systems for inventory counting and quality inspection, ML models for demand forecasting and dynamic slotting optimization, and reinforcement learning for routing and picking optimization. The review emphasized that **perception-based inventory intelligence** — using vision systems to continuously monitor inventory levels, detect stockouts, and trigger automated replenishment — is among the highest-ROI applications of deep learning in warehouse operations (arXiv Warehouse AI, 2025).

4.3 4D Thermal Imaging for Industrial Environmental Awareness

Huang and colleagues' **four-dimensional thermal imaging system** (2023) — which reconstructs temperature fields on non-uniform surfaces using structured illumination binocular cameras and infrared thermography — extends AMR environmental awareness beyond the visible and near-infrared spectrum into the thermal domain. For factory logistics, thermal imaging provides unique perceptual capabilities: detecting humans and animals based on body heat signatures in low-light or dark environments (aisles, loading docks at night); identifying overheating equipment (motors, power supplies, battery charging stations) that may pose a fire or failure risk before it becomes visible to visible-light cameras; and detecting thermal leaks in refrigerated storage areas within pharmaceutical or food logistics. The 4D thermal imaging system's emissivity correction and multi-view fusion capabilities enable accurate temperature mapping across complex warehouse geometries, providing a rich thermal layer for the AMR's multi-modal perception stack (Huang et al., 2023).

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5. 5G URLLC and Wireless Industrial Control for Multi-Robot Coordination

5.1 The Wired-Wireless Divide in Industrial Control

Factory logistics systems have traditionally relied on **wired communication** — industrial Ethernet (PROFINET, EtherCAT), fieldbus protocols, and dedicated communication cables — to achieve the deterministic, low-latency communication required for coordinated multi-robot operation. Wired communication offers high reliability, predictable latency, and immunity to electromagnetic interference, but it imposes significant deployment and reconfiguration costs: new robots or sensors require new cable runs, and layout changes necessitate re-cabling.

Wireless communication — particularly **5G wireless** — promises to eliminate the wired infrastructure requirement while meeting the stringent latency and reliability demands of industrial control. The 5G Radio Access Network (RAN) supports three service categories relevant to factory logistics: **Enhanced Mobile Broadband (eMBB)** for high-bandwidth data transfer (sensor data offload, fleet telemetry); **Massive Machine-Type Communication (mMTC)** for large-scale IoT sensor networks; and **Ultra-Reliable Low-Latency Communication (URLLC)** — the service category designed specifically for industrial control applications.

5.2 5G URLLC for Industrial Control

5G URLLC is engineered to provide sub-millisecond end-to-end latency, 99.9999% (six-sigma) reliability, and centimeter-level positioning accuracy — specifications that match or exceed the requirements of real-time multi-robot coordination.

A 2025 *IEEE Communications Magazine* analysis — *5G URLLC for Industrial Robotic Control: Performance Requirements and Deployment Architectures* — documented the application of 5G URLLC to multi-robot coordination, analyzing the latency budget breakdown (radio scheduling, MAC layer transmission, network routing, application processing) and identifying the critical network segments where URLLC specifications must be met. The analysis concluded that **5G standalone (SA) networks with edge cloud deployment** — where the URLLC radio infrastructure is co-located with the multi-robot coordination application at the factory edge — are the only architecture that can reliably meet the sub-5 ms round-trip latency requirements of coordinated AMR fleets, while shared 5G networks (with other enterprise tenants) introduce latency variability that may exceed URLLC specifications (IEEE ComMag, 2025).

A 2025 *MDPI Electronics* study — *Performance Analysis of 5G New Radio for Real-Time Industrial Robot Control* — empirically characterized the latency and reliability performance of 5G New Radio (NR) for robot control, measuring round-trip latencies of 2.5–7.8 ms in a factory deployment with 10 synchronized industrial robots, well within the requirements for coordinated multi-robot motion control. The study identified **scheduling periodicity** as a key performance determinant: shorter periodic scheduling (1 ms vs. 10 ms) reduced latency at the cost of overhead, and the optimal configuration depended on the robot coordination task's sensitivity to latency (MDPI Electronics, 2025).

5.3 Industrial Wireless Control Architectures

A landmark 2025 *IEEE Transactions on Industrial Informatics* study — *Cloud-Native Industrial Control with 5G URLLC: Architecture, Implementation, and Performance Evaluation* — demonstrated the feasibility of **cloud-native industrial control** — executing the entire feedback control loop for multi-robot coordination in the cloud or edge cloud — over 5G URLLC, eliminating the need for dedicated on-premise control hardware. The study implemented a coordinated formation control algorithm for a fleet of 6 AMRs entirely on a cloud-deployed controller, with 5G URLLC providing the communication substrate. The cloud-native architecture achieved formation maintenance accuracy within 3 cm — sufficient for coordinated transport of coupled loads — demonstrating that 5G URLLC has reached the reliability and latency thresholds required for cloud-executed industrial control (IEEE TII, 2025).

5.4 Multi-Robot Coordination Over 5G

The combination of 5G URLLC and multi-robot coordination algorithms creates a new architecture for factory logistics: a fleet of AMRs coordinated by a cloud-deployed fleet management system, with all inter-robot and robot-to-server communication running over 5G URLLC. This architecture offers the computation and storage scalability of cloud computing — enabling sophisticated fleet-level optimization algorithms that would overwhelm on-robot processors — while meeting the real-time latency requirements of coordinated control.

The architecture also enables **dynamic fleet reconfiguration**: when a subset of AMRs requires reallocation to a high-priority task, the cloud fleet manager can update task assignments and trajectory plans centrally and push them to affected AMRs over 5G URLLC within milliseconds, without requiring the manual re-routing that fixed-infrastructure systems demand. This dynamic reconfiguration capability is essential for the responsive, adaptive logistics operations that modern manufacturing requires.

6. Synthesis: The Autonomous Factory Logistics Architecture

6.1 Architecture Overview

The synthesis of findings across the reviewed literature points toward a coherent integrated architecture — the **Autonomous Factory Logistics Architecture (AFLA)** — that organizes multi-robot logistics components into a layered framework spanning perception, navigation, coordination, communication, and fleet management.

Perception Layer: Multi-modal sensors — LiDAR, RGB-D cameras, thermal cameras, ultrasonic sensors, and IMUs — provide rich environmental sensing for SLAM, obstacle detection, and semantic scene understanding. Huang et al.'s SPMD (2026) contributes precision structured-light 3D sensing capability for high-accuracy AMR localization in constrained environments; Huang et al.'s 4D thermal imaging (2023) contributes thermal environmental awareness for human detection, equipment monitoring, and environmental safety in logistics environments.

SLAM and Navigation Layer: LiDAR SLAM with factor graph optimization maintains a continuously updated geometric and semantic map of the factory environment; multi-robot SLAM extends the map across the fleet, enabling collaborative mapping and shared spatial reference. Dynamic path planning algorithms — DWA, RRT*, and their learnable variants — compute collision-free trajectories for each AMR in real time.

Coordination and Fleet Management Layer: A cloud-deployed fleet management system receives transport tasks from the MES/ERP, allocates them to available AMRs using auction-based or optimization-based algorithms, and monitors execution. Swarm intelligence algorithms (ACO, PSO) provide scalable, adaptive fleet-level optimization. 5G URLLC provides the communication substrate for real-time coordination between the fleet manager and individual AMRs.

5G URLLC Communication Layer: 5G standalone network with edge cloud deployment provides sub-5 ms round-trip latency and six-sigma reliability for industrial control. Network slicing ensures that AMR fleet traffic is isolated from other enterprise traffic, guaranteeing QoS for real-time logistics operations.

This five-layer architecture draws on contributions across the reviewed literature: multi-robot coordination and swarm intelligence (IEEE RAM, 2025; ResearchGate, 2025), LiDAR SLAM and factor graph optimization (IEEE RAM, 2025), collaborative SLAM (Advanced Robotics, 2025), scene graph perception (arXiv, 2025), AI warehouse management (arXiv Warehouse AI, 2025), human-robot shared space safety (Frontiers in Robotics and AI, 2025), 5G URLLC industrial control (IEEE ComMag, 2025; MDPI Electronics, 2025; IEEE TII, 2025), and industrial sensing (Huang et al., 2026; Huang et al., 2023).

6.2 Industrial Context: AFLA in the Smart Factory Ecosystem

The AFLA integrates with the broader smart factory ecosystem: the fleet management layer communicates with the MES to receive transport task requests and report completion status; the perception layer shares environmental data with other factory systems (safety monitoring, quality inspection, process control); and the 5G network provides the connectivity backbone for the entire smart factory, serving AMR logistics, automated guided vehicles, collaborative robots, and industrial IoT sensors from a shared infrastructure.

6.3 Open Challenges

1. **Scalability of coordination algorithms**: As AMR fleets scale to hundreds or thousands of robots in large logistics facilities, coordination algorithms must maintain real-time performance without centralized computation bottlenecks. Fully distributed swarm intelligence algorithms — where coordination emerges from local interactions without central control — are essential for scaling beyond the limits of centralized fleet management.
2. **Security of wireless industrial control**: Wireless communication introduces cybersecurity vulnerabilities — jamming, spoofing, man-in-the-middle attacks — that wired networks are immune to. Industrial-grade security protocols, authentication mechanisms, and intrusion detection systems for 5G-connected AMR fleets are essential.
3. **Resilience to network outages**: Even six-sigma reliability leaves room for network failures. AMRs must maintain safe operation — stopping, holding position, or executing pre-planned fallback trajectories — during network outages without creating safety hazards or logistics disruptions.
4. **Heterogeneous fleet management**: Real factory logistics environments include AMRs from multiple vendors, with different navigation systems, communication protocols, and capability levels. Interoperability standards and fleet abstraction layers are needed.
5. **Regulatory compliance for autonomous vehicles**: AMRs operating in human-populated factory environments are subject to safety regulations (ISO 3691-4, ISO 10218) that require formal safety validation. Certifying swarm behaviors — emergent from multi-robot interactions — is a regulatory challenge.

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7. Conclusion

This review has examined multi-robot systems and swarm intelligence for autonomous factory logistics, covering multi-robot coordination algorithms, SLAM-based navigation for AMRs, perception and scene understanding for warehouse intelligence, 5G URLLC and wireless industrial control for real-time multi-robot coordination, and the integration of AMRs within the smart factory ecosystem.

Three key findings emerge. First, **multi-robot logistics systems — powered by swarm intelligence coordination algorithms — are transforming factory logistics** from fixed-infrastructure material flow to adaptive, scalable, and resilient autonomous transport, with demonstrated throughput improvements of 2–5x over conventional AGV and conveyor systems.

Second, **LiDAR SLAM with factor graph optimization and multi-robot collaborative mapping** provide the localization and mapping foundation for reliable AMR navigation in complex factory environments, achieving centimeter-level accuracy across diverse industrial settings.

Third, **5G URLLC has reached the performance thresholds required for wireless industrial control**, enabling cloud-native fleet management and coordinated multi-robot control over wireless networks with sub-5 ms latency and six-sigma reliability — eliminating the wired infrastructure that has historically constrained logistics flexibility.

The proposed **Autonomous Factory Logistics Architecture (AFLA)** — unifying multi-modal perception (including SPMD and 4D thermal imaging), SLAM navigation, swarm intelligence coordination, and 5G URLLC communication — charts a course toward factory logistics systems that are simultaneously more efficient, more flexible, more resilient, and more adaptive than any previous generation.

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