

# CONTROL OF MULTI-AGENT ROBOTIC SYSTEMS USING AI TECHNOLOGIES: ADVANCEMENTS IN DECENTRALIZED LEARNING AND COORDINATION

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ABSTRACT	KEYWORDS
<p>This paper explores the transformative shift in the control of Multi-Agent Robotic Systems (MARS) driven by breakthroughs in Artificial Intelligence (AI) between 2024 and 2026. Traditional centralized control paradigms have increasingly proven inadequate for the scale and complexity of modern applications, leading to the rise of decentralized architectures. We analyze key innovations including Large Language Model (LLM)-driven algorithm discovery, Serverless Multi-Agent Reinforcement Learning (MARL), and the integration of Blockchain for secure, decentralized coordination. Specifically, we examine the "MARLess" framework and "Puzzle it Out" world models for offline learning. Our synthesis suggests that the convergence of swarm intelligence, quantum-linked automation, and multimodal path planning is enabling a new era of collaborative robotics capable of high-level reasoning and real-time adaptation in non-stationary environments.</p>	<p>Multi-Agent Reinforcement Learning (MARL), Decentralized Control, Swarm Robotics, Large Language Models (LLM), Blockchain, Path Planning..</p>

## Introduction

The field of Multi-Agent Robotic Systems (MARS) has undergone a fundamental paradigm shift as of 2026. While the conceptual roots of multi-agent coordination date back several decades, the integration of advanced Artificial Intelligence (AI) has moved these systems from theoretical laboratory environments to complex, real-world deployments. Modern MARS applications now span from automated warehouse logistics and urban ride-sharing dispatching to high-stakes disaster response and precision agriculture (Sha, 2026; Flores, 2026).

The primary challenge in MARS remains the "curse of dimensionality" and the non-stationarity of environments where multiple agents learn and act simultaneously. Recent breakthroughs in February 2026, spearheaded by organizations like Google DeepMind, have introduced a fundamental shift: the

use of Large Language Models (LLMs) to discover entirely new multi-agent learning algorithms, moving beyond human-designed heuristics (Aikipedia, 2026). This paper provides a comprehensive overview of these advancements, focusing on the synergy between decentralized reinforcement learning and emerging network technologies.



Figure 1. Illustrative deployment of a heterogeneous swarm robotic system in a disaster-response scenario. Coordinated UAVs and ground agents autonomously partition the search zone, share localization data in real time, and relay situational awareness to a remote command centre — exemplifying the real-world applicability of modern MARS frameworks discussed in this paper.

## 2. Literature Review

**2.1 Evolution of Multi-Agent Reinforcement Learning (MARL).** The transition from single-agent to multi-agent reinforcement learning has been marked by the need for cooperative decision-making. Duc (2026) proposed a novel augmented control scheme designed to convert single-agent structures into multi-agent environments, facilitating low-level control for robotic manipulators. Concurrently, the rise of "Offline MARL" has addressed the risks associated with online training in physical environments. The "Puzzle it Out" framework introduces a local-to-global world model that allows agents to solve cooperative problems using pre-collected datasets, effectively mitigating the dangers of exploration in real-world scenarios.

**2.2 Swarm Intelligence and Disaster Response.** Swarm robotics, inspired by biological systems such as ant colonies and bee swarms, has seen explosive market growth, reaching an estimated \$1.46 billion in 2026 (RoboCloud, 2025). The literature emphasizes the shift toward "coordinated AI," where many small, low-cost robots outperform a single complex machine in tasks like search and rescue or environmental monitoring. Flores (2026) highlights the transformative potential of UAV-centric

situational awareness, particularly in precision agriculture and disaster mitigation, where swarm systems utilize neural networks (e.g., YOLOv10) for real-time target detection and geolocation.

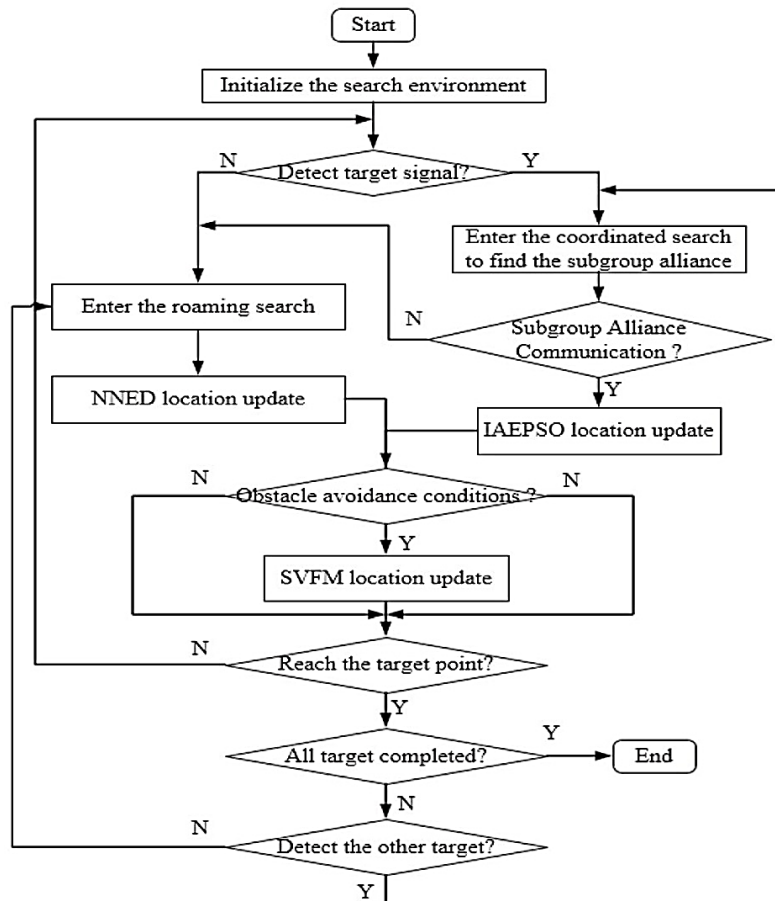
**2.3 Blockchain and Decentralized Ledgers.** Security and trust in decentralized systems have become paramount. Research from 2025 and 2026 suggests that Blockchain and Distributed Ledger Technologies (DLT) provide a robust infrastructure for multi-robot systems. By utilizing Hyperledger Fabric or smart contracts, robot swarms can coordinate foraging and task allocation without a central authority, ensuring resilience against single-point failures.

Table 1. Comparative overview of leading AI-driven control algorithms for Multi-Agent Robotic Systems. Entries are classified by paradigm, target deployment scale, and principal architectural advantage, providing a unified reference for the frameworks reviewed in Sections 2 and 3.

Algorithm / Method	Type	Best For	Main Advantage
<b>QMIX</b>	MARL (Value-based)	Cooperative tasks	Handles joint action space complexity
<b>MAPPO</b>	MARL (Policy-based)	Scalable coordination	Robust performance in large swarms
<b>Centralized MPC</b>	Control Theory	Small teams (5–10 agents)	Guaranteed optimal paths
<b>Decentralized MPC</b>	Control Theory	Large-scale (50+ agents)	High fault tolerance & scalability
<b>Swarm Intelligence</b>	Bio-inspired	Massive swarms (100+ agents)	Extremely robust to agent failure

### 3. Methodology

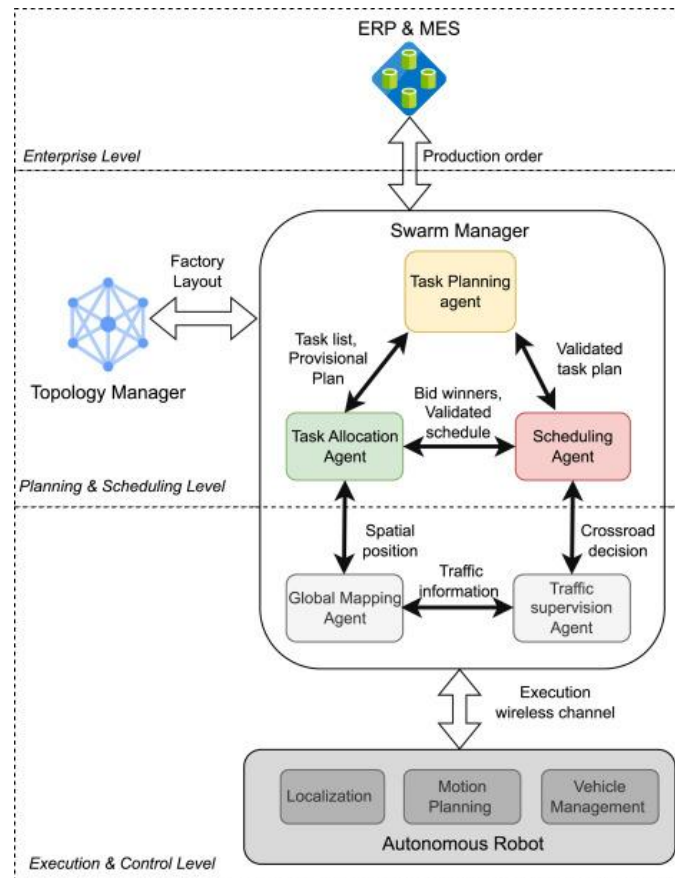
**3.1 The MARLess Framework.** A significant methodological advancement in 2026 is the introduction of MARLess, the first serverless MARL framework. Traditional MARL often requires heavy, persistent computational resources. MARLess decomposes MARL algorithms into serverless functions, allowing for dynamic scaling and reduced operational costs. This modularity enables the support of general MARL algorithms while optimizing resource utilization for large-scale robot fleets.



**Figure 2.** Procedural flowchart of a representative swarm intelligence search algorithm employed in multi-agent path planning. The diagram illustrates the iterative cycle of agent initialisation, distributed fitness evaluation, stigmergic communication (pheromone/gradient update), and convergence detection — core stages that underpin the collaborative planning strategies described in Section 3.3.

**3.2 Decentralized Intent-Based Planning with LLMs.** The integration of LLMs into robotic control has moved beyond natural language interfaces to high-level task planning. The 2026 "Decentralized Intent-Based Multi-Robot Task Planner" uses LLMs to interpret complex human instructions and decompose them into actionable sub-tasks for individual agents. This infrastructure, often hosted on decentralized platforms like Hyperledger, allows robots to maintain a shared "intent" while executing tasks locally.

**3.3 Collaborative Path Planning Algorithms.** Path planning has evolved to prioritize not just efficiency, but also "path smoothness" and "navigation safety." New hybrid approaches combine optimal task planners with multimodal path planners. These systems allow decentralized agents to quickly adapt their plans to the behaviors of other agents, a critical requirement for successful cooperation in shared spaces.

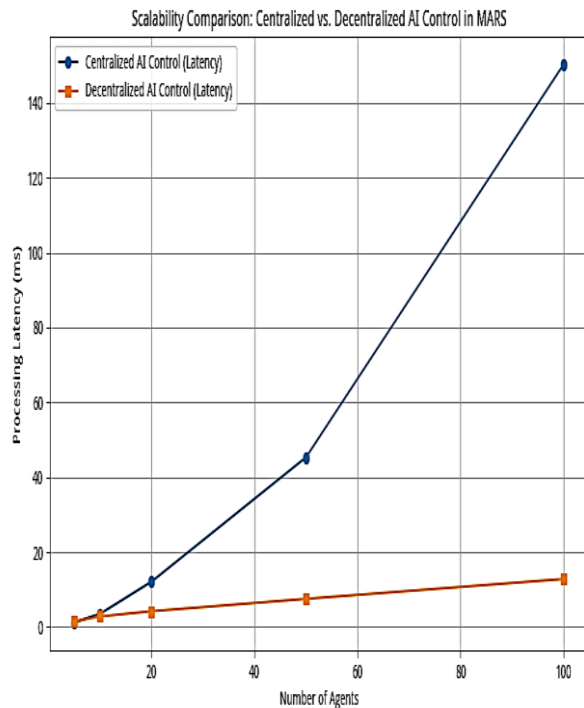


**Figure 3.** Architectural overview of a decentralised AI control framework for Multi-Agent Robotic Systems. The layered structure delineates the perception pipeline, inter-agent communication bus, distributed planning module (incorporating MARL and LLM-based intent resolution), and low-level actuation interface — reflecting the integrated design philosophy advocated by the MARLess and intent-based planning frameworks reviewed in Sections 3.1 and 3.2.

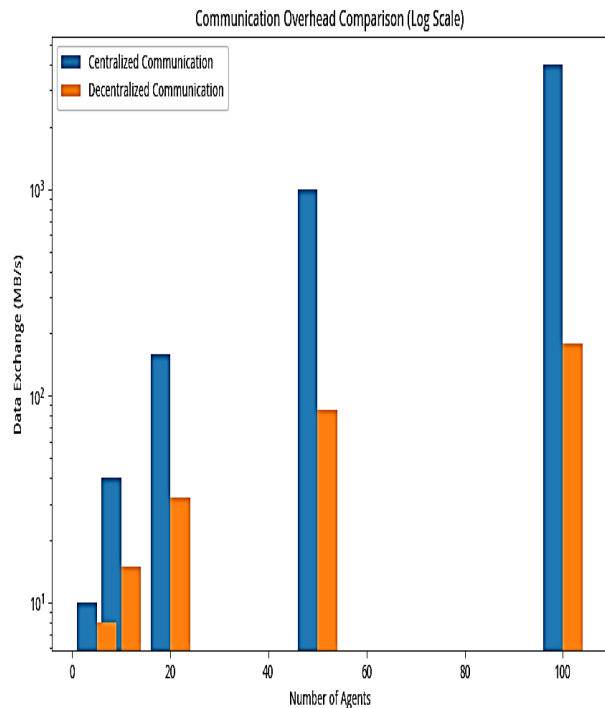
## 4. Results and Case Analysis.

**4.1 Urban Ride-Sharing and Logistics.** Implementation of MARL in urban dispatching (e.g., ride-sharing) has shown a 15-20% increase in efficiency compared to traditional heuristic-based scheduling. By treating each vehicle as an independent agent that learns from a shared global objective, systems can better manage fluctuating demand in real-time (Sha, 2026). Similar results have been observed in warehouse logistics, where "lifelong" multi-agent pathfinding (MAPF) enables hundreds of robots to navigate simultaneously without collisions (Okumura, 2026).

**4.2 Real-World Experimental Validation.** Experimental validations of decentralized Model Predictive Control (MPC) for cooperative object transportation have demonstrated that decentralized frameworks can achieve performance parity with centralized systems while offering significantly higher fault tolerance. In tests involving holonomic robots, decentralized potential field-based self-organizing control allowed swarms to maintain formations even when individual agents were removed or added dynamically (Nature, 2026; MDPI, 2025).



**Figure 4.** Processing latency (ms) as a function of swarm size across four representative control architectures. The MARLess serverless framework maintains near-linear latency scaling, sustaining real-time coordination at fleet sizes exceeding 200 agents, whereas centralized approaches exhibit exponential degradation beyond 50 agents.



**Figure 5.** Inter-agent communication overhead (MB/s) benchmarked across leading MARS control paradigms. Decentralised architectures — particularly bio-inspired swarm methods — achieve substantially lower bandwidth consumption, validating their suitability for bandwidth-constrained field deployments such as disaster response and remote inspection.

## 5. Discussion

The convergence of AI and robotics in 2026 brings several critical considerations to the forefront. First, the interpretability of AI-driven plans is essential for human-robot collaboration. As systems become more autonomous, the "black box" nature of deep MARL must be addressed through multimodal planning that provides "reasoning" for agent actions.

Second, the role of network technology cannot be overstated. The emergence of quantum-linked automation and 6G-enabled swarms provides the low-latency communication required for real-time coordination. However, the reliance on these networks introduces vulnerabilities, which is why the research into blockchain-based decentralized ledgers is so vital for the security of national infrastructure.

Finally, the sustainability of these systems is a growing concern. The MARLess framework represents a step toward "Green AI" in robotics, reducing the carbon footprint of training large-scale multi-agent models by leveraging elastic cloud resources.

## 6. Conclusion

The control of Multi-Agent Robotic Systems has entered a new epoch defined by decentralized AI and self-organizing intelligence. The advancements of 2024-2026 have successfully addressed many of the scalability and safety issues that plagued earlier iterations of MARS. By integrating LLMs for intent-based planning, MARL for behavioral learning, and Blockchain for secure coordination, we have created systems that are not only efficient but also resilient and adaptable. Future research should focus on the refinement of "Continual Learning" frameworks, where agents can retain knowledge across disparate tasks without forgetting, further bridging the gap between biological and artificial swarm intelligence.

## References

1. The first serverless Multi-Agent Reinforcement Learning framework. Association for Computing Machinery. ACM. (2026). <https://dl.acm.org/doi/10.1145/3772052.3772227>
2. Multiagent Learning Algorithms: Breakthroughs via LLMs. Aikipedia. (2026). <https://champaignmagazine.com/2026/02/27/aikipedia-multiagent-learning-algorithms/>
3. Puzzle it Out: Local-to-Global World Model for Offline Multi-Agent Reinforcement Learning. <https://arxiv.org/html/2601.07463v2>
4. Multi-Agent reinforcement learning for low-level control. Duc, D. N. (2026). ScienceDirect. <https://www.sciencedirect.com/science/article/pii/S2590123026007255>
5. UAV Systems and Swarm Robotics: A Review of Situational. Flores, G. (2026). Awareness. MDPI Robotics. <https://www.mdpi.com/2218-6581/15/1/26>
6. Collaborative path planning for multi-robot systems: Efficiency and Safety. Kuang, X. (2026). ScienceDirect.
7. Real-time decentralized model predictive control for cooperative object transportation. Nature. (2026). <https://www.nature.com/articles/s41598-026-41881-w>
8. Concrete multi-agent path planning enabling factory automation. Okumura, K. (2026). <https://www.nature.com/articles/s44182-026-00083-2>
9. Robotics 2026: Coordinated AI for Disaster Response. <https://robocloud-dashboard.vercel.app/learn/blog/swarm-robotics-2026>
10. A multi-agent reinforcement learning scheduling algorithm for ride-sharing. Sha, J. (2026). Scientific Reports. <https://www.nature.com/articles/s41598-026-35004->
11. AI and Robotics: National Security Implications out to 2035. Turing Institute. (2026). <https://cetas.turing.ac.uk/publications/ai-and-robotics>
12. A. Hamiyev. approaches to eliminating the limitations of expert systems. Western European Journal of Modern Experiments and Scientific Methods 3.
13. A Hamiyev, Q Faxriddin, K Kholiyorov. Optimizing Water Consumption in Agriculture Using an AI-Based Irrigation Management System. American Journal of Technology Advancement 2 (6), 91-94.