A Survey on Challenges and Emerging Frontiers of Multi-Agent Systems

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Abstract. Multi-Agent Systems (MAS) have emerged as a fundamental approach for solving dynamic and distributed problems across domains such as robotics, communication networks, and intelligent decision-making. MAS agents are characterized by autonomy, sociality, and flexibility. Recent advances such as deep reinforcement learning (DRL), large language model (LLM)-based agents, and context awareness have broadened MAS capabilities, but existing surveys are often limited to specific subdomains or focus on outdated platforms, ignoring the convergence between learning-based and language-based systems. This review provides a comprehensive, technically rigorous view that connects classical MAS theory with emerging paradigms. We analyze cross-cutting system challenges, including scalability, cybersecurity, and privacy, and synthesize recent model families across five functional research areas: (1) MAS for Complex Problem Solving and Planning; (2) Embodied MAS for Physical Environments; (3) MAS for Emergent Communication and Decentralized Coordination; (4) MAS for Human-AI Teaming and Social Intelligence; (5) Toward Generalist and Multi-tasking MAS. This work aims to consolidate the fragmented literature, highlight common challenges, and outline future research opportunities for developing scalable, general, and interoperable MAS systems.

Keywords: Multi-Agent Systems (MAS) · Agent Architectures · Deep

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Reinforcement Learning (DRL) · Large Language Models (LLMs) · Generalist Agents · Context-Aware Systems · Coordination, Communication · Multi-Tasking

1 Introduction

The complexity of real-world environments, including coordinating robot formations (unmanned aerial vehicle (UAV) swarms) in autonomous vehicles managing traffic [55], disaster relief [42], decentralized smart grid management [58], self-energized communication systems [41], and integrated space-are-ground communications [40], require artifical intelligence (AI) to progress beyond isolated decision-making, enable real-time adaptation, decentralized control, and collaboration across diverse agents. Multi-agent systems (MAS) have become a key paradigm to address this, enabling autonomous agents to sense, act, and learn in complex environments in pursuit of shared or competing goals [49]. MAS are now widely used in engineering fields to enhance efficiency and fault tolerance, such as modeling distributed producers and consumers in smart grids and improving resilience in future wireless networks [15, 17, 45].

Originating from the field of distributed artificial intelligence (DAI), traditional MAS research has explored key architectures such as reactive, deliberative, hybrid, and learning agents, as well as coordination mechanisms such as contract nets, auctions, and negotiation protocols. Recent breakthroughs in deep reinforcement learning (DRL), large language models (LLMs), and multimodal perception have significantly expanded the capabilities of MAS. These breakthroughs in DRL have accelerated the growth of multi-agent reinforcement learning (MARL), which offers promising approaches for distributed coordinated control (DCC) under communication constraints. Furthermore, the integration of agents based on LLM and context awareness has significantly expanded the scope of MAS. These advances have led to a strong convergence between learning-based and language-based systems in modern MAS research.

Several recent surveys have explored aspects of the MAS landscape, but their scopes remain fragmented, overlooking the convergence between learning-based and language-based systems [12, 15, 19, 22, 56]. To address the limitations and gaps of the existing surveys, this paper provides a unified and technically rigorous overview of MAS, bridging classical architectures with emerging learning-based paradigms. We aim to deliver a comprehensive perspective from theory to practice, helping researchers gain a deeper understanding of MAS and fostering future breakthroughs. More specifically, our main contributions in this article are listed as follows:

- **Extension of the MAS Taxonomy (Section 2):** connecting classical categories with modern paradigms, such as LLM-powered agents, DRL-based coordination, and communication-centric learning.

- **Survey of Emerging MAS Paradigms (Section 3):** reviewing five functional research areas and identifying their limitations across diverse application domains.
- **Derivation of cross-cutting challenges (Section 4):** distilling the most prominent challenges, including scalability, security, privacy, and fault-tolerance, from the limitations observed in recent paradigms, providing a foundation for future research directions.

Together, these contributions establish a unified perspective that consolidates fragmented literature, highlights common limitations, and sets the stage for advancing scalable and trustworthy MAS.

2 Foundation and taxonomy of MAS

2.1 Definition and Properties

MAS are defined as systems comprising autonomous agents interacting in a shared environment, where each perceives and acts independently to achieve individual or common goals [49]. Agents, the basic components of MAS, can be **software-based** (e.g., in digital environments, networks, or simulations) or **embodied** (hardware entities such as robots or internet of things (IoT) devices). The agents are characterized several key properties [48]:

- **Autonomy:** Agents operate independently, controlling their internal states and actions without external intervention.
- **Social ability:** An agent interacts with other agents (and possibly humans) via some kind of agent-communication language.
- **Reactivity:** Agents promptly perceive dynamic changes in the environment and respond in a timely manner.
- **Pro-activeness:** Agents pursue goal-directed behaviors by taking the initiative beyond simple reactivity.

MAS deployment offers advantages such as parallelism, distribution, openness, and high fault tolerance.

2.2 Agent Types

Agents in MAS are classified by their decision-making abilities and behavior, as shown in Table 1 and illustrated in Fig. 1. Traditional architectures include reactive, deliberative, hybrid, and learning agents. Modern MAS paradigms have extended this taxonomy by integrating advanced AI models, notably DRL-based agents and LLM-powered agents, which enable advanced coordination and language-mediated planning.

2.3 System architectures in MAS

The architectural design of MAS fundamentally affects their operational capabilities, scalability, and robustness. Architectures dictate how agents coordinate, share information, and achieve goals.

Table 1: Grouped taxonomy of agent types in MAS

Agent Type	Description	Ref.
Traditional Architectures		
Reactive	Operate on simple stimulus–response rules without reasoning.	[49]
Deliberative	Maintain explicit models of environment & goals, use symbolic reasoning & planning.	[11]
Hybrid	Combine reactive behaviors with high-level planning.	[49]
Learning-based	Adapt functional behavior based on environmental feedback.	[33]
Modern Architectures		
DRL-based Agents	Use DRL; extend to MARL (centralized, decentralized, distributed).	[25]
LLM-powered Agents	Augmented with LLMs for language-mediated reasoning, planning, and coordination.	[19]

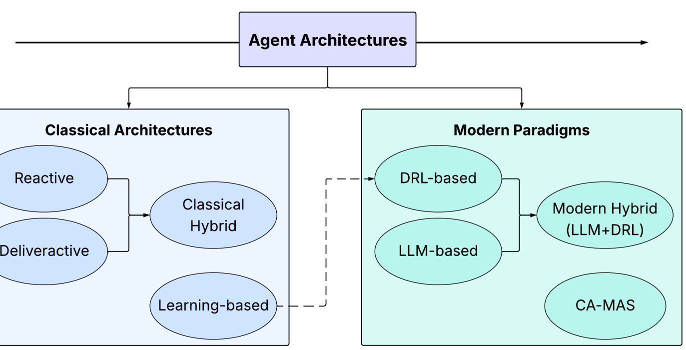

Fig. 1: Taxonomy of MAS Agent Architectures illustrating the relationship between classical and modern paradigms, including DRL-based, LLM-based, and Hybrid approaches.

Control Structure As shown in Fig. 2, architectures can be centralized, relying on a single control center, which suffers from poor scalability and a single point of failure [20]. Decentralized/distributed architectures improve fault tolerance and flexibility by distributing decision-making [10]. Hybrid architectures seek to balance these benefits, often exemplified by Centralized Training with Decentralized Execution (CTDE) in MARL [57].

Communication Topology The network of agents is often modeled by a weighted directed graph (digraph) [52]. Topologies can be static or dynamic (also known as switching topology) [22].

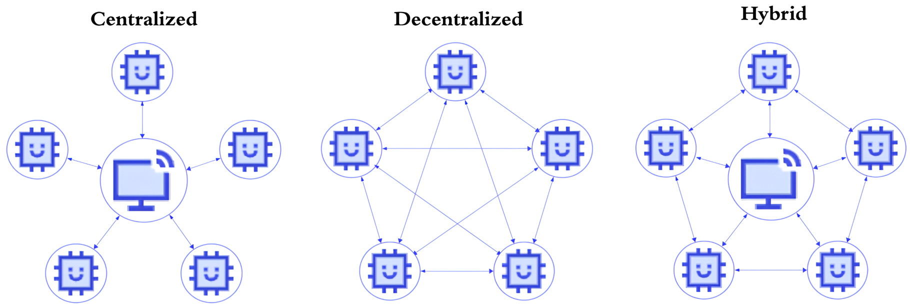

Fig. 2: Comparison of MAS control structures. (a) Centralized: agents depend on a central coordinator. (b) Decentralized: agents interact directly. (c) Hybrid: agents coordinate both with a central entity and among themselves.

Agent Composition MAS can be homogeneous (identical agents) or heterogeneous (HMAS), where agents possess diverse dynamics and functionalities [7].

2.4 Evolution of MAS

Over the past decades, MAS have evolved through a series of architectural and algorithmic transformations, as illustrated in Fig. 3. Originating from DAI in the 1970s–80s, the focus was on distributed problem solving. The 1990s shifted toward standardization with communication frameworks like the Contract Net Protocol and belief–desire–intention (BDI) model [30,39], standardized by Foundation for Intelligent Physical Agents (FIPA) [18]. The 2000s introduced norm-governed systems (e.g., MOISE+ (model of organization for multi-agent systems)) to manage social structures [14].

A significant turning point occurred in the 2010s with the rise of MARL, leveraging Deep Q-Networks (DQNs) [23] and value-function factorization (e.g., QMIX (Monotonic Value Function Factorisation for Deep MARL) [31]) for complex, learning-based coordination. Concurrently, Context-Aware MAS (CA-MAS) began integrating semantic reasoning [24, 34]. Most recently, the 2020s have seen the integration of LLMs (e.g., AutoGen [51]) and LLM-mediated MARL (DyLAN [21]), converging learning-based and language-based systems.

3 Survey of Emerging MAS Paradigms

The advancement of MAS has birthed diverse paradigms to tackle complex challenges across multiple domains, drawing from impactful models in peer-reviewed IEEE and AAMAS publications (2024-2025). A central issue is the assumption of full observability, often unfeasible as agents perceive only partial, local data in dynamic settings. This section examines five key areas, exploring their limitations and applicability. A comparison of the core mechanisms discussed in these paradigms is presented in Table 2.

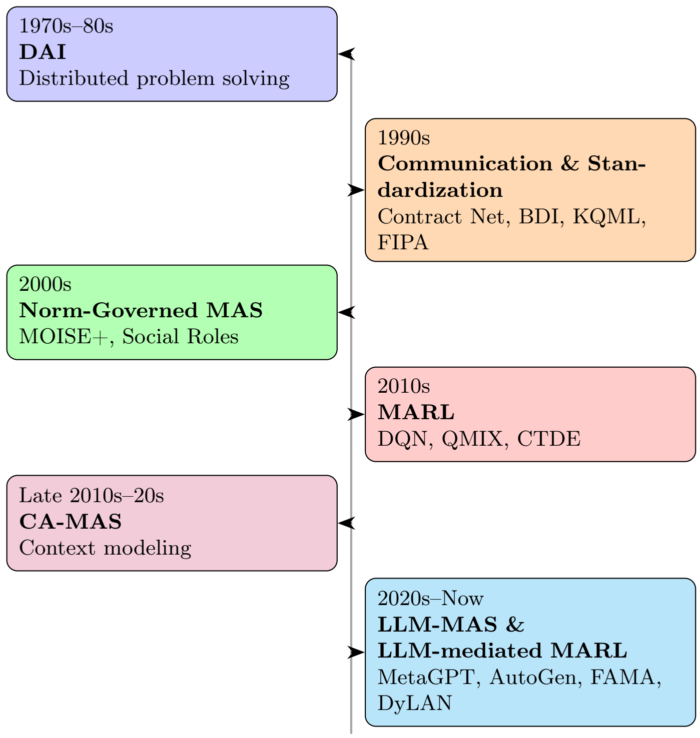

Fig. 3: Timeline of MAS evolution highlighting key paradigms and representative frameworks.

3.1 MAS for Complex Problem Solving and Planning

This direction focuses on optimizing outcomes in high-dimensional cooperative or competitive problems. The DRL domain utilizes algorithms like QMIX (part of the CTDE framework) [31]. As summarized in Table 2, while these methods effectively coordinate actions, MARL faces significant limitations with non-stationarity (environment altered by simultaneous learners) and the exponential complexity of joint state-action spaces. For continuous systems, Neurodynamics (e.g., zeroing neural network (ZNN)) provides an alternative [43], though robust protocols for Prioritized Multi-Objective Optimization (MOO) remain an open challenge [38].

3.2 Embodied MAS for Physical Environments

This paradigm addresses applying MAS to physical agents (robots, UAVs). It relies on distributed cooperative control (DCC) mechanisms, such as Adaptive Event-Triggered Consensus (ETC), to manage tasks like formation control while optimizing communication [13]. Safe RL with QMIX also helps bridge sim-to-real

Table 2: Comparison of Core Mechanisms in Emerging MAS Paradigms

Paradigm / Section	**Core Mechanism**	**Strengths**	**Limitations / Challenges**
3.1. Problem Solving	QMIX (MARL /CTDE)	Factorizes joint Q-function, ensuring decentralized greedy actions align with centralized optimum.	Non-stationarity; exponential complexity of joint state-action spaces.
3.1. Problem Solving	Neuro-dynamics (ZNN)	Alternative mathematical framework for optimizing continuous dynamical systems.	Developing protocols for Prioritized Multi-Objective Optimization (MOO).
3.2. Embodied MAS	Event-Triggered Consensus (ETC)	Reduces communication overhead by triggering updates only when errors exceed a threshold.	Scalability to thousands of agents; robustness to intermittent communication.
3.3. Communication	Security Observers	Anomaly observers and elastic control structures to maintain consensus.	Defending against Denial-of-Service (DoS) attacks; trade-off between safety and utility.
3.4. Human-AI Teaming	AutoGen (LLM-Agents)	Uses LLM-based agents with advanced reasoning to emulate social intelligence and collaboration.	Latency and computational cost of LLMs; barrier to real-time interaction.
3.4. Human-AI Teaming	Differential Privacy (DP)	Adds controlled noise (Laplace/Gaussian) to shared data to protect individual contributions.	The accuracy-privacy trade-off; balancing utility with data protection.

gaps [29]. While effective in HMAS (e.g., UAV-UGV (unmanned ground vehicle) coordination [54]) and platooning [53], major challenges persist. As noted in Table 2, scalability to thousands of agents and robustness to intermittent communication remain unresolved [13, 31].

3.3 MAS for Emergent Communication and Coordination

This area focuses on designing robust communication protocols for open networked systems (e.g., smart cities). It employs mechanisms like Event-Triggered Control (ETC) to reduce communication overhead [16, 28] and security defenses (e.g., anomaly observers) to handle cyberattacks like Denial-of-Service (DoS) [3, 5]. However, open MAS are highly vulnerable, creating a trade-off between algorithm safety and utility. Despite advances, achieving scalability remains the ultimate barrier, as computational complexity grows exponentially [27, 37].

3.4 MAS for Human-AI Teaming and Social Intelligence

This paradigm explores MAS collaboration with humans in complex social domains (e.g., healthcare). It uses LLM-based agents (e.g., AutoGen for social intelligence [50] and Differential Privacy (DP) to protect data in decentralized networks [47], as detailed in Table 2. Critical challenges include the accuracy-privacy trade-off, resolving norm conflicts, and the significant latency and computational cost of LLMs, which barrier real-time interaction [1].

3.5 Toward Generalist and Multi-tasking MAS

This final direction represents the aspirational goal of Multi-Agent Systems (MAS) research: creating versatile, adaptive, and efficient systems across multiple tasks and domains with minimal retraining. The search for Generalist MAS, such as models based on unified Transformer architectures (e.g., MetaGPT, RT-2, UniPi), faces two persistent limitations. First, scalability is the most severe constraint for learning-based MAS. Developing and evaluating large-scale Parallel Distributed MAS (PDMAS) platforms is complex, as the joint state-action space increases exponentially, making simulation and reliable deployment highly challenging [4, 9]. Second, generalist models often exhibit worse performance compared to specialized models in individual tasks due to lower task-specific precision [44]. Additionally, LLM-orchestrated systems show potential for multi-tasking but are prone to hallucinations and control inconsistency in long-horizon scenarios [6, 19].

Future work must focus on developing distributed learning algorithms, such as federated learning, that rely only on local communication to enhance scalability [8]. A unified framework is needed to assess interoperability across different application domains [32]. Furthermore, hybridizing LLM-driven reasoning with advanced learning algorithms, such as reinforcement learning (e.g., LEHR (LLM-driven evolutionary hybrid rewards for MARL)), can combine high-level planning with robust low-level control [19, 46].

4 Cross-cutting System Challenges

The examination of emerging MAS paradigms in Section 3 highlighted notable advancements, including QMIX for cooperative planning and AutoGen for facilitating human-AI interactions. However, this review also uncovered persistent constraints such as scalability issues, resilience deficiencies, elevated computational demands, and inherent trade-offs between security and privacy. These limitations manifest across diverse application domains, encompassing robotics, healthcare, and energy management systems. Importantly, such deficiencies transcend individual models, representing fundamental, cross-cutting challenges that compromise the overall reliability and practical deployment of MAS architectures. To systematically address these, this section delineates the challenges into three interrelated categories: (A) Robustness and Efficiency in Distributed Control, (B) Cybersecurity and Privacy Safeguards, and (C) Diagnosis, Fault-Tolerance, and Recovery Mechanisms. For each, we analyze underlying causes, empirical implications, and potential avenues for mitigation, drawing on recent literature to underscore their interdisciplinary nature.

4.1 Robustness and Efficiency in Distributed Control

Distributed Cooperative Control (DCC) in MAS is frequently impeded by factors such as intermittent network connectivity and heterogeneous agent dynamics, which can degrade stability and coordination. Event-Triggered Control (ETC) remains a promising strategy to alleviate communication burdens by initiating data exchanges only when required. Yet empirical evaluations indicate persistent efficiency gaps. For example, Acha and Yi (2025) [2] reported a 29% improvement in control robustness for a four-drone MAS, with individual agents achieving up to 97.4% accuracy under noisy communication conditions and requiring thresholds of 5 Hz for stability and 50% trust for reliability. While these results validate ETC under small-scale robotics, scalability to larger fleets remains uncertain. Similarly, simulations in large-scale IoT-based MAS [26] demonstrated reliability ranging from 1.00× to 4.73× baseline across 1000 iterations, but only under controlled conditions, raising concerns about generalization to real-world deployments. These findings highlight that, although ETC and neurodynamic approaches improve efficiency, robustness degrades when scaling to heterogeneous or resource-limited environments. Future work could explore machine learning (ML)-augmented DCC that dynamically tunes thresholds to sustain coordination beyond current experimental limits.

4.2 Cybersecurity and Privacy Protection

The integration of MAS into open and interconnected networks amplifies vulnerabilities to adversarial threats and data misuse. Denial-of-Service (DoS) and communication overload remain key risks. Saxena and Lal (2025) [36] highlighted that LLM-enhanced MAS deployments exhibited 500–800 ms latency in healthcare and autonomous systems, with 34% simulation bias and significant energy wastage in edge-based deployments. These results underscore the difficulty of preserving responsiveness under high-load or adversarial conditions. Complementary experimental evidence from Acha and Yi (2025) [2] indicated that trust-based communication thresholds (e.g., 50% trust level) can improve security and reduce noise sensitivity, but at the cost of limiting flexibility. Privacy concerns add another layer: while differential privacy remains central, available studies reveal utility compromises, though quantitative evidence here is sparse. Overall, the evidence suggests that MAS security frameworks must balance lightweight, latency-aware defenses with adaptive privacy safeguards. Hybrid solutions combining anomaly detection, trust calibration, and cryptographic protections are emerging as viable directions but require rigorous validation at scale.

4.3 Diagnosis, Fault-Tolerance, and Recovery

Effective diagnosis and recovery remain central to MAS resilience, particularly in heterogeneous and safety-critical settings. Centralized diagnostic approaches scale poorly, making decentralized verification mechanisms essential. Experimental evidence from O'Neill and Soh (2022) [26] demonstrated that intelligent transfer mechanisms improved fault tolerance by 1.27× to 6.34× across IoT-based MAS, with repeated testing over 1000 iterations confirming moderate reliability gains. Similarly, Acha and Yi (2025) [2] reported notable improvements in drone-based MAS, where decentralized control increased accuracy to 97.4% and improved resilience under noisy conditions. These results underscore the potential of hybrid trust-based and adaptive recovery strategies, though the small scale of current studies limits generalizability. Furthermore, norm-governed MAS (NorMAS) continue to encounter conflicts, such as balancing efficiency with safety, which, without effective arbitration, risk propagating systemic errors [35]. Emerging proposals for priority-based resolution and reflective learning provide conceptual foundations, but empirical evidence remains limited. Advancing this area will require integrating sensor-level diagnostics, explainable decision traces, and norm conflict arbitration into hybrid recovery frameworks validated across diverse domains.

In summary, these cross-cutting challenges demand concerted interdisciplinary interventions, fusing advancements in control theory, cybersecurity, and AI to fortify MAS. By addressing robustness through adaptive algorithms, bolstering security via balanced privacy techniques, and enhancing fault-tolerance with distributed mechanisms, MAS can achieve greater reliability across fields. Table 3 below summarizes key challenges, implications, and mitigation strategies, providing a comparative overview derived from the discussed literature.

Table 3: Overview of Cross-Cutting Challenges in MAS

Challenge Category	**Implications**	**Mitigation Strategies**	**Refs.**
Robustness, Efficiency	Stability degraded by connectivity/dynamics. Scalability drops.	Adaptive ETC, ML-augmented DCC.	[2,26]
Cybersecurity, Privacy	DoS/misuse cause latency/bias. Privacy-utility trade-off.	Lightweight defenses, anomaly detection, crypto.	[2,36]
Diagnosis, Fault-Tolerance	Centralized scales poorly. Norm conflicts persist.	Decentralized diagnostics, norm arbitration.	[2, 26, 35]

5 Conclusion and Future Directions

This survey has explored the evolution of MAS, highlighting significant progress alongside persistent challenges in robustness, security, and fault-tolerance. While advancements demonstrate potential, limitations in scalability, generalizability, and performance trade-offs remain evident, particularly in large-scale and safety-critical applications. These findings underscore the need for further development to ensure reliability.

To advance MAS toward robust, deployable systems, future research should focus on three key directions:

- **Scalability:** Develop adaptive communication protocols to ensure reliable coordination among thousands of agents in heterogeneous fleets, addressing dynamic thresholds and evaluating impacts on societal safety.
- **Security and Privacy:** Design lightweight mechanisms, such as adaptive privacy models and zero-trust architectures, to mitigate adversarial attacks and latency overheads while preserving utility, especially in healthcare and smart grid contexts.
- **Human–MAS Teaming:** Enhance fault recovery and trust through explainable decision traces and norm arbitration, fostering effective collaboration in high-stakes domains like disaster response and medical robotics with a focus on ethical alignment.

These efforts should integrate hybrid architectures combining reinforcement learning, language-based reasoning, and adaptive security frameworks. By addressing these challenges, MAS can transition from small-scale demonstrations to reliable, real-world deployments, delivering benefits such as improved public safety, equitable healthcare access, and sustainable urban development.

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References

1. Abdelzaher, T., Hu, Y., Kara, D., Kimura, T., Misra, A., Ramani, V., Tardieu, O., Wang, T., Wigness, M., Youssef, A.: The bottlenecks of AI: challenges for embedded and real-time research in a data-centric age **61**(2), 185–236. https://doi.org/10.1007/s11241-025-09452-w, https://link.springer.com/10.1007/s11241-025-09452-w
2. Acha, S., Yi, S.: Cooperative intelligent control of multi-agent systems (MAS) through communication, trust, and reliability **3**(1), 53–67. https://doi.org/10.59247/csol.v3i1.171, https://ejournal.csol.or.id/index.php/csol/article/view/171
3. Amini, A., Mohammadi, A., Hou, M., Asif, A.: Secure dynamic event-triggering control for consensus under asynchronous denial of service **5**, 1125124. https://doi.org/10.3389/fcomp.2023.1125124, https://www.frontiersin.org/articles/10.3389/fcomp.2023.1125124/full
4. Canese, L., Cardarilli, G.C., Di Nunzio, L., Fazzolari, R., Giardino, D., Re, M., Spanò, S.: Multi-agent reinforcement learning: A review of challenges and applications **11**(11), 4948. https://doi.org/10.3390/app11114948, https://www.mdpi.com/2076-3417/11/11/4948
5. Cetinkaya, A., Ishii, H., Hayakawa, T.: An overview on denial-of-service attacks in control systems: Attack models and security analyses **21**(2), 210. https://doi.org/10.3390/e21020210, https://www.mdpi.com/1099-4300/21/2/210

6. Darwish, A.M., Rashed, E.A., Khoriba, G.: Mitigating LLM hallucinations using a multi-agent framework **16**(7), 517. https://doi.org/10.3390/info16070517, https://www.mdpi.com/2078-2489/16/7/517
7. Dorri, A., Kanhere, S.S., Jurdak, R.: Multi-agent systems: A survey **6**, 28573–28593. https://doi.org/10.1109/ACCESS.2018.2831228, https://ieeexplore.ieee.org/document/8352646/
8. Dritsas, E., Trigka, M.: Federated learning for IoT: A survey of techniques, challenges, and applications **14**(1), 9. https://doi.org/10.3390/jsan14010009, https://www.mdpi.com/2224-2708/14/1/9
9. Dähling, S., Razik, L., Monti, A.: Enabling scalable and fault-tolerant multi-agent systems by utilizing cloud-native computing **35**(1), 10. https://doi.org/10.1007/s10458-020-09489-0, https://link.springer.com/10.1007/s10458-020-09489-0
10. Ferber, J., Ferber, J.: Multi-agent systems: an introduction to distributed artificial intelligence. Addison-Wesley, 1. publ edn.
11. Fikes, R.E., Nilsson, N.J.: Strips: A new approach to the application of theorem proving to problem solving **2**(3), 189–208. https://doi.org/10.1016/0004-3702(71)90010-5, https://linkinghub.elsevier.com/retrieve/pii/0004370271900105
12. Gjikopulli, A.: A survey on multi-agent systems (MAS) . https://doi.org/10.2313/NET-2020-11-1_11, https://www.net.in.tum.de/fileadmin/TUM/NET/NET-2020-11-1/NET-2020-11-1_11.pdf, medium: PDF Publisher: Chair of Network Architectures and Services, Department of Computer Science, Technical University of Munich
13. Hou, Z., Zhou, Z., Yuan, H., Wang, W., Wang, J., Xu, Z.: Adaptive event-triggered consensus of multi-agent systems in sense of asymptotic convergence **24**(2), 339. https://doi.org/10.3390/s24020339, https://www.mdpi.com/1424-8220/24/2/339
14. Hübner, J.F., Sichman, J.S., Boissier, O.: A model for the structural, functional, and deontic specification of organizations in multiagent systems. In: Bittencourt, G., Ramalho, G.L. (eds.) Advances in Artificial Intelligence, vol. 2507, pp. 118–128. Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-36127-8_12, http://link.springer.com/10.1007/3-540-36127-8_12, series Title: Lecture Notes in Computer Science
15. Izmirlioglu, Y., Pham, L., Son, T.C., Pontelli, E.: A survey of multi-agent systems for smartgrids **17**(15), 3620. https://doi.org/10.3390/en17153620, https://www.mdpi.com/1996-1073/17/15/3620
16. Jiang, Z.P., Liu, T.: Small-gain theory for stability and control of dynamical networks: A survey **46**, 58–79. https://doi.org/10.1016/j.arcontrol.2018.09.001, https://linkinghub.elsevier.com/retrieve/pii/S1367578818301160
17. Kaada, S., Tran, D.H., Van Huynh, N., Morel, M.L.A., Jelassi, S., Rubino, G.: Multi-Agent Deep Reinforcement Learning for Resilience Optimization in 5G RAN. arXiv preprint arXiv:2407.18066 (2024)
18. Labrou, Y., Finin, T., Yun Peng: Agent communication languages: the current landscape **14**(2), 45–52. https://doi.org/10.1109/5254.757631, http://ieeexplore.ieee.org/document/757631/
19. Li, X., Wang, S., Zeng, S., Wu, Y., Yang, Y.: A survey on LLM-based multi-agent systems: workflow, infrastructure, and challenges **1**(1), 9. https://doi.org/10.1007/s44336-024-00009-2, https://link.springer.com/10.1007/s44336-024-00009-2

20. Li, Y., Tan, C.: A survey of the consensus for multi-agent systems **7**(1), 468–482. https://doi.org/10.1080/21642583.2019.1695689, https://www.tandfonline.com/doi/full/10.1080/21642583.2019.1695689
21. Liu, Z., Zhang, Y., Li, P., Liu, Y., Yang, D.: A dynamic LLM-powered agent network for task-oriented agent collaboration
22. Maldonado, D., Cruz, E., Abad Torres, J., Cruz, P.J., Gamboa Benitez, S.D.P.: Multi-agent systems: A survey about its components, framework and workflow **12**, 80950–80975. https://doi.org/10.1109/ACCESS.2024.3409051, https://ieeexplore.ieee.org/document/10546975/
23. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., Hassabis, D.: Human-level control through deep reinforcement learning **518**(7540), 529–533. https://doi.org/10.1038/nature14236, https://www.nature.com/articles/nature14236
24. Morganti, G., Perdon, A.M., Conte, G., Scaradozzi, D.: Multi-agent system theory for modelling a home automation system. In: Cabestany, J., Sandoval, F., Prieto, A., Corchado, J.M. (eds.) Bio-Inspired Systems: Computational and Ambient Intelligence, vol. 5517, pp. 585–593. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-02478-8_74, http://link.springer.com/10.1007/978-3-642-02478-8_74, series Title: Lecture Notes in Computer Science
25. Nguyen, T.T., Nguyen, N.D., Nahavandi, S.: Deep reinforcement learning for multiagent systems: A review of challenges, solutions, and applications **50**(9), 3826–3839. https://doi.org/10.1109/TCYB.2020.2977374, https://ieeexplore.ieee.org/document/9043893/
26. O'Neill, V., Soh, B.: Improving fault tolerance and reliability of heterogeneous multi-agent IoT systems using intelligence transfer **11**(17), 2724. https://doi.org/10.3390/electronics11172724, https://www.mdpi.com/2079-9292/11/17/2724
27. Peng, C., Li, F.: A survey on recent advances in event-triggered communication and control **457-458**, 113–125. https://doi.org/10.1016/j.ins.2018.04.055, https://linkinghub.elsevier.com/retrieve/pii/S0020025518303062
28. Püttschneider, J., Golembiewski, J., Wagner, N.A., Wietfeld, C., Faulwasser, T.: Towards event-triggered NMPC for efficient 6g communications: Experimental results and open problems. In: 2025 IEEE 19th International Conference on Control & Automation (ICCA). pp. 218–225. IEEE. https://doi.org/10.1109/ICCA65672.2025.11129801, https://ieeexplore.ieee.org/document/11129801/
29. Qiu, Z., Zhang, L., Chi, Y., Li, Z.: Active obstacle avoidance of multi-rotor UAV swarm based on stress matrix formation method **13**(1), 86. https://doi.org/10.3390/math13010086, https://www.mdpi.com/2227-7390/13/1/86
30. Rao, A.S., Georgeff, M.P.: BDI agents: From theory to practice
31. Rashid, T., Samvelyan, M., de Witt, C.S., Farquhar, G., Foerster, J., Whiteson, S.: Monotonic value function factorisation for deep multi-agent reinforcement learning
32. Rosic, M., Sumic, D., Males, L.: Semantic interoperability of multi-agent systems in autonomous maritime domains **14**(13), 2630. https://doi.org/10.3390/electronics14132630, https://www.mdpi.com/2079-9292/14/13/2630
33. Russell, S.J., Norvig, P.: Artificial intelligence: a modern approach. Prentice Hall series in artificial intelligence, Pearson, fourth edition, global edition edn.

34. Savaglio, C., Ganzha, M., Paprzycki, M., Bădică, C., Ivanović, M., Fortino, G.: Agent-based internet of things: State-of-the-art and research challenges **102**, 1038–1053. https://doi.org/10.1016/j.future.2019.09.016, https://linkinghub.elsevier.com/retrieve/pii/S0167739X19312282
35. Savarimuthu, B.T.R., Cranefield, S.: Norm creation, spreading and emergence: A survey of simulation models of norms in multi-agent systems **7**(1), 21–54. https://doi.org/10.3233/mgs-2011-0167
36. Saxena, P., , R.L.: Leveraging large language models in multiagent system **7**(2), 41697. https://doi.org/10.36948/ijfmr.2025.v07i02.41697, https://www.ijfmr.com/research-paper.php?id=41697
37. Severson, T.A., Croteau, B., Rodríguez-Seda, E.J., Kiriakidis, K., Robucci, R., Patel, C.: A resilient framework for sensor-based attacks on cyber–physical systems using trust-based consensus and self-triggered control **101**, 104509. https://doi.org/10.1016/j.conengprac.2020.104509, https://linkinghub.elsevier.com/retrieve/pii/S0967066120301246
38. Shokoufeh Naderi, Maude-Josée Blondin: A mapping and state-of-the-art survey on multi-objective optimization methods for multi-agent systems . https://doi.org/10.1109/access.2023.3341295
39. Smith: The contract net protocol: High-level communication and control in a distributed problem solver **C-29**(12), 1104–1113. https://doi.org/10.1109/TC.1980.1675516, https://ieeexplore.ieee.org/document/1675516/
40. Tran, D.H., Chatzinotas, S., Ottersten, B.: Satellite-and cache-assisted UAV: A joint cache placement, resource allocation, and trajectory optimization for 6G aerial networks. IEEE Open Journal of Vehicular Technology **3**, 40–54 (2022)
41. Tran, D.H., Chatzinotas, S., Ottersten, B.: Throughput maximization for backscatter-and cache-assisted wireless powered UAV technology. IEEE Transactions on Vehicular Technology **71**(5), 5187–5202 (2022)
42. Tran, D.H., Nguyen, V.D., Chatzinotas, S., Vu, T.X., Ottersten, B.: UAV relay-assisted emergency communications in IoT networks: Resource allocation and trajectory optimization. IEEE Transactions on Wireless Communications **21**(3), 1621–1637 (2021)
43. V. Katsikis, Bolin Liao, Cheng Hua: Survey of neurodynamic methods for control and computation in multi-agent systems . https://doi.org/10.3390/sym17060936
44. Wang, C., Tang, H., Ding, W.: MAMGDT: Enhancing multi-agent systems with multi-game decision transformer. In: Proceedings of the 30th Annual International Conference on Mobile Computing and Networking. pp. 1962–1967. ACM. https://doi.org/10.1145/3636534.3694719, https://dl.acm.org/doi/10.1145/3636534.3694719
45. Wang Yue Dong, M.: A survey on multi agent system and its applications in power system engineering pp. 1–11. https://doi.org/10.53759/832X/JCIMS202301001, https://anapub.co.ke/journals/jcims/jcims_abstract/2023/jcims_volume_01/jcims_volume1_1.html
46. Wei, Y., Shan, X., Li, J.: LEHR: LLM-driven evolutionary hybrid rewards for multi-agent reinforcement learning. In: Xu, B., Qiu, J. (eds.) Cognitive Computation and Systems, vol. 2515, pp. 283–295. Springer Nature Singapore. https://doi.org/10.1007/978-981-96-7352-0_24, https://link.springer.com/10.1007/978-981-96-7352-0_24, series Title: Communications in Computer and Information Science

47. Williamson, S.M., Prybutok, V.: Balancing privacy and progress: A review of privacy challenges, systemic oversight, and patient perceptions in AI-driven healthcare **14**(2), 675. https://doi.org/10.3390/app14020675, https://www.mdpi.com/2076-3417/14/2/675
48. Wooldridge, M., Jennings, N.R.: Agent theories, architectures, and languages: a survey pp. 1–39. https://doi.org/10.1007/3-540-58855-8_1
49. Wooldridge, M.J.: An introduction to multiagent systems. Wiley, 2. ed., repr edn.
50. Wu, Q., Bansal, G., Zhang, J., Wu, Y., Li, B., Zhu, E., Jiang, L., Zhang, X., Zhang, S., Liu, J., Awadallah, A., White, R.W., Burger, D., Wang, C.: AutoGen: Enabling next-gen LLM applications via multi-agent conversations
51. Xi, Z., Chen, W., Guo, X., He, W., Ding, Y., Hong, B., Zhang, M., Wang, J., Jin, S., Zhou, E., Zheng, R., Fan, X., Wang, X., Xiong, L., Zhou, Y., Wang, W., Jiang, C., Zou, Y., Liu, X., Yin, Z., Dou, S., Weng, R., Qin, W., Zheng, Y., Qiu, X., Huang, X., Zhang, Q., Gui, T.: The rise and potential of large language model based agents: a survey **68**(2), 121101. https://doi.org/10.1007/s11432-024-4222-0, https://link.springer.com/10.1007/s11432-024-4222-0
52. Xiaohua Ge, Qing-Long Han, Xianming Zhang, Derui Ding, Boda Ning: Distributed coordination control of multi-agent systems under intermittent sampling and communication: a comprehensive survey . https://doi.org/10.1007/s11432-024-4355-1
53. Xie, S., Hu, J., Ding, Z., Arvin, F.: Cooperative adaptive cruise control for connected autonomous vehicles using spring damping energy model **72**(3), 2974–2987. https://doi.org/10.1109/TVT.2022.3218575, https://ieeexplore.ieee.org/document/9933795/
54. Xiong, H., Deng, H., Liu, C., Wu, J.: Distributed event-triggered formation control of UGV-UAV heterogeneous multi-agent systems for ground-air cooperation **37**(12), 458–483. https://doi.org/10.1016/j.cja.2024.05.035, https://linkinghub.elsevier.com/retrieve/pii/S1000936124002000
55. Xu, X., Gu, L., Bilal, M., Khan, M., Wen, Y., Liu, G., Yuan, Y.: Multi-agent reinforcement learning based edge content caching for connected autonomous vehicles in IoV. ACM Transactions on Autonomous and Adaptive Systems **20**(3), 1–26 (2025)
56. Zhang, D., Feng, G., Shi, Y., Srinivasan, D.: Physical safety and cyber security analysis of multi-agent systems: A survey of recent advances **8**(2), 319–333. https://doi.org/10.1109/JAS.2021.1003820, https://ieeexplore.ieee.org/document/9317716/
57. Zhang, K., Yang, Z., Başar, T.: Multi-agent reinforcement learning: A selective overview of theories and algorithms. In: Vamvoudakis, K.G., Wan, Y., Lewis, F.L., Cansever, D. (eds.) Handbook of Reinforcement Learning and Control, vol. 325, pp. 321–384. Springer International Publishing. https://doi.org/10.1007/978-3-030-60990-0_12, https://link.springer.com/10.1007/978-3-030-60990-0_12, series Title: Studies in Systems, Decision and Control
58. Zhou, X., Honari, K., Liang, H., Rouhani, S., Dick, S.: Blockchain-based Decentralized Stochastic Energy Management in IoT-enabled Smart Grid with Voltage Regulation Coordination. IEEE Internet of Things Journal (2025)