Proceedings of the 7th International Conference on Computing and Data Science
DOI: 10.54254/2755-2721/2025.22345

# *Review on Multi-agent Systems Consensus Control*

**Juntong Zhao**

*Northeastern University at Qinhuangdao, Qinhuangdao, China*
*1557458758@qq.com*

***Abstract:*** This review paper focuses on expanding application scenarios of consensus in multi-agent systems (MASs), particularly in smart manufacturing, intelligent transportation, and public safety. It provides a comprehensive analysis of recent methods for solving consensus problem. The paper focuses on various control, including distributed control, optimization-based consensus, event-triggered consensus control, game-theoretic consensus, and novel approaches based on fundamental theoretical research. The paper summarizes the main challenges in achieving consensus and highlights future research directions aimed at overcoming these challenges. By offering a comprehensive overview and analysis, this review paper aims to assist researchers and practitioners in selecting the optimal method for practical applications and fostering further advancements in consensus.

***Keywords:*** Multi-agent systems, Consensus, Distributed Control

## 1. Introduction

As a distributed artificial intelligence framework, multi-agent systems leverage interconnected agents' self-organization capabilities to replace conventional centralized approaches with modular and flexible distributed methodologies, thereby improving problem-solving efficiency [1]. They play an important role in life because they enable decentralized, flexible, and efficient problem-solving in a wide variety of domains. By harnessing the power of multiple agents to collaborate, adapt, and scale, MASs can tackle challenges that would be difficult or impossible for single-agent systems to address. The maturation of MASs has propelled innovations in autonomous coordination, yet real-world implementations face multi-source stochasticity (e.g., adversarial attacks and sensor drift) and spatiotemporal environmental variability, reinforcing the need for hybrid architectures that embed federated learning mechanisms for distributed knowledge sharing and topology-aware communication protocols to mitigate latency-induced divergence [2]. As a result, it is important to address agreement problems in [3]. At the same time, to solve the Consensus in Multi-Agent System is a main problem.

In recent years, the application scenarios of consensus in multi-agent systems are continuously expanding. It is gradually expanding to fields such as smart manufacturing, intelligent transportation, and public safety. Practical implementations of MASs are constrained by non-stationary external inputs, scalability-driven energy consumption, and distributed decision-making bottlenecks, highlighting the critical need for event-triggered protocols to optimize trade-offs between robustness and operational costs [4]. This review explores some recent methods for solving multi-agent consensus, providing a brief description of each method along with their advantages and disadvantages. By analyzing these methods, the aim of this review is to offer a comprehensive

DOI: 10.54254/2755-2721/2025.22345

analysis to help select the optimal method for practical applications, as well as to identify future development directions and the challenges ahead.

However, in many practical engineering scenarios, the requirement for all agents' states to converge to a single value often fails to meet the complex demands of real industrial environments [5]. So the initial purpose of this review is to provide a comprehensive analysis of methods for addressing multi-agent system consensus, and offer a comprehensive overview for those beginning their research. It aims to describe the advantages and disadvantages of various methods to adapt them to specific contexts. By focusing on this review, it can provide a clear developing direction in the problems for Multi-Agent System Consensus. Finally, the objective of this paper is to contribute to the resolution of more complex multi-agent system consistency issues in practical applications and to facilitate their broader utilization.

## 2. Control Equations and Analysis

This section delineates the principal theoretical frameworks while concurrently elucidating their respective advantages and predominant domains of application.

### 2.1. Distributed Control

Core Idea: Use local information exchange among agents to achieve global consensus through distributed control laws.

Theoretical Framework:

Each agent updates its state based on its own state and the states of its neighbors:

$$\dot{x}_i(t) = \sum_{j \in \mathcal{N}_i} a_{ij}(x_j(t) - x_i(t)) \tag{1}$$

Where $\mathcal{N}_i$ is the set of neighbors of agent $i$, and $a_{ij}$ is the interaction weight.

The system converges to consensus if the communication graph is connected:

$$\lim_{t \to \infty} x_i(t) = x^*, \forall i \in \{1,2,\ldots,N\} \tag{2}$$

Advantages: The simulation study results demonstrate the effectiveness and its advantages in terms of formation control performance and saving energy consumption [6].

Application Scenarios: UAV formation control, smart grids, distributed sensor networks.

### 2.2. Optimization-Based Consensus

Core Idea: Formulate the consensus problem as an optimization problem and solve it using distributed optimization algorithms.

Theoretical Framework:

Define a global objective function:

$$\min_{x_1,x_2,\ldots,x_N} \sum_{i=1}^{N} f_i(x_i) + \frac{\lambda}{2}\sum_{i=1}^{N} \sum_{j \in \mathcal{N}_i} \| x_i - x_j \|^2 \tag{3}$$

where $f_i(x_i)$ is the local objective function of agent $i$, and $\lambda$ is a regularization parameter.

Use distributed gradient descent to update states:

$$x_i(t+1) = x_i(t) - \eta\left(\nabla f_i(x_i(t)) + \lambda \sum_{j \in \mathcal{N}_i} (x_i(t) - x_j(t))\right) \tag{4}$$

Advantages: Can handle constraints and complex objective functions.

Application Scenarios: Resource allocation, distributed machine learning, task scheduling.

DOI: 10.54254/2755-2721/2025.22345

### 2.3. Event-Triggered Consensus Control

Core Idea: Reduce communication and computation by updating control inputs only when specific triggering conditions are met.

Theoretical Framework:

Define a triggering condition, e.g., update when the state error exceeds a threshold:

$$\| x_i(t) - x_j(t) \| > \delta \tag{5}$$

Update the control input only at triggering times $t_k$ :

$$u_i(t) = \sum_{j\in\mathcal{N}_i} a_{ij}(x_j(t_k) - x_i(t_k)) \tag{6}$$

The system converges to consensus with reduced communication:

$$\lim_{t\to\infty} \| x_i(t) - x_j(t) \| = 0 \tag{7}$$

Advantages: Saves communication and computational resources.

Application Scenarios: Wireless sensor networks, low-power devices, distributed control systems.

### 2.4. Game-Theoretic Consensus

Core Idea: Model the multi-agent system as a game and achieve consensus through Nash equilibrium or other game-theoretic concepts.

Theoretical Framework:

Each agent maximizes its utility function:

$$U_i(x_i, x_{-i}) = -\sum_{j\in\mathcal{N}_i} \| x_i - x_j \|^2 \tag{8}$$

Iteratively update states to reach Nash equilibrium:

$$x_i^{k+1} = \arg\max_{x_i} U_i(x_i, x_{-i}^k) \tag{9}$$

The system converges to consensus:

$$\lim_{k\to\infty} \| x_i^k - x_j^k \| = 0 \tag{10}$$

Advantages: Suitable for competitive or cooperative multi-agent systems.

Application Scenarios: Economic models, smart grids, distributed resource allocation.

Here are some novel methods.

### 2.5. Federated Learning-Based Consensus Optimization

Core Idea: Combine Federated Learning (FL) with distributed optimization to achieve consensus in multi-agent systems.

Theoretical Framework:

Each agent trains a local model and achieves global consensus through parameter aggregation:

$$\theta_i^{k+1} = \theta_i^k - \eta\nabla f_i(\theta_i^k) + \lambda\sum_{j\in\mathcal{N}_i} (\theta_j^k - \theta_i^k) \tag{11}$$

The objective is to minimize the global loss function:

$$\min_{\theta} \sum_{i=1}^{N} f_i(\theta) \tag{12}$$

Advantages: Protects data privacy and is suitable for distributed data scenarios.

Application Scenarios: Distributed machine learning, smart IoT, edge computing.

DOI: 10.54254/2755-2721/2025.22345

### 2.6. Physics-Informed Neural Networks (PINN) for Consensus Control

Core Idea: Embed system dynamics into neural networks using Physics-Informed Neural Networks (PINNs) to achieve consensus control.

Theoretical Framework:

Define the system dynamics:

$$\dot{x}_i = f(x_i, u_i) \tag{13}$$

Use neural networks to approximate the control policy $u_i = \pi(x_i; \theta)$.

Optimize network parameters with physical constraints:

$$\min_{\theta} \sum_{i=1}^{N} \| \dot{x}_i - f(x_i, \pi(x_i; \theta)) \|^2 + \lambda \sum_{i=1}^{N} \sum_{j\in\mathcal{N}_i} \| x_i - x_j \|^2 \tag{14}$$

Advantages: Combines physical models with data-driven methods for high precision and generalization.

Application Scenarios: Complex dynamic systems, intelligent robotics, aerospace.

### 2.7. Machine Learning-Based Consensus

Core Idea: Use machine learning techniques (e.g., reinforcement learning, neural networks) to learn consensus policies from data.

Theoretical Framework:

Define a reward function to encourage consensus:

$$r_i = -\sum_{j\in\mathcal{N}_i} \| x_i - x_j \|^2 \tag{15}$$

Train a policy $\pi_i$ using reinforcement learning:

$$\pi_i^* = \arg\max_{\pi_i} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_i(t)\right] \tag{16}$$

Use neural networks to approximate the policy or value function.

Advantages: Adaptable to complex and dynamic environments.

Application Scenarios: Autonomous vehicles, robotic swarms, distributed optimization.

## 3. Some Novel Approaches

Focusing on Intentional delay: Time delay is often inevitable due to the finite process time of interactions among agents and may influence system performance [7]. To address this issue, one can utilize intentional delay. By introducing delays, the system's sensitivity to external disturbances can be reduced, thereby enhancing its stability and reliability. However, intentional delays may also bring negative impacts. For instance, excessive delays can lead to degraded system performance or even instability. Additionally, the introduction of intentional delays may increase the complexity and design challenges of the system. So in the future, Better control over intentional delay is crucial.

Focusing on predefined-time dynamic event-triggered approach: The predefined-time dynamic event-triggered approach offers flexibility and stability, enabling precise control while reducing consumption. In future work, the proposed PDT dynamic ET control scheme can be attempted to be extended to other systems, such as hybrid-order/fractional-order chaotic systems, robotics, smart grids [4].

Focusing on Observer: The problem of unavailability of information in the topology switching process is solved by the designed observer. Subsequently, a novel fixed-time consensus controller based on observer is proposed [8]. Therefore, in the future, we can establish appropriate controllers

DOI: 10.54254/2755-2721/2025.22345

to enable the system to reach consensus, and this can also significantly enhance the stability of the system.

## 4. Future Work

Security and Privacy in Consensus Control - Privacy-preserving consensus protocols are also expected to be a key area of research. These protocols will need to strike a balance between security, privacy, and system performance.

Scalable and Robust Communication Protocols - Effective communication is the backbone of consensus in MAS. As systems grow in size, traditional communication protocols may become inefficient or unreliable. Future research will focus on developing scalable and robust communication protocols that can handle large numbers of agents while minimizing latency and packet loss. This includes exploring new technologies such as 5G and edge computing to enhance communication efficiency.

Real-Time Adaptation to Environmental Changes - MAS operating in real-world environments, such as autonomous vehicles or disaster response systems, must adapt quickly to changing conditions. Future consensus strategies will need to incorporate real-time adaptation mechanisms that allow agents to respond to environmental changes without disrupting the overall system. This includes developing algorithms that can dynamically adjust control parameters and communication strategies based on real-time feedback.

Cross-Domain Interoperability - As MAS are deployed across diverse domains, such as smart cities, healthcare, and industrial automation, achieving interoperability between systems with different protocols and standards becomes a significant challenge. Future consensus frameworks will need to bridge these gaps by developing universal communication protocols and middleware that can translate between different data formats. This will enable seamless collaboration between heterogeneous systems, unlocking new possibilities for large-scale MAS applications.

Resilience to Network Failures and Attacks - The increasing reliance on MAS in critical applications makes resilience to network failures and cyber-attacks a top priority. Network disruptions, whether caused by hardware failures or malicious attacks, can severely impact the system's ability to achieve consensus. Future control strategies will need to incorporate robust fault detection and recovery mechanisms. This includes developing algorithms that can identify and isolate faulty agents, reconfigure the network topology, and maintain consensus even under adverse conditions. These attackers, or adversaries, attempt to affect consensus with malice or steal information via various media. A typical group of adversaries can pretend to be a normal agent and send forged messages to others, so as to sabotage consensus. Thus, it is meaningful to design a resilient algorithm that can protect the consensus process against adversaries [9].

## 5. Main Challenge

Dynamic Role Adaptation and Conflict Resolution - Ensuring agents can dynamically adapt their roles and behaviors in real-time while resolving conflicts that arise from overlapping or contradictory objectives.

Heterogeneous Communication Protocols - Establishing seamless communication across agents with diverse architectures, languages, and protocols, while maintaining consistency and avoiding misinterpretation.

## 6. Conclusion

Consensus control in multi-agent systems (MAS) addresses challenges like resource constraints, environmental uncertainties, and agent heterogeneity through methodologies such as distributed

DOI: 10.54254/2755-2721/2025.22345

control, optimization-based strategies, event-triggered mechanisms, and game-theoretic models, balancing efficiency, adaptability, and robustness. Innovations like federated learning and physics-informed neural networks merge data-driven and model-based approaches for enhanced precision. Key challenges include managing stability-complexity trade-offs (e.g., intentional delays) and ensuring resilience against adversarial threats. Future priorities involve scalable communication protocols, real-time adaptation, cross-domain interoperability, and robust security frameworks as MAS expand into critical infrastructure. Integrating theory with practice will advance smarter, safer autonomous systems across diverse applications.

## References

[1] *Qiu, W., Wang, J., & Shen, D. (2025). Consensus control for multi-agent systems with unknown faded neighborhood information via iterative learning scheme. Inf. Sci., 708, 122050.*

[2] *X. You, C. Hua and X. Guan,(2018) "Event-Triggered Leader-Following Consensus for Nonlinear Multiagent Systems Subject to Actuator Saturation Using Dynamic Output Feedback Method," in IEEE Transactions on Automatic Control, vol. 63, no. 12, pp. 4391-4396.*

[3] *Olfati-Saber, R., & Murray, R.M. (2004). Consensus problems in networks of agents with switching topology and time-delays. IEEE Transactions on Automatic Control, 49, 1520-1533.*

[4] *Zou, H., Zhang, G., & Chen, Z. (2025). Optimal bipartite consensus control for nonlinear MASs: A new predefined-time dynamic event-triggered approach. Chaos, Solitons & Fractals.*

[5] *Y. Yang, B. Shen and Q. -L. Han. (2024) Dynamic Event-Triggered Scaled Consensus of Multi-Agent Systems in Reliable and Unreliable Networks. in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 54, no. 2, pp. 1124-1136.*

[6] *Gong, H., Er, M.J., Liu, Y., & Fan, G. (2025). Distributed data-driven three-dimensional optimal formation control for underactuated AUVs with actuator saturation and unknown dynamics. Ocean Engineering.*

[7] *Ma, Q., & Xu, S. (2023). Intentional delay can benefit consensus of second-order multi-agent systems. Autom., 147, 110750.*

[8] *Kong, B., Fu, X. (2025) Observer-Based Leaderless Fixed-Time Consensus of Multi-Agent Systems with Time-Varying Topology. Arab J Sci Eng.*

[9] *Huang, M., Wu, Y., & Huang, Q. (2025). Resilient and privacy-preserving consensus for multi-agent systems. Inf. Sci., 700, 121843.*