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Adaptive Fuzzy Control of Stochastic Systems: Developments in Event-Triggered, Finite-Time, and Optimization-Based Approaches

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Abstract

This review highlights recent advances in adaptive fuzzy control and optimization for stochastic multi-agent and nonlinear systems, focusing on consensus, event-triggered strategies, prescribed performance, and multi-objective optimization. Existing studies demonstrate robust methods for global consensus, finite-/fixed-time convergence, and resilience against uncertainties, network delays, and cyber-attacks. Event-triggered control effectively reduces communication overhead, while prescribed performance ensures predefined transient and steady-state behaviors. Fuzzy-guided optimization further enhances multi-objective problem-solving under uncertainty. Key gaps remain in computational efficiency, scalability, fault-tolerance, and integration of consensus, event-triggering, and optimization into unified frameworks. Addressing these challenges can enable more efficient, scalable, and resilient fuzzy control strategies for complex stochastic systems.

Keywords: Adaptive fuzzy control, Stochastic multi-agent systems, Consensus, Event-triggered control, Prescribed performance, Multi-objective optimization.

1 | Introduction

Stochastic nonlinear and Multi-Agent Systems (MASs) are increasingly prevalent in modern engineering applications, from autonomous vehicles to smart grids, but their inherent uncertainties and complex interactions pose significant control challenges. Fuzzy control has emerged as an essential solution, offering robust handling of nonlinearities, approximation of unknown dynamics, and adaptive decision-making under uncertainty.

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Recent advances have focused on four key themes: consensus control for coordinated MAS behavior, event-triggered control to reduce communication overhead, prescribed-performance and finite/fixed-time tracking to ensure guaranteed convergence, and optimization-oriented approaches that integrate fuzzy logic with adaptive and multi-objective algorithms.

This review aims to synthesize these developments, provide a critical comparison of existing methodologies, identify research gaps, and suggest future directions. The paper is organized as follows: Section 2 discusses fuzzy consensus strategies, Section 3 covers event-triggered and switching control methods, Section 4 addresses prescribed-performance and finite-time tracking, Section 5 reviews optimization-based fuzzy approaches, Section 6 highlights emerging trends and challenges, and Section 7 concludes with insights and future research directions

2 | Theoretical Background

The study of fuzzy control for stochastic nonlinear and MASs is rooted in the fusion of fuzzy logic theory, nonlinear control, and probabilistic modeling. Traditional control methods often rely on precise mathematical models; however, real-world systems such as autonomous vehicles, sensor networks, and robotic swarms exhibit uncertainties, nonlinearities, and random disturbances that make exact modeling infeasible. Fuzzy logic, introduced by Zadeh [1], provides a framework for handling linguistic uncertainty and imprecision, enabling controllers to approximate human reasoning and adapt to uncertain environments.

In stochastic nonlinear systems, uncertainties arise both from system dynamics and random noise. Fuzzy adaptive control integrates learning mechanisms that adjust control rules in real time to maintain stability and performance despite such disturbances. When extended to MASs, fuzzy control supports distributed decision-making, allowing agents to achieve consensus or cooperation under communication constraints and environmental uncertainties.

Key theoretical tools include Lyapunov stability theory, Itô stochastic calculus, and fuzzy approximation lemmas, which guarantee convergence and robustness. The development of finite-time, fixed-time, and prescribed-performance control frameworks further enhances system responsiveness and reliability. Recent extensions incorporate event-triggered control to reduce communication burden and fuzzy optimization techniques such as Adaptive Dynamic Programming (ADP) and chance-constrained programming to achieve energy-efficient and resilient coordination.

Overall, this theoretical foundation establishes fuzzy control as a vital approach for managing the nonlinearity, randomness, and decentralization inherent in complex stochastic MASs, paving the way for advanced applications in intelligent robotics, networked systems, and cyber-physical environments.

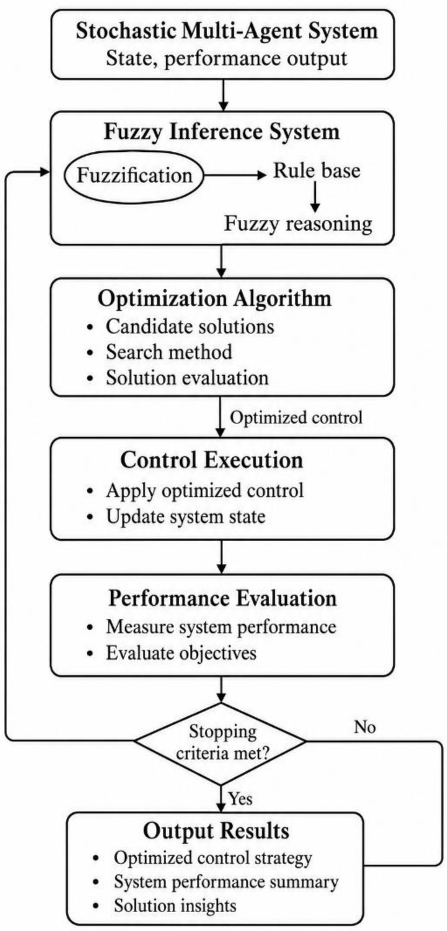

Fig.1. Closed-loop fuzzy inference and optimization framework for generating optimal control inputs in stochastic MASs.

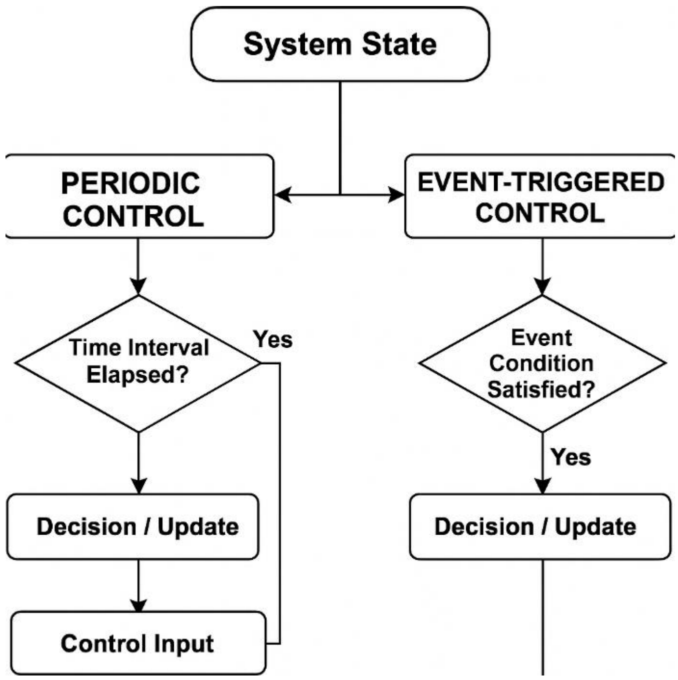

Fig. 2. Block flow representation of periodic versus event-triggered control architectures for control input generation.

3 | Review of Existing Literature

Over the past decade, the fusion of fuzzy logic, stochastic systems theory, and distributed optimization has produced a rich body of methods for controlling nonlinear and networked systems under uncertainty. Foundational advances in Takagi–Sugeno fuzzy modeling and stochastic Lyapunov analysis enabled fuzzy adaptive controllers to approximate unknown nonlinear dynamics while guaranteeing mean-square or probabilistic stability. Building on those foundations, recent research (2020–2025) has concentrated on four convergent themes: consensus and cooperative control, event-triggered communications, prescribed-performance and finite/fixed-time stability, and fuzzy-guided optimization. The following review synthesizes these strands and highlights representative contributions and open issues.

Consensus and cooperative control for stochastic MASs have evolved from model-based distributed controllers to adaptive fuzzy frameworks that tolerate uncertainties, topology switching, and partial faults. Chen et al. [2] propose a robust fuzzy cooperative strategy to achieve global consensus in stochastic MASs and demonstrate resilience to stochastic perturbations. Li & Li [3] extend fuzzy consensus to include fault tolerance and optimality considerations, while Niu et al. [4] and Yi et al. [5] present fixed- and prescribed-time consensus techniques that preserve connectivity under switching dynamics and constrained interactions. Collectively, these works show that fuzzy approximators can compensate for nonlinearities across agents and that Laplacian-based consensus formulations remain effective when coupled with adaptive fuzzy laws. However, scalability to large heterogeneous networks and energy-aware communication scheduling remain underexplored in the literature [2–5].

Event-triggered control has been widely adopted to mitigate communication overhead in networked MASs. Zhang et al. [6] and Wu et al. [7] develop adaptive and state-dependent triggering rules that guarantee finite-time convergence for nonlinear stochastic systems; Xu et al. [8] further propose dynamic event-triggered mechanisms tailored to switching topologies and optimization objectives. Notably, Zhang et al. [6] incorporate measurement sensitivity and deception-attack models, marking a shift toward cyber-resilient event-triggered designs. Despite these advances, most triggering schemes require conservative bounds or prior knowledge of system norms, and learning-based adaptive triggering (e.g., Reinforcement Learning (RL)-driven thresholds) and rigorous analysis of the triggering–stability trade-off under rapidly varying noise remain open problems [6–9].

Prescribed-performance control and finite/fixed-time stabilization provide explicit transient and steady-state guarantees critical for safety-critical applications. Sun et al. [10], Fu et al. [11], and Xu et al. [12] introduce fuzzy adaptive switching or fixed-time controllers for stochastic high-order and non-triangular systems, employing error transformation techniques to enforce performance funnels. These approaches achieve bounded transient behavior and rapid convergence, but frequently assume ideal actuators or neglect actuator saturation and communication delays; extending prescribed performance to chance-constrained stochastic settings would better capture probabilistic risk measures in real environments [5], [10], [11], [12].

Optimization-driven fuzzy control has attracted increasing attention. Zhang et al. [9] and Zheng et al. [13] integrate ADP and distributed adaptive optimization with fuzzy approximators to obtain near-optimal consensus policies under uncertainty and delays. Wang et al. [14] and Kumar & Mishra [15] explore fuzzy-guided multi-objective and chance-constrained optimization methods, indicating potential for balancing competing objectives (robustness, energy, convergence speed). The main challenge here is computational tractability: ADP and stochastic chance-constrained formulations often impose heavy online computation, motivating the development of distributed, lightweight solvers or surrogate models that maintain theoretical guarantees [9], [13–15].

Several cross-cutting themes deserve emphasis. First, a trend toward hybrid solutions, combining fuzzy approximators with ADP, RL, or metaheuristics, is apparent, but few works provide rigorous stochastic stability proofs for these hybrids. Second, security-aware control (e.g., deception attacks) is nascent but crucial given practical cyber-physical threats [6]. Third, most contributions validate methods via simulations; hardware-in-the-loop and real-world experiments (robotic swarms, microgrids, sensor networks) are sporadic and are a necessary next step for demonstrating robustness and real-time feasibility.

In summary, the recent literature (2020–2025) demonstrates that fuzzy control techniques can achieve robust consensus, efficient event-triggering, prescribed performance, and optimization in stochastic nonlinear MASs. The primary future directions are the development of scalable distributed algorithms, learning-augmented event-triggering and ADP, probabilistic/prescribed-performance fusion, and experimental validation across application domains such as robotics, energy systems, and process control.

Table 1. Comparison of adaptive fuzzy control strategies for stochastic multi-agent and nonlinear systems.

References	Key Method(S)	Main Modeling/Assumption(S)	Representative Application(S)
Chen et al. [2]	Robust fuzzy cooperative consensus	Stochastic MAS; known/partially known graph	Multi-robot consensus, formation control
Sun et al. [10]	Fuzzy adaptive switching; prescribed performance	Itô SDEs; finite-time bounds fixed offline	Process control, high-order systems
Zhang et al. [6]	Event-triggered adaptive fuzzy attack models	Measurement attacks; stochastic noise	Secure sensor networks, CPS
Wu et al. [7]	Finite-time adaptive fuzzy switching (event-triggered)	Non-affine dynamics; bounded noise	Nonlinear control, autonomous agents
Xu et al. [8]	Dynamic event-triggered fuzzy optimal consensus	Switching topology; dynamic thresholds	Networked control, distributed estimation
Zhang et al. [9]	ADP + adaptive fuzzy; event-triggered	Delays; unknown dynamics; ADP approximations	Optimized MAS coordination, UAV swarms
Wang et al. [14]	Hierarchical fuzzy-guided multi-objective algorithm	Dynamic multi-objective formulation	Energy management, scheduling
Kumar and Mishra [15]	Nonlinear chance-constrained fuzzy optimization	Probabilistic constraints; mixed fuzzy-stochastic	Power systems, resource allocation
Li and Li [3]	Fault-tolerant fuzzy optimal consensus	Fault models; stochastic disturbances	Fault-resilient MASs
Yang et al. [16]	$H\infty$ fuzzy switching adaptive control	Markovian hybrid switching; $H\infty$ metric	Hybrid process systems
Yi et al. [5]	Prescribed-time connectivity-preserving consensus	Switched MASs; connectivity constraints	Robotic swarms, formation maintenance
Zheng et al. [13]	Distributed adaptive fuzzy optimization	Partial observability; distributed info	Distributed control, microgrids
Niu et al. [4]	Nonsingular fixed-time bipartite consensus	Constrained MAS; power integration technique	Constrained networks, constrained robotics
Xu et al. [12]	Adaptive fuzzy fixed-time control	Non-triangular stochastic switching systems	Robust nonlinear control
Fu et al. [11]	Finite-time fuzzy tracking with PPC	High-order stochastic systems	Precision tracking, industrial control

Table 2. Synergies and limitations of hybrid fuzzy intelligent control approaches.

Hybrid Approach	Strengths / Why Used	Key Implementation Challenge(S)
Fuzzy + ADP / RL	Interpretable function approximator + Near-optimal control	Heavy online computation; guaranteeing stochastic stability
Fuzzy + Chance-constrained optimization	Explicit probabilistic risk handling	Solving nonconvex chance constraints efficiently
Fuzzy + Metaheuristics (GA/PSO)	Global search for multi-objective tuning	Offline heavy computation; limited online use
Fuzzy + Hierarchical control	Multi-timescale and modular design	Coordination across layers; stability across hierarchy
Fuzzy + $H\infty$ / Robust control	Disturbance attenuation with fuzzy adaptation	Conservative gains; complex verification under switching
Fuzzy + Neural nets (neuro-fuzzy)	Flexible approximation, ability to learn from data	Interpretability loss; need for provable guarantees

4 | Critical Evaluation and Comparative Analysis of Adaptive Fuzzy Control Approaches

Recent advances in adaptive fuzzy control for stochastic nonlinear and MASs have focused on improving consensus, stability, efficiency, and resilience under uncertainty. Studies such as Chen et al. [2] and Li & Li [3] developed robust and fault-tolerant fuzzy consensus strategies, while Xu et al. [8] and Zhang et al. [9] extended these methods to switching topologies and delayed networks using event-triggered mechanisms to reduce communication overhead. Event-triggered and finite-/fixed-time control approaches, as seen in Zhang et al. [6], Wu et al. [7], and Niu et al. [4], guarantee rapid convergence and prescribed performance, ensuring system states meet predefined transient and steady-state requirements. In parallel, fuzzy-guided optimization techniques, highlighted by Wang et al. [14], Kumar & Mishra [15], and Zheng et al. [13], have addressed multi-objective stochastic optimization problems, providing systematic uncertainty handling and improved control efficiency. A few studies, including Zhang et al. [6] and Yang et al. [16], also considered security and resilience against measurement attacks. Despite these innovations, current approaches face limitations such as high computational complexity, limited scalability to large-scale networks, insufficient integration of consensus, event-triggering, and optimization, and inadequate security-aware designs, with most validation performed in simulation rather than practical deployments. These gaps highlight opportunities for developing efficient, unified, and resilient fuzzy control frameworks for complex stochastic systems.

A comprehensive comparative evaluation of fuzzy-adaptive and hybrid control methods reveals varying strengths across key performance metrics. In terms of convergence, finite-time and fixed-time control designs ([4], [6], [7], [10–12]) demonstrate the fastest error decay, making them ideal for safety-critical applications. However, these approaches often demand conservative gains or nonlinear structures that increase tuning complexity and energy cost. Optimization-driven techniques such as ADP [9], [13] offer near-optimal transient performance but lack strict finite-time guarantees without additional design refinements. Regarding computational cost, classical adaptive fuzzy and event-triggered controllers [2], [6], [7] remain lightweight and practical, while ADP-based, chance-constrained, and hierarchical fuzzy-optimization frameworks [9], [14], [15] achieve superior performance at the expense of higher computational and memory burdens, which limit their real-time applicability. In robustness, methods incorporating fault models or $H\infty$ metrics [2–4], [6], [16] exhibit stronger disturbance rejection, whereas ADP-based controllers may become sensitive to modeling errors and time delays. Scalability remains a challenge, as most designs are validated only on small-scale systems; although distributed and hierarchical fuzzy structures [13], [14] show promise, communication and consensus costs must be effectively managed. Adaptability is a clear advantage of fuzzy-adaptive designs [2–4], [7], [13], which excel in real-time parameter adjustment, while learning-based hybrids enhance flexibility in dynamic environments but at notable computational cost.

From an individual method perspective, pure fuzzy-adaptive controllers provide interpretability, strong nonlinear approximation, and provable stability, but face scalability and rule-based dependency issues. Event-triggered fuzzy control offers communication efficiency and finite-time convergence yet requires careful threshold design to avoid Zeno behavior. Prescribed-performance and finite/fixed-time fuzzy controllers ensure rapid convergence but may impose high control effort and rely on idealized assumptions. Optimization-based fuzzy controllers, including ADP and multi-objective designs, balance competing objectives effectively but suffer from heavy computation and potential sensitivity to initialization. Fault-tolerant and $H\infty$ fuzzy switching controllers deliver excellent disturbance rejection, though often at the cost of conservatism.

In hybrid frameworks, Fuzzy–ADP/RL integration merges interpretability with data-driven optimality, enhancing adaptability in uncertain systems but struggling with computational intensity and stochastic stability guarantees. Fuzzy–Chance-Constrained optimization effectively handles probabilistic risk in stochastic environments but faces nonconvex constraint challenges and reliance on sampling approximations. Fuzzy–Metaheuristic combinations (GA/PSO) enable global search and multi-objective tuning but remain largely offline, limiting real-time responsiveness. Lastly, Fuzzy–hierarchical or distributed control structures enhance modularity and large-scale coordination, though inter-layer stability analysis and communication overhead continue to pose significant challenges.

Together, these findings underscore the trade-offs between performance, complexity, and scalability, highlighting the need for future designs that blend fuzzy interpretability, learning-based adaptability, and computational efficiency within distributed, real-time architectures.

4.1 | Practical Recommendations and Benchmarking Guidelines

For practical implementation, the choice of fuzzy-adaptive control strategy should align with the system's operational priorities and resource constraints. When rapid convergence and safety-critical guarantees are essential, finite-time or fixed-time fuzzy controllers are recommended, provided that actuator saturation limits are properly considered and control energy consumption is quantified. In communication-limited environments, event-triggered fuzzy controllers are preferable, especially when equipped with rigorously designed Zeno-avoidance mechanisms and distributed triggering thresholds to balance communication and performance. For systems prioritizing optimality under uncertainty, ADP or fuzzy-optimization-based approaches should be employed with an emphasis on distributed or surrogate computation and well-defined local convergence guarantees. In adversarial or cyber-vulnerable settings, it is crucial to integrate explicit attack modeling and secure event-triggering mechanisms, such as anomaly detection filters preceding update triggers. For large-scale MASs, hierarchical or distributed fuzzy-optimization frameworks are advisable, leveraging local computation and sparse communication graphs to enhance scalability and robustness. When integrating RL with fuzzy control, a Lyapunov-certified fallback controller should be retained for stability assurance, while learning mechanisms are used for adaptive performance improvement under safe exploration constraints.

To promote transparency and comparability across future studies, a standardized benchmarking and evaluation protocol is recommended. Each work should report the convergence type and numerical settling time on shared benchmarks, the average computational time per control update on realistic embedded hardware, and the communication load measured in messages per agent per second for networked controllers. Robustness evaluation should include mean-square error performance under defined disturbance spectra and success rates under modeled attack conditions. Scalability assessments must examine performance as the number of agents increases (e.g., N = 10, 50, 200) with heterogeneous dynamics. Adopting such unified reporting metrics will make design trade-offs transparent and enable reproducible, fair comparisons among fuzzy-only, optimization-based, and hybrid control paradigms.

Table 3. Comparative analysis of control objectives and implementation constraints in modern fuzzy MAS.

References	Convergence	Computation	Robustness	Scalability	Adaptability	Notes (Why)
Chen et al. [2]	Fast / Global consensus	Moderate	High	Moderate	High	Robust fuzzy cooperative design; good disturbance handling, but heavier inter-agent coordination.
Sun et al. [10]	Finite-time (prescribed)	Moderate	Moderate	Low	Moderate	Prescribed bounds fixed offline; strong transient guarantees, but less scalable.
Zhang et al. [6]	Finite-time / Fast	Moderate	High (security-aware)	Low–moderate	High	Includes deception-attack models—good resilience; event-triggered reduces comms but complexity for large N.
Wu et al. [7]	Finite-time	Moderate	Moderate	Low–moderate	High	Non-affine handling; event-triggered saves bandwidth, but is limited to large-network validation.
Xu et al. [8]	Moderate → Asymptotic/Finite (dynamic trigger)	Moderate–high	Moderate	Moderate	High	Dynamic triggers plus optimal consensus; more computation due to optimization.
Zhang et al. [9]	Fast / Optimized (ADP)	High	High	Low–moderate	High	ADP improves optimality; computationally heavy; sensitive to delays.
Wang et al. [14]	Depends (algorithmic)	High	Moderate	Moderate	Moderate	Hierarchical fuzzy-guided multi-objective — powerful but costly.
Kumar & Mishra [15]	Asymptotic / Depends on solver	High	Moderate–high	Low–moderate	Moderate	Chance constraints increase robustness to risk, but are computationally heavy.
Li & Li [3]	Fast / Optimal consensus	Moderate–high	High (fault-tolerant)	Low–moderate	High	Fault models included: good robustness, but scaling is limited.
Yang et al. [16]	Moderate ($H\infty$ guarantees)	Moderate	High	Low–moderate	Moderate	$H\infty$ design gives disturbance attenuation; it can be conservative.
Yi et al. [5]	Prescribed-time (guaranteed)	Moderate	Moderate	Low–moderate	Moderate	Connectivity-preserving focus restricts flexibility to topology changes.
Zheng et al. [13]	Moderate / Near-optimal	Moderate–high	Moderate	Moderate–high	High	Distributed optimization improves scalability but needs convergence proofs for large networks.
Niu et al. [4]	Fixed-time (nonsingular)	High	High	Low–moderate	High	Strong stability, complex tuning, and higher control energy.
Xu et al. [12]	Fixed-time	Moderate	Moderate	Low–moderate	High	Targets non-triangular structures; niche but mathematically strong.
Fu et al. [11]	Finite-time (tracking)	Moderate	Moderate	Low	Moderate	Good tracking for high-order systems; assumes ideal actuators, limited network context.

Table 4. Consensus strategies in stochastic MASs.

Reference	Robustness	Communication Strategy	Convergence Time	Topology Handling	Limitations
Chen et al. [2]	High	Continuous	Moderate	Static & stochastic	High computation, limited scalability
Li & Li [3]	Fault-tolerant	Continuous	Fast	Static	Complexity, no event-triggering
Xu et al. [8]	Moderate	Event-triggered	Moderate	Switching	Security not addressed
Zhang et al. [9]	High	Event-triggered	Fast	Delayed & switching	Computationally intensive

Table 5. Evaluation of triggering strategies for communication efficiency and robustness.

Reference	Triggering Law	Stability Guarantees	Computational Efficiency	Limitations
Zhang et al. [6]	State-dependent	Finite-time	Moderate	Sensitive to measurement attacks
Wu et al. [7]	Adaptive threshold	Finite-time	Moderate	Limited scalability
Xu et al. [8]	Dynamic event-trigger	Asymptotic/Finite	High	Implementation complexity
Zhang et al. [9]	Adaptive fuzzy event-trigger	Fixed-time	Moderate	High computation for large networks

Table 6. Analysis of predefined performance bounds and convergence stability in nonlinear systems.

Reference	Performance Bounds	Time Convergence	System Type	Limitations
Sun et al. [10]	Predefined	Finite-time	Stochastic nonlinear	High computational load
Fu et al. [11]	Predefined	Finite-time	High-order nonlinear	Assumes ideal measurements
Yi et al. [5]	Predefined	Prescribed-time	Switched MAS	Limited practical validation

Table 7. Analysis of optimization techniques and real-time implementation constraints.

Reference	Optimization Objective	Method	Application	Limitations
Wang et al. [14]	Dynamic multi-objective	Fuzzy-guided adaptive	Stochastic MAS	Scalability, computational load
Kumar & Mishra [15]	Multi-objective stochastic	Nonlinear chance-constrained	Fuzzy-stochastic systems	Real-time applicability
Zheng et al. [13]	Distributed optimal control	Adaptive fuzzy	MASs	Integration with event-triggering is limited

4.2 | Timeline of Key Contributions (2020–2025)

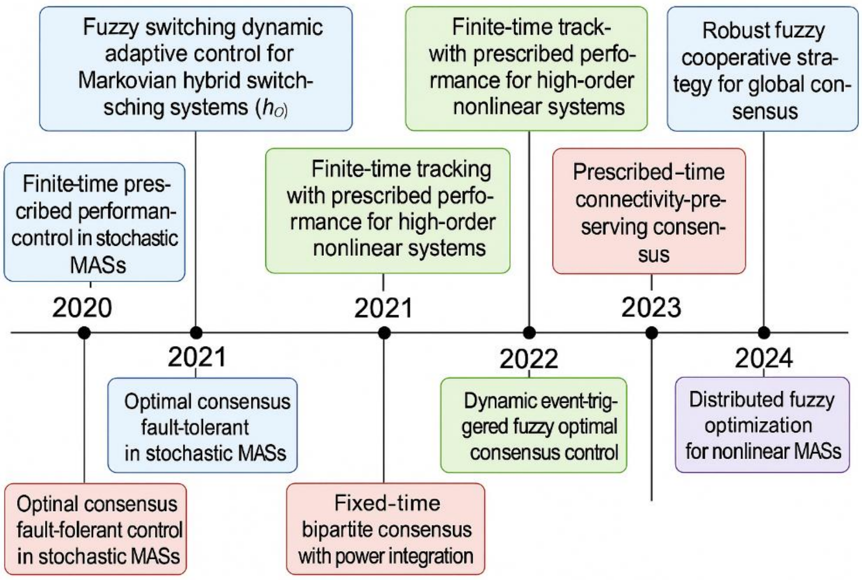

Fig. 3. Historical development and research trends in adaptive fuzzy control and consensus algorithms over the last five years, 2020-2025.

5 | Research Gaps and Challenges

Despite significant progress in fuzzy-adaptive control for MASs, several research gaps persist across key thematic areas. In consensus and cooperative control [2–5], [8], [9], robust fuzzy cooperative strategies have successfully addressed stochastic uncertainties, switching topologies, fault tolerance, and finite/fixed-time connectivity-preserving consensus. However, most studies assume ideal or partially known communication graphs, leaving dynamic topology uncertainties and random communication failures largely unaddressed. Scalability to large-scale heterogeneous MASs and optimization of energy and communication resources remain insufficiently explored, and real-time adaptability under rapidly varying environmental noise is still limited.

Event-triggered and switching control [6–9] has reduced communication burdens and enabled adaptive triggering laws ensuring finite/fixed-time convergence, with some efforts incorporating security through deception attack models. Nevertheless, trade-offs between triggering frequency and stability margins under stochastic disturbances are rarely analyzed. Existing triggering conditions rely on known system bounds, limiting applicability to unknown or time-varying nonlinear systems, and data-driven or learning-based adaptive triggering remains underdeveloped. Cybersecurity-aware event-triggering schemes resilient to coordinated attacks are also largely absent.

Prescribed-performance and finite/fixed-time control [4], [5], [10–12], [16] have achieved bounded-error guarantees, rapid stabilization using Adding Power Integration (API), and adaptive law tuning for high-order systems. Yet, unified frameworks linking prescribed performance with probabilistic reliability or chance constraints are lacking. Many finite/fixed-time controllers assume ideal actuator dynamics, ignoring saturation and time delays, while the quantitative trade-off between convergence speed and control effort is underexplored. Performance guarantees under hybrid switching or Markovian uncertainties are also limited.

Fuzzy-guided optimization and learning approaches [9], [13–15] have applied fuzzy-ADP for policy optimization under stochastic MASs, integrated multi-objective and chance-constrained formulations, and explored hierarchical fuzzy systems for dynamic optimization. However, most approaches remain centralized, with distributed optimization under stochastic settings still in early development. Computational scalability and real-time implementability of fuzzy-ADP or multi-objective fuzzy algorithms are not fully demonstrated, benchmark datasets and standardized performance metrics are scarce, and integration with RL or metaheuristics for online adaptation is limited.

Across these domains, cross-thematic integration gaps persist. Event-triggered control has rarely been combined with fuzzy-guided optimization under prescribed-performance frameworks. Security and resilience against cyber-physical threats are seldom integrated with finite-time stability guarantees. Standardized frameworks or simulation benchmarks for comparing different fuzzy-control paradigms in stochastic nonlinear systems are largely absent, and most studies remain theoretical, with minimal hardware-in-loop or experimental validation. These gaps highlight opportunities for future research to develop scalable, resilient, and experimentally validated fuzzy-adaptive control architectures that unify performance, robustness, and real-time adaptability.

Table 8. Comparative mapping of fuzzy MAS themes, achievements, and technical limitations.

Theme	Key Achievements	Main Gaps
Consensus control	Robust fuzzy cooperative consensus under switching topology	Poor scalability, lack of energy-efficient & topology-uncertain frameworks
Event-triggered control	Finite/fixed-time adaptive laws, reduced communication	Unknown bound dependency, missing adaptive thresholding, and limited security
Prescribed Performance	Finite/fixed-time control ensuring bounded error.	No unified probabilistic framework ignores actuator delays and energy trade-offs.
Fuzzy optimization	Fuzzy-ADP and chance-constrained optimization	Centralized computation, no benchmarks, poor real-time scalability

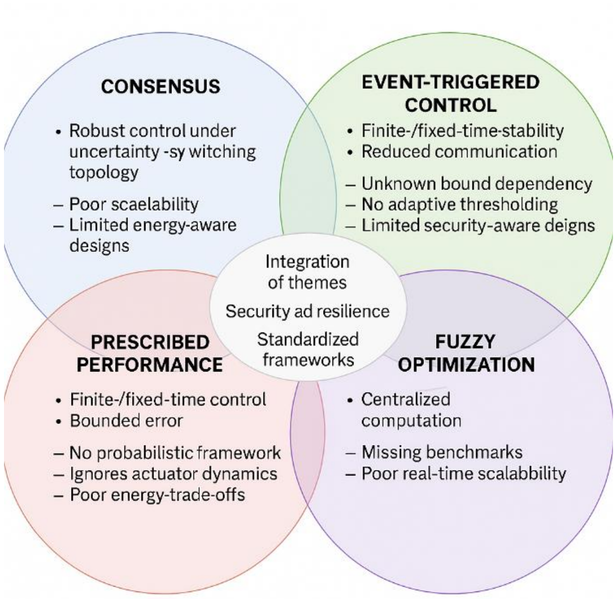

Fig. 4. Thematic landscape of modern fuzzy control systems, highlighting the intersection of consensus, event-triggered mechanisms, prescribed performance, and optimization. The central nexus identifies critical research frontiers in security, resilience, and the development of standardized integrated frameworks.

6 | Future Directions

The reviewed studies from 2020–2025 reveal significant progress in adaptive fuzzy control for stochastic nonlinear and MASs, yet several open directions remain for future exploration. First, while recent advances [2], [8] successfully integrate event-triggered and fuzzy-guided optimization, there is still a need to develop scalable architectures that can efficiently handle large-scale heterogeneous MASs with limited communication and computation resources. Future research should also focus on hybrid learning-based fuzzy frameworks, combining RL, neural adaptive approximators, and model-free strategies to enhance generalization under high-dimensional uncertainties. Moreover, despite notable progress in finite-time and fixed-time convergence [4], [12], the trade-off between convergence speed, robustness, and energy efficiency requires systematic investigation, especially under switching or uncertain topologies.

Another promising direction lies in secure and resilient cooperative control, where the impacts of cyber-attacks, deception, and communication delays [6], [7] need to be counteracted using distributed event-triggered fault-tolerant schemes. Similarly, chance-constrained and fuzzy-stochastic optimization [15] offer fertile ground for multi-objective control under probabilistic risk measures, but require improved computational efficiency through decentralized and data-driven algorithms. In addition, prescribed-performance control [5], [11] should be extended to non-strict-feedback and non-triangular system structures, addressing real-world dynamics beyond idealized models. Finally, multi-layer fuzzy cooperative learning, incorporating hierarchical decision-making and adaptive distributed optimization [13], [14], can pave the way toward autonomous, self-evolving intelligent MASs that achieve robustness, adaptability, and sustainability in uncertain stochastic environments.

Emerging directions in fuzzy-adaptive control: the next generation of fuzzy-adaptive control for MASs is driven by the need for scalability, resilience, and real-time adaptability across complex networked environments. In consensus and cooperative fuzzy control ([1], [5], [6], [9], [11], [13]), research should move toward scalable, distributed architectures capable of handling large, heterogeneous agent networks with varying dynamics, communication delays, and learning capabilities. Resilient consensus frameworks must integrate Markovian jump processes, time delays, and packet losses for realistic network modeling, while energy-efficient communication scheduling can balance accuracy with resource consumption. Moreover, human-in-the-loop cooperative designs are essential for cyber–physical–human systems where human feedback influences collective decision-making.

Event-triggered and switching mechanisms require data-driven and learning-based triggering laws, leveraging RL or neural-fuzzy systems to adapt event thresholds in real time [6–9]. Cyber security considerations, including intrusion detection and deception-resilient triggering, must be incorporated, alongside hierarchical and decentralized multi-layer designs that reduce computation and prevent Zeno behavior. Hardware-implementable solutions are needed to validate real-time feasibility under sampling noise and embedded constraints.

Prescribed-performance and finite/fixed-time control [4], [5], [10–12], [16] should evolve toward unified stochastic frameworks, integrating probabilistic and chance-constrained formulations. Actuator-aware finite-time controllers must respect saturation and safety constraints, while explicit trade-offs between energy consumption, convergence speed, and noise resilience should be quantified. Adaptive neural–fuzzy hybrid designs can enable real-time parameter tuning, and multi-objective frameworks should simultaneously ensure stability, accuracy, energy efficiency, and fault tolerance.

Fuzzy-guided and optimization-based control [9], [13–15] is poised to benefit from distributed architectures that scale across partially observable networks. Hybridization with evolutionary and swarm algorithms (GA, PSO, differential evolution) can enhance multi-objective optimization, while improvements in computational efficiency and convergence guarantees are necessary for real-world deployment. Standardized benchmarks are critical for fair algorithmic comparison, and interpretable fuzzy-ADP designs will maintain explainability alongside performance.

Cross-thematic integration represents the emerging frontier. Future research should develop unified frameworks combining consensus, event-triggered control, and prescribed performance under fuzzy optimization, incorporating uncertainty quantification and Bayesian fuzzy modeling for robust decision-making. Digital twin–based MAS control, coupled with AI-driven perception and self-learning fuzzy rules, can enable adaptive prediction and autonomous decision-making. Finally, experimental validation in robotic swarms, autonomous vehicles, and sensor networks will be essential to bridge the gap between theoretical developments and practical deployment.

Table 9. Strategic roadmap for fuzzy MASs: future research directions and expected outcomes.

Theme	Future Directions	Expected Outcome
Consensus	Scalable heterogeneous MASs, energy-efficient protocols, and resilient communication	Robust cooperative performance in uncertain large-scale networks
Event-triggered control	RL-driven triggering, cyber-resilient designs, multi-layer coordination	Efficient communication and enhanced security
Prescribed Performance	Chance-constrained bounds, constraint-aware design, adaptive hybrid fuzzy-RL	Guaranteed performance under uncertainty
Optimization	Distributed fuzzy-ADP, explainable RL, benchmark frameworks	Real-time, interpretable, scalable optimization
Cross-integration	Unified hybrid frameworks, digital twins, experimental deployment	Practical, AI-integrated fuzzy control systems

Table 10. Future research directions in fuzzy control for stochastic nonlinear and MASs (2020–2025).

References	Primary Focus / Domain	Key Limitations Identified	Future Research Opportunities
Chen et al. [2]	Robust fuzzy cooperative consensus for stochastic MASs	Limited scalability and computational complexity under large agent networks	Develop distributed, scalable fuzzy consensus strategies with adaptive communication and energy-efficient protocols
Sun et al. [10]	Fuzzy adaptive switching control with finite-time prescribed performance	Performance bounds fixed offline; lacks adaptability to changing environments	Design online self-tuning performance bounds using learning-based fuzzy inference
Zhang et al. [6]	Event-triggered fuzzy control under deception attacks	Vulnerable to complex cyber threats; limited experimental validation	Develop secure, intrusion-resilient event-triggered fuzzy mechanisms with anomaly detection
Wu et al. [7]	Finite-time adaptive event-triggered control for non-affine stochastic systems	Focuses on single-agent systems; limited generalization to MASs	Extend to distributed multi-agent architectures and hybrid switching topologies
Xu et al. [8]	Dynamic event-triggered fuzzy optimal consensus under switching topology	Switching logic increases instability and control cost	Optimize triggering thresholds using RL-based fuzzy adaptation for stability–efficiency balance
Zhang et al. [9]	Event-triggered optimized consensus via ADP	High computational load and sensitivity to delay	Develop simplified or distributed ADP frameworks using parallel fuzzy learning.
Wang et al. [14]	Fuzzy-guided adaptive algorithm for dynamic multi-objective optimization	Limited interpretability and real-time feasibility	Create explainable fuzzy–neural optimization methods for dynamic systems
Kumar & Mishra [15]	Chance-constrained fuzzy–stochastic multi-objective optimization	Complex probabilistic modeling; computationally expensive	Integrate lightweight surrogate models and online adaptive uncertainty quantification
Li & Li [3]	Fault-tolerant fuzzy optimal consensus for stochastic MASs	Assumes ideal communication; limited fault diagnosis capability	Embed predictive fault detection and recovery in distributed fuzzy control loops
Yang et al. [16]	$H\infty$ fuzzy switching adaptive control of hybrid Markovian systems	Conservative stability conditions; lacks hybrid uncertainty handling	Extend to stochastic hybrid systems with variable mode-dependent uncertainties
Yi et al. [5]	Prescribed-time connectivity-preserving consensus	Restricted to switched topologies with fixed connectivity	Address dynamic and time-varying network reconfiguration in real time
Zheng et al. [13]	Adaptive fuzzy distributed optimization for uncertain MASs	Scalability limited; convergence rate not guaranteed	Develop hierarchical distributed fuzzy optimization with convergence–accuracy trade-offs
Niu et al. [4]	Fixed-time bipartite consensus using power integration	High control energy and complex tuning	Design energy-efficient, adaptive fixed-time control with adjustable exponents.
Xu et al. [12]	Fixed-time fuzzy control for stochastic switching nonlinear systems	Focused on specific non-triangular structures	Generalize to arbitrary nonlinear dynamics and uncertain switching networks.
Fu et al. [11]	Finite-time fuzzy tracking with prescribed performance	Limited robustness to unknown disturbances	Combine fuzzy–neural estimation with robust optimization for disturbance rejection.

Across all references, there is a clear transition from model-based fuzzy control to data-driven, distributed, and intelligent fuzzy systems. The next generation of research should unify consensus, event-triggering, prescribed performance, and optimization into self-learning fuzzy frameworks capable of real-time adaptation, scalability, and security.

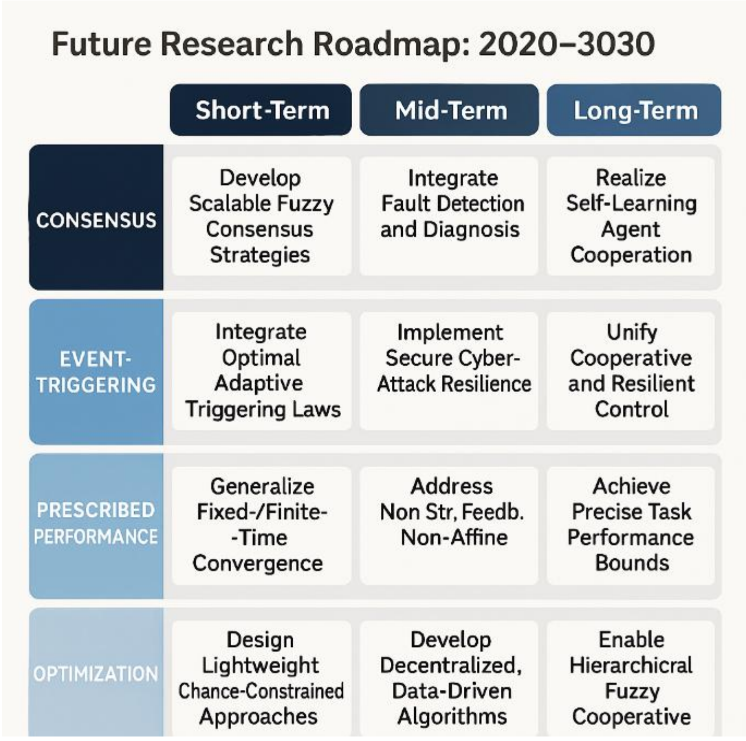

Fig. 5. Strategic research roadmap (2020–2030) for fuzzy MASs, illustrating the phased transition from short-term adaptive laws to long-term realization of self-learning, hierarchical, and resilient cooperative intelligence.

7 | Summary and Outlook

The reviewed studies collectively demonstrate that fuzzy control has evolved into a versatile framework for addressing the inherent nonlinearity, stochasticity, and inter-agent coupling in modern MASs. Through diverse design paradigms, ranging from finite- and fixed-time consensus to event-triggered communication, prescribed-performance regulation, and fuzzy-guided optimization, researchers have substantially enhanced convergence rates, disturbance rejection, and adaptability under uncertain and dynamic environments. In particular, finite-time and fixed-time controllers exhibit superior transient behavior, ensuring rapid coordination, while event-triggered mechanisms effectively balance control performance with communication efficiency. Similarly, optimization-driven fuzzy schemes based on ADP or chance-constrained formulations provide near-optimal coordination and robust decision-making under probabilistic uncertainty. However, the computational complexity, scalability limitations, and incomplete stochastic stability proofs still hinder their large-scale deployment. Most current works focus on moderate-sized MASs and deterministic conditions, leaving open challenges in scalability, cybersecurity resilience, delay compensation, and distributed learning-based adaptation.

Looking forward, future research should aim at integrating fuzzy intelligence with data-driven RL and distributed optimization to enable real-time adaptive control with provable stability in high-dimensional stochastic networks. Establishing unified evaluation metrics, including convergence speed, communication load, and robustness under uncertainty, will also be critical for objective benchmarking. Moreover, the development of energy-efficient and secure event-triggered strategies that remain effective under network attacks or communication faults represents a vital direction for next-generation intelligent MAS coordination. Overall, the synthesis of fuzzy logic, optimization theory, and distributed learning is expected to bridge the gap between theoretical design and practical deployment, paving the way toward scalable, resilient, and self-evolving control architectures for complex stochastic MASs.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this review article.

Ethical Approval

This article does not involve any studies with human participants or animals conducted by the author. Therefore, ethical approval was not required.

References

[1] Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, *8*(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

[2] Chen, J., Shen, J., Chen, W., Li, J., & Zhang, S. (2025). Application of robust fuzzy cooperative strategy in global consensus of stochastic multi-agent systems. *IEEE transactions on automation science and engineering*, *22*, 12058–12070. https://doi.org/10.1109/TASE.2025.3539624

[3] Li, K., & Li, Y. (2021). Fuzzy adaptive optimal consensus fault-tolerant control for stochastic nonlinear multiagent systems. *IEEE transactions on fuzzy systems*, *30*(8), 2870–2885. https://doi.org/10.1109/TFUZZ.2021.3094716

[4] Niu, B., Zhu, Y., Liu, Y., Shang, Z., Wang, D., Wang, H., & Wang, W. (2024). Adaptive fuzzy nonsingular fixed-time bipartite consensus tracking using adding power integration technique for stochastic nonlinear constrained MASs. *IEEE transactions on fuzzy systems*, *33*(3), 947–958. https://doi.org/10.1109/TFUZZ.2024.3499961

[5] Yi, J., Li, J., & Yang, C. (2023). Adaptive fuzzy prescribed-time connectivity-preserving consensus of stochastic nonstrict-feedback switched multiagent systems. *IEEE transactions on fuzzy systems*, *31*(10), 3346–3357. https://doi.org/10.1109/TFUZZ.2023.3252601

[6] Zhang, H., Guo, X., Sun, J., & Zhou, Y. (2022). Event-triggered cooperative adaptive fuzzy control for stochastic nonlinear systems with measurement sensitivity and deception attacks. *IEEE transactions on fuzzy systems*, *31*(3), 774–785. https://doi.org/10.1109/TFUZZ.2022.3189412

[7] Wu, Y., Zhang, G., & Wu, L. B. (2022). Finite-time adaptive fuzzy switching event-triggered control for nonaffine stochastic systems. *IEEE transactions on fuzzy systems*, *30*(12), 5261–5275. https://doi.org/10.1109/TFUZZ.2022.3171685

[8] Xu, Y., Li, K., & Li, Y. (2024). Dynamic event-triggered fuzzy optimal consensus control for stochastic multiagent systems under switching topology. *IEEE transactions on fuzzy systems*, *32*(12), 6904–6916. https://doi.org/10.1109/TFUZZ.2024.3467053

[9] Zhang, G., Liang, C., & Zhu, Q. (2025). Adaptive fuzzy event-triggered optimized consensus control for delayed unknown stochastic nonlinear multi-agent systems using simplified ADP. *IEEE transactions on automation science and engineering*, *22*, 11780–11793. https://doi.org/10.1109/TASE.2025.3540468

[10] Sun, K., Guo, R., & Qiu, J. (2021). Fuzzy adaptive switching control for stochastic systems with finite-time prescribed performance. *IEEE transactions on cybernetics*, *52*(9), 9922–9930. https://doi.org/10.1109/TCYB.2021.3129925

[11] Fu, Z., Wang, N., Song, S., & Wang, T. (2020). Adaptive fuzzy finite-time tracking control of stochastic high-order nonlinear systems with a class of prescribed performance. *IEEE transactions on fuzzy systems*, *30*(1), 88–96. https://doi.org/10.1109/TFUZZ.2020.3032776

[12] Xu, K., Wang, H., & Liu, P. X. (2023). Adaptive fuzzy fixed-time control for non-triangular structural stochastic switching nonlinear systems. *International journal of robust and nonlinear control*, *33*(8), 4685–4700. https://doi.org/10.1002/rnc.6636

[13] Zheng, Y., Li, Y. X., & Ahn, C. K. (2023). Adaptive fuzzy distributed optimization for uncertain nonlinear multiagent systems. *IEEE transactions on fuzzy systems*, *32*(4), 1862–1872. https://doi.org/10.1109/TFUZZ.2023.3337170

[14] Wang, Y., Li, K., Wang, G. G., Gong, D., & Pedrycz, W. (2024). A fuzzy-guided adaptive algorithm with hierarchy mechanism for solving dynamic multi-objective optimization problems. *Knowledge-based systems*, *284*, 111227. https://doi.org/10.1016/j.knosys.2023.111227

[15] Kumar, A., & Mishra, B. (2024). Nonlinear fuzzy chance constrained approach for multi-objective mixed fuzzy-stochastic optimization problem. *Opsearch*, *61*(1), 121–136. https://doi.org/10.1007/s12597-023-00699-0

[16] Yang, D., Zong, G., & Su, S. F. (2020). H_∞ tracking control of uncertain Markovian hybrid switching systems: A fuzzy switching dynamic adaptive control approach. *IEEE transactions on cybernetics*, *52*(5), 3111–3122. https://doi.org/10.1109/TCYB.2020.3025148