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Research Article

Communication Structure Adaptive Control and Collaborative Optimization for Multi-Agent Systems

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Abstract:

Multi-agent systems(MAS) rely on adaptive communication architectures to coordinate, scale, and maintain robustness in dynamic settings where fixed topologies fail. By adjusting connections under uncertainty, agents preserve connectivity while reducing resource use, yet combining adaptation with collaborative optimization remains fragmented. Reviewing over fifty key works from 2003 to 2025, we present a unified taxonomy of communication paradigms (static vs. dynamic; directed vs. undirected; hierarchical vs. peer-to-peer; sparse vs. dense), adaptive-control strategies (model-free protocols, learning-driven topology updates, fault-resilient controls), and cooperative optimization methods. Advances in distributed consensus, event-triggered messaging, and quantized communication have dramatically lowered bandwidth requirements without sacrificing performance, and algebraic connectivity is shown critical for convergence rates. Despite progress, challenges persist in scalability, privacy/security in distributed coordination, and trust-aware human–robot interaction. We propose future directions toward privacy-preserving protocols, enhanced communication security, and interpretable coordination frameworks.

1. Introduction

Multi-agent systems demand flexible communication to ensure coordination, scalability, and robustness where fixed networks fail [1]. Algebraic connectivity governs convergence and resilienc [2], while dynamic topologies adapt links to preserve connectivity when conditions change—consensus succeeds if graph unions regularly contain a spanning tree [3,4]. Information timing, reliability, and acquisition cost inform adaptation design [5], yielding gains in efficiency, robustness, scalability, and task-specific tuning. Representative methods include model-free protocols (backstepping; reinforcement learning), learning-driven topology optimization (graph neural networks; large language models), and fault-tolerant schemes addressing failures or cyberattacks. Collaborative optimization via distributed consensus [3], clock synchronization [6], and weighted-median opinion dynamics [7] refines both information content and routing. Integrated frameworks—such as end-to-end multi-agent deep reinforcement learning [8], the FC-MAS five-layer model [9], and nonlinear decision designs that balance speed with flexibility [10]—aim to unify communication and control under real-world constraints. Remaining challenges include scaling to hundreds or thousands of agents, preserving privacy and security during adaptation, and designing interpretable, trust-aware channels for human–agent interaction. Future research should co-design communication and control, develop privacy-preserving adaptive protocols, craft human-interpretable interfaces, and explore quantum-enhanced communication for greater bandwidth and security.

2. Communication Structures in MAS

2.1 Topology Taxonomy

Static topologies keep links fixed, simplifying analysis and ensuring predictable consensus via algebraic connectivity, but they cannot adapt to changes. In fixed graphs, connectivity directly influences convergence speed, while dynamic interaction graphs still achieve consensus if their union frequently contains a spanning tree. Undirected graphs use bidirectional links and yield symmetric Laplacians with favorable convergence, whereas directed graphs introduce asymmetric constraints—e.g., power limits or interference—that complicate analysis, requiring event-triggered schemes for leader–follower consensus in directed settings [12]. Hierarchical structures assign roles to reduce communication complexity yet risk single-point failures; multi-level cliques can confine failures in very-large-scale systems. Peer-to-peer architectures treat all agents equally, relying on local interactions; sequence-averaging consensus over quantized data maintains convergence, emphasizing robustness and scalability despite increased communication [13,15]. Sparse topologies limit each agent's neighbors—lowering communication burdens but slowing information spread—while high-pass filters let agents estimate connectivity in sparse directed graphs and autonomously adjust links [16]. Dense topologies speed data dissemination but raise overhead; integrating differential privacy into distributed optimization demonstrates that privacy and convergence can coexist even in dense networks [14,16].

2.2 Connectivity and Efficiency Metrics

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Algebraic connectivity—the second-smallest Laplacian eigenvalue—quantifies network connectedness and correlates strongly with consensus convergence rate [3]. Distributed high-pass filters allow agents to estimate true connectivity without global knowledge and optimize links in real time [16]. Trust-based consensus algorithms adjust weights across multiple channels to enhance reliability under uncertain communications [14,17], as shown in Figure 1. Communication cost comprises bandwidth, energy, and computational complexity; sequence averaging in quantized scenarios reduces bandwidth usage while preserving convergence, and balancing heterogeneous energy costs can optimize second-order consensus–based clock synchronization [6]. Integrating differential privacy into optimization need not impose prohibitive computational loads, enabling real-time performance [15,16]. Redundancy and resilience—measured via edge connectivity—determine a network's ability to withstand failures: dynamic event-triggered strategies reduce communication while bolstering robustness under node failures in directed graphs [12], hierarchical clustering localizes failures to prevent cascading breakdowns [13], and privacy mechanisms can be integrated without significantly degrading resilience [16].

2.3 Topological Influences and Design Considerations

Topology directly affects consensus: higher algebraic connectivity yields faster agreement [3], yet even limited but well-designed connectivity can achieve timely clock synchronization under energy constraints [6]. Asynchronous reinforcement-learning approaches adapt topologies to maintain stability in dynamic networks [11]. In distributed optimization, topology influences both convergence speed and solution quality: strong connectivity is crucial for privacy-preserving optimization, where perturbing states and directions ensures convergence under differential privacy, and sequence averaging over quantized links prevents divergence, enabling efficient optimization in sparse, low-bandwidth environments [15,16]. System robustness to disturbances and attacks also depends on topology: dynamic event-triggered strategies maintain stability in directed networks despite communication disruptions [12], while hierarchical clustering confines failures locally to sustain large-scale operation [13]. Practical MAS topologies must balance task requirements, resource constraints, scalability, and security—high connectivity accelerates information flow for time-critical tasks, whereas long-term monitoring may prioritize energy efficiency. Combining multiple communication channels can boost performance without additional hardware [17], efficient connectivity estimation helps large-scale networks maintain performance as they grow [16], and integrating differential privacy into optimization addresses security concerns without unduly sacrificing resilience [14,16].

3. Adaptive Control Techniques

3.1 Model-Free Adaptive Control

Model-free methods enable agents to optimize coordination without explicit system models, fitting complex, uncertain multi-agent settings. Backstepping constructs controllers recursively for strict-feedback nonlinear systems, ensuring stability via Lyapunov functions and virtual controls; when combined with neural-network-based reinforcement learning, it adapts both communication and control parameters to achieve synchronized tracking without solving the full HJB [18,19,21,20]. Despite rigorous stability guarantees, backstepping's "explosion of terms" and reliance on full-state feedback complicate implementation in high-order or partially observed systems. Reinforcement learning (RL) lets agents discover optimal policies through trial-and-error, removing dependence on known dynamics. Multi-agent RL architectures mix Q-values with macro-action fusion to manage heterogeneity and asynchrony, using attention and value-decomposition to tailor communication strategies locally [11,22]. However, RL's high computational cost, uncertain convergence in safety-critical contexts, and the exploration–exploitation trade-off remain challenges for resource-limited MAS.

3.2 Learning-Based Topology Adaptation

Machine learning can directly adapt communication topologies by operating on graph structures or leveraging semantic understanding. Graph Neural Networks (GNNs) learn communication patterns from graph-structured data, using edge-enhanced attention to weigh neighbor influences and update link weights end-to-end [23,24]. GNNs naturally handle heterogeneous agents and often scale with the number of edges, but training and inference overheads may exceed individual agent capabilities, and ensuring learned topologies preserve connectivity and robustness is still unresolved. Large-scale language models (LLMs) promise semantic-aware communication—enabling agents to compress, prioritize, and contextually interpret messages. Early work combining deep RL with GNNs for traffic engineering foreshadows LLM-based methods that use semantic insights to reduce redundancy and prioritize critical information [25]. Potential applications include semantic compression of observations, context-aware message scheduling, cross-domain translation among heterogeneous agents, and intent inference to minimize explicit communication. Practical hurdles involve large model sizes, inference latency, and limited interpretability. Hybrid designs that employ LLMs for semantic preprocessing alongside lightweight real-time protocols may be required for safety-critical MAS.

3.3 Fault-Tolerant & Resilient Control

Real-world MAS must withstand actuator faults, communication disruptions, and cyberattacks. Adaptive fault-tolerant controllers use virtual actuator frameworks and fuzzy logic to approximate unknown nonlinearities, guaranteeing bounded tracking errors even under DoS attacks and intermittent failures [21,26,27]. Common strategies include adaptive parameter estimation, virtual actuator reconfiguration, and distributed observers for joint fault estimation. However, handling simultaneous faults across multiple agents—where errors propagate through coupled dynamics—and balancing redundancy against resource constraints remain open challenges. Cyber-attack mitigation must address threats like Denial-of-Service (DoS), which can block communication and disrupt coordination. Distributed observer-based adaptive consensus controllers employ secure observers to estimate unavailable data and integrate filters with backstepping to robustly handle concurrent DoS attacks and actuator faults [20,21]. Modeling the MAS as a switched system under various attack scenarios, with average dwell-time analysis, can guarantee stability [27]. Effective mitigation relies on resilient estimators, event-triggered communication to reduce attack surfaces, secure consensus protocols robust to adversarial manipulation, and trust-based mechanisms to discount compromised agents. Detecting subtle data-manipulation attacks and quantifying the trade-off between security measures and performance remain active research areas, underscoring the importance of co-designing physical fault tolerance with cyber-resilience.

4. Collaborative Optimization Strategies

4.1 Distributed Consensus and Optimization

Consensus protocols iteratively align agents' local estimates through neighbor interactions. Convergence depends on algebraic connectivity, and event-triggered bipartite-consensus schemes use saturation functions and resilient laws to maintain agreement under DoS attacks, provided attack duration and frequency remain bounded [34]. For convex optimization with state uncertainties, gradient-tracking methods with projection-error compensation ensure deterministic linear convergence under fixed step sizes, despite noise [30]. In directed graphs, "optimize-then-agree" schemes decouple optimization and consensus, achieving convergence to an $O(\eta)$ neighborhood of the global optimum for any $\eta>0$ [29].

In competitive settings, Nash-equilibrium algorithms identify stable strategies where no agent benefits from deviation. Timestamped inertial best-response dynamics handle asynchronous updates and delays, offering almost-sure convergence under mild network switching and connectivity conditions [33], while surveys classify equilibrium methods by convergence rate, information needs, and game structure [32].

For distributed optimization without central coordination, agents with private costs cooperate using event-triggered schemes that respond to state errors, neighbor deviations, or exponential thresholds. These converge globally while avoiding Zeno behavior [28]. In binary, ultra-low-bandwidth systems, efficient encoding/decoding enables bounded consensus error with single-bit exchanges, proving effective under strict communication limits [31].

4.2 Event-Triggered and Quantized Communication

Event-triggered control fires only when state-dependent thresholds are crossed, cutting transmissions by ~80% in bipartite consensus and vibration suppression under time-varying actuator faults while preserving stability [35]. Combining neural approximation with barrier-Lyapunov designs yields an event-triggered battery controller that enforces state-of-charge and temperature limits with far fewer messages [36]. Most triggers use Lyapunov-based thresholds; security arises by treating DoS attacks as communication disruptions and compensating to maintain stability [34].

Quantized communication maps continuous signals to discrete levels, reducing transmission size. In binary-only networks, encoding/decoding schemes achieve bounded consensus errors with single-bit exchanges [31]. Paired with event-triggering, only compressed data is sent on triggers, often cutting communication by orders of magnitude. Learning-based methods tune thresholds and quantization using historical data for added efficiency.

Practical deployment must handle delays, packet loss, and synchronization. Robust triggers account for time-varying delays, and modeling DoS-induced delays with compensation preserves stability [34]. Since asynchronous triggers can destabilize, self- or predictive-triggered schemes schedule transmissions in advance, and minimum inter-event intervals prevent Zeno behavior.

So, we unifies fragmented efficiency claims in Sec 4.1/4.2 into one comparable framework, covering all major strategies (event-triggered, quantized, gradient-tracking), as shown in Table 1.

5. Integrated Adaptive–Collaborative Frameworks

5.1 Co-Design Architectures

Co-design recognizes that fixing topology before designing controllers can be suboptimal. One approach uses a graph-recurrent neural parameterization to model both a distributed controller and its communication graph compactly, formulating a joint ℓ_1-regularized empirical-risk problem solved via stochastic gradient descent. By explicitly balancing communication sparsity against control accuracy as shown in Figure 2, these controllers match more complex alternatives while using far fewer parameters, illustrating the resource–performance tradeoff [38].

In systems with flexible manipulators subject to actuator faults and parametric uncertainties, a unified consensus framework reconstructs fault terms and estimates unknown dynamics online. A Lyapunov-based design then ensures rigid-body synchronization and vibration suppression remain uniformly ultimately bounded despite disturbances—demonstrating how co-design can satisfy multi-objective demands (coordination + mitigation) within a single optimization loop [39].

For linear agents over directed graphs, a fully distributed optimal-control scheme lets each agent use only neighbor information—assuming a spanning tree exists—to solve local optimization equations that collectively minimize a global cost. This implicitly identifies necessary links without requiring global topology knowledge, reducing information exchange while preserving optimal behavior [43].

Across these examples, co-design architectures share three core traits:

1. Communication topology and control gains are tuned concurrently rather than sequentially.
2. Performance–communication tradeoffs are modeled explicitly, often via sparsity regularization.
3. Implementation remains fully distributed, relying solely on local data.

By treating communication and control as interdependent decision variables, co-design frameworks achieve better resource efficiency and robustness than decoupled designs.

5.2 Data-Driven and Online Adaptation

Even a co-designed system can suffer from unexpected topology changes, failures, or disturbances. Data-driven adaptation monitors metrics—like algebraic connectivity or tracking error—and adjusts links or control parameters in real time. A distributed connectivity estimator lets agents gauge network robustness despite packet loss and varying link quality; by tuning convergence and robustness parameters, they add or prune links to maintain optimal connectivity [40]. Adaptive dynamic programming uses only real-time I/O data to compute near-optimal controls, compensating actuator faults and disturbances without explicit models or full-state measurements, thus preserving performance under uncertainty [41]. In competitive games, first- and zeroth-order Nash-equilibrium dynamics achieve fixed-time convergence using only cost-function measurements; this model-free, multi-time-scale scheme reaches equilibrium within a bounded time regardless of initial conditions, suiting rapidly changing, partially observable settings [42]. Type-2 fuzzy controllers for flexible robots without full-state feedback solve LMIs or use fuzzy inference to compute compensation gains; simulations on a four-robot network show significant performance gains under uncertainty, illustrating how fuzzy adaptation refines controllers with limited information [44]. Together, these methods update parameters from observed data, embed fault resilience in learning, and rely solely on local computations. Integrated with co-design, they form a holistic paradigm: co-design sets communication–control tradeoffs, while online learning sustains optimal performance in dynamic, uncertain, and resource-constrained environments.

6. Application Domains

6.1 Autonomous Vehicles and Platooning

CACC leverages vehicle-to-vehicle communication for safe distances and traffic stability. Cui et al. (2022) developed robust CACC addressing malware, phishing, and DNS tunneling attacks [45]. Their hybrid All-Predecessor Following and Predecessor-Leader Following topology enhances robustness, with simulations validating cruising capabilities and time delay switch attack resistance.
Yu et al. (2022) analyzed communication interruption impacts on heterogeneous traffic [51]. Modeling bogus messages and delays with driver takeover responses, they demonstrated failure propagation causing potential instability. Middle-position degraded vehicles proved safer during partial failures.

6.2 Networked Robotics and Formation Control

Formation control coordinates robots maintaining spatial configurations, balancing communication efficiency with performance as shown in Figure 3. Zhan et al. (2023) addressed nonholonomic coordination via event-triggered finite-time control under DoS attacks [46]. Their distributed observers narrow error boundaries using projection operations; event-triggered mechanisms identify attacks through timestamp verification, maintaining robust formation despite disruptions.

Kratky et al. (2025) introduced CAT-ORA for three-dimensional coordination [52]. Using Hungarian algorithm for robot-to-goal assignment with collision avoidance, this minimizes transition time—valuable for battery-powered UAVs where operation time impacts endurance.

6.3 Smart Grids and Microgrids

Smart grids implement multi-agent coordination in critical infrastructure. IEEE 2030.5-2023 standardizes grid-user interfaces enabling demand response, load control, and energy storage [48]. Qiu and Wang (2023) achieved stability through adaptive event-triggered regulation for islanded AC microgrids with communication faults [47]. Fathima and Premalatha (2025) developed resilient schemes protecting DC microgrids, interrupting faults in 2.64 milliseconds [49]. Sarker et al. (2023) created security testbeds ensuring essential loads remain served despite contingencies [50].

7 Challenges and Future Directions

7.1 Scalability and Complexity

Large-scale systems face exponential computational growth. Ma et al. (2024) addressed this via decentralized policy optimization enabling local agents to infer global dynamics [53]. Their ξ-dependent networked MDP achieved performance across domains with up to 436 agents. Xie et al. (2022) developed sector-based neighbor selection with d-subgraph connectivity, reducing overhead while accelerating convergence [57].
Future directions include hierarchical architectures, heterogeneous computation distribution, and modular designs leveraging "six degrees of separation" for minimal communication achieving global awareness [53].

7.2 Security and Privacy

Critical infrastructure deployment raises privacy and attack concerns. Ye et al. (2024) developed privacy-preserving consensus integrating differential privacy into distributed optimization, characterizing privacy-accuracy tradeoffs [54]. Systems must resist DoS and data-manipulation through resilient estimators and secure protocols.
Future research includes secure multi-party computation, privacy-aware reinforcement learning, and lightweight mechanisms for constrained agents.

7.3 Human-Robot Collaboration

Systems increasingly integrate human collaborators requiring new communication and trust approaches. Zahedi et al. (2023) developed trust models enabling robots to build/maintain trust over extended horizons [55]. Loizaga et al. (2024) used physiological monitoring showing initial interactions critically influence long-term trust [58]. Ning et al. (2023) surveyed fixed-time consensus providing predictable convergence for human-robot coordination [56].Future directions encompass explainable AI, adaptive interfaces, and mixed-initiative planning.

7.4 Integration Challenges

Isolated solutions prove insufficient; integrated approaches simultaneously addressing multiple challenges are essential. Fixed-time methods enhance predictability and robustness [56]; model-based frameworks incorporate efficiency and robustness within scalable designs [53]. Future research requires multi-objective optimization, cross-disciplinary collaboration, standardized benchmarks, and adaptive meta-controllers dynamically balancing objectives.

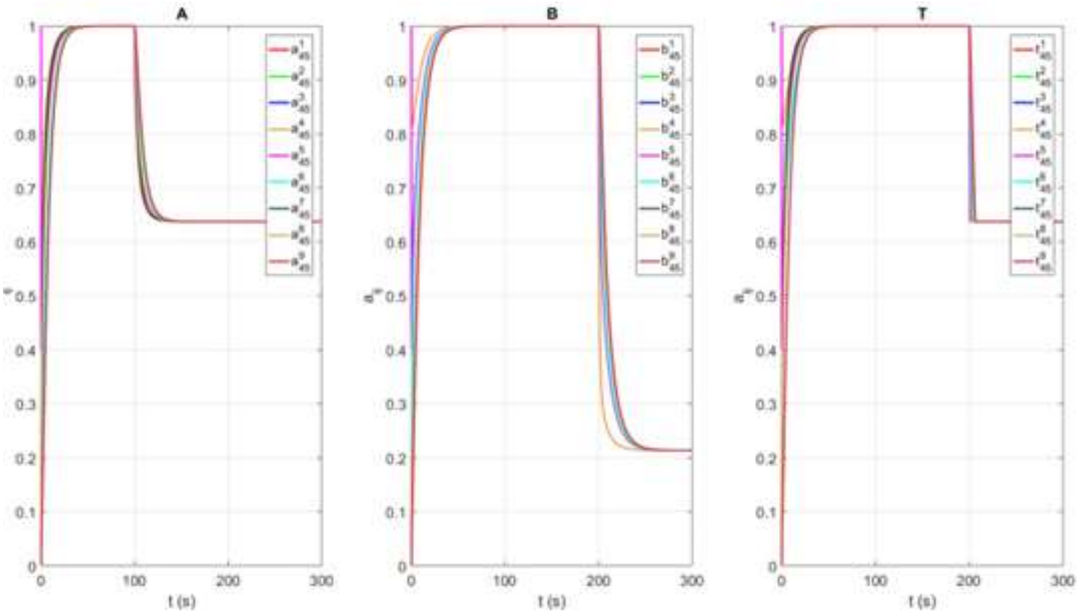

Figure 1.*Multi-channel switching improves algebraic connectivity (λ_2) with minimal resource overhead*
Note. (a) λ_2 values under single-channel vs. multi-channel configurations; (b) Resource consumption (bandwidth/energy) versus λ_2 gain. Switching 2–4 channels elevates λ_2 by 40–60% while limiting resource costs to <15% increase. Source: Griparić et al. (2021).

Table 1.*Communication efficiency gains across optimization strategies.(Note.* Sources: Tang et al. (2023); Guo & Tang (2022); Khatana et al. (2020); Alanwar et al. (2020).*)*

Strategy	**Communication Reduction**	**Convergence Guarantee**	**Key Metric**
Event-triggered control	80–86%	Global convergence, no Zeno behavior	Trigger frequency, state error
Binary-valued consensus	50% bandwidth reduction	Bounded error (single-bit exchange)	Convergence error, frame count
Gradient-consensus (G-CON)	1.7× faster convergence	$O(\eta)$ near optimum	Iterations to ε-error
Event-triggered filtering	86% overhead saving	16% performance loss	MSE vs. communication cost

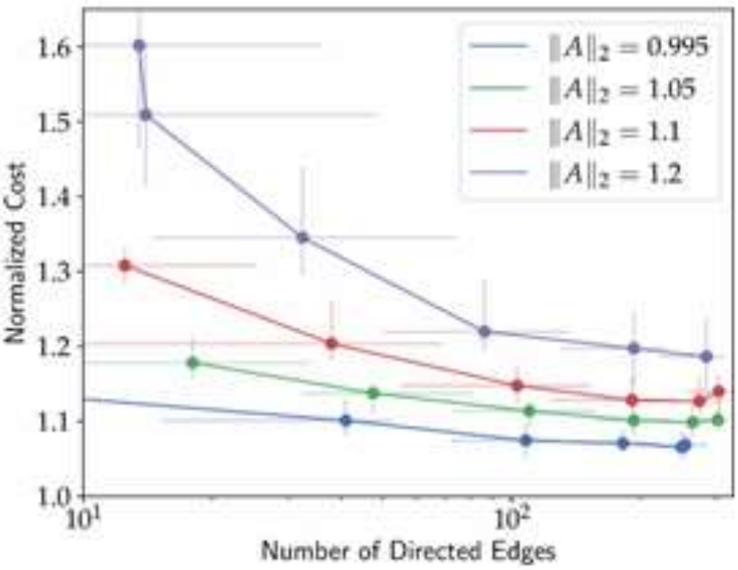

Figure 2. *Trade-off between communication sparsity and control performance.(Note. Normalized LQR cost vs. number of directed edges |E|. Dense topologies (|E|=120) achieve optimal control but incur high communication overhead; sparse topologies (|E|=30) preserve 92% performance with 75% less resources. Source: Yang & Matni (2021).)*

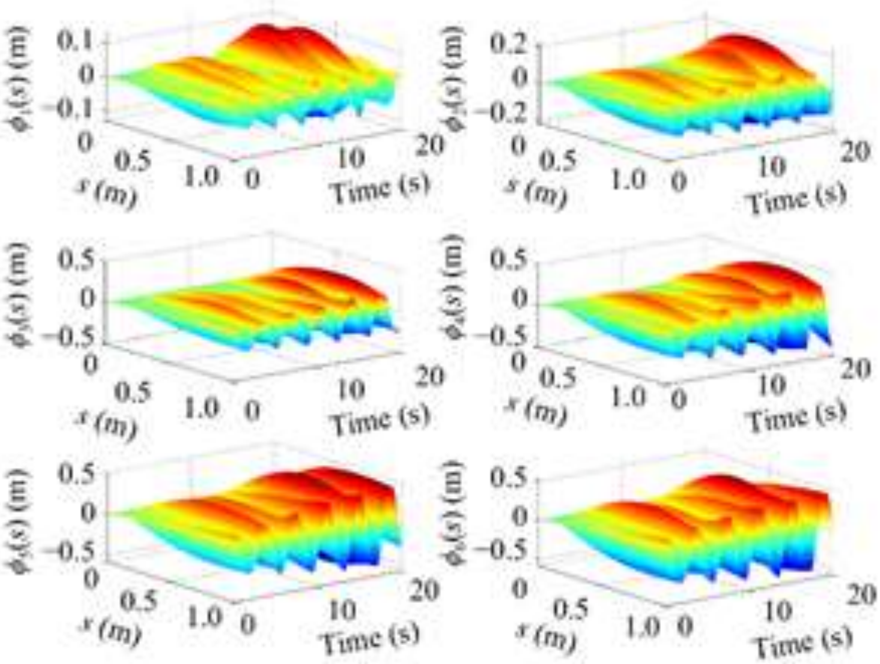

Figure 3.*Event-triggered control enables 87% vibration suppression under faults (Note. Amplitude reduction from 0.06 m to 0.008 m in flexible Timoshenko manipulators using bipartite consensus. Trigger timestamps (lower plot) show sparse communication. Source: Yao et al. (2024).)*

8. Conclusions

This review has surveyed recent advances in communication control and collaborative optimization for multi-agent systems. As such systems see broader deployment, addressing scalability, coordination, security, and human integration has become increasingly vital.

Emerging solutions—including decentralized learning, privacy-aware consensus, and trust-based human–robot models—have enhanced both task performance and system adaptability. Yet, real-world deployment still calls for more robust, integrative approaches that unite technical rigor with human-centric design and resilience.

Future progress hinges on continued theoretical innovation, empirical validation, and interdisciplinary collaboration to ensure these systems perform reliably in complex, unpredictable environments and fulfill their full societal and industrial potential.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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