

AI-Driven Cooperative Mechanisms for Edge-Intelligent Communication Systems

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Abstract. As edge-intelligent communication systems are increasingly deployed in complex scenarios (e.g. unmanned aerial vehicles, UAVs) there is a growing demand for more efficient, secure operations and greater flexible cooperative capabilities. This research aims to meet these important needs. In such systems, diverse devices must collaborate using cooperative mechanisms to handle data processing and task execution collectively, while also satisfying strict latency and privacy constraints. In the aerospace environment, satellite constellations need to coordinate data exchange across vast orbital distances. The Space-Air-Ground Integrated Networks (SAGIN) must achieve seamless connectivity among aircraft, UAVs, and ground stations. Consequently, the aerospace environment presents unprecedented challenges for communication systems. The aerospace environment features unique limitations that differ from those of ground networks. High mobility causes rapid signal loss and frequent switching. The sparse placement of space and air nodes worsens connection instability. Energy shortages exacerbate this problem, as the limited power supply restricts satellites and drones from operating fully. At the same time, the aerospace system demands an extremely high level of reliability and safety, functioning under conditions with nearly zero failure tolerance. In this context, this study conducted a systematic review of the collaborative mechanisms driven by artificial intelligence (AI) and constructed a classification system covering five categories: data collaboration, model collaboration, reasoning collaboration, decision collaboration, and resource collaboration. By clarifying their roles, performance benefits, and application relevance, we aim to create a clear framework that applies not only to general 5G/6G edge intelligent communication but also suits the aerospace network.

Keywords: AI-Driven, Cooperative Mechanisms, Edge-Intelligent Communication System.

1. Introduction

The rapid development of modern communication networks is driving a shift from centralized cloud computing to edge intelligent communication systems. In the aerospace field, edge intelligence becomes particularly important because intelligent processing can be directly deployed on distributed nodes, such as satellites, aircraft, unmanned aerial vehicles (UAVs), ground stations, and deep space probes [1]. By enabling local data processing, these systems can support faster decision-

making and reduce reliance on remote cloud resources, thereby more effectively meeting the demands for latency-sensitive and critical tasks.

In this context, artificial intelligence (AI) plays a crucial role in the intelligent decision-making process during data transmission and processing. The enhanced AI-based communication mechanism not only ensures the rapid and reliable transmission of data but also optimizes resource allocation, task scheduling, and system adaptability. The integration of these capabilities enables real-time, context-aware, and scalable edge services.

In aerospace missions, communication and data processing are often limited by bandwidth constraints and link latency. If all data were sent back to the ground center for processing, it would be inefficient and could cause us to miss critical opportunities. The idea of an AI-based edge-intelligent communication system aims to solve this problem. It moves some AI capabilities to edge nodes near the mission site, allowing the system to process data locally, make quick decisions, and adapt based on environmental changes. This reduces the load on the ground center and provides the system with more independence and stability, which are vital for safely and reliably completing aerospace missions. However, traditional cloud-centered architectures face issues like high latency, inefficient bandwidth use, and security risks. These architectures are characterized by rapid node movement, sparse spatial distribution, unstable communication links, and highly dynamic operating conditions [2].

Nevertheless, achieving this integration still faces many challenges, including the diversity of hardware capabilities, the changing network conditions, the imbalance in energy use, and the limited coordination among communication links. High mobility causes rapid channel fading and frequent handovers, while sparse node distribution creates coverage gaps, and unstable links complicate cooperative operations. Additionally, the limited energy supplies of satellites and drones make resource management more difficult. At the same time, the strict real-time and safety demands of aerospace systems require unprecedented reliability and zero tolerance for errors to ensure [3].

This paper provides a comprehensive review and forward-looking perspective on collaboration mechanisms based on AI within edge-intelligent communication systems. The research begins with the development of edge communication systems and their influence on the aerospace and aviation sectors. By integrating methods like federated learning, it examines intelligent task data screening and autonomous collaborative mechanisms. Moreover, it discusses representative application scenarios involving multi-node cooperation and collaborative decision-making, such as inter-satellite link coordination, space-air-ground integrated communications, and autonomous edge processing in deep-space missions [4]. The goal is to advance interdisciplinary convergence in aerospace intelligent systems and to establish a robust theoretical and practical foundation for the development of next-generation infrastructures featuring low latency, high computational efficiency, and enhanced privacy protection.

2. Theoretical basis

2.1. Architecture of edge-intelligence communication system

The edge-intelligent communication system is an overall architecture in which AI processing capabilities are directly integrated into the edge nodes of communication networks. These edge nodes may include base stations, routers, MEC (Multi-access Edge Computing) servers, and on-board terminals, as illustrated in Figure 1. Its goal is to process data and make decisions near the data source. This reduces latency, saves bandwidth, and improves privacy [5]. The system has three layers: Terminal, Edge, and Cloud.

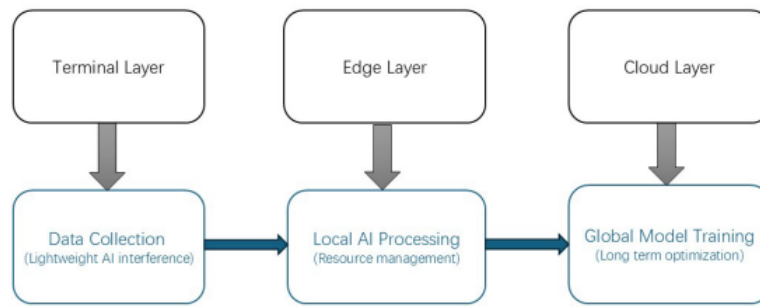


Figure 1. Structural diagram of an edge intelligent communication system

The Terminal Layer includes smartphones, IoT sensors, and vehicle devices. It collects data and can run lightweight AI models for basic analysis. The Edge Layer consists of base stations, routers, and MEC servers. It handles local AI processing and manages resources. It can schedule tasks dynamically and support cooperation between nodes [6]. The Cloud Layer is made up of large data centers. It trains global models and performs long-term optimization. Updated models are sent back to the edge to improve system performance.

This “terminal-edge-cloud” design allows tasks to be shared across layers. It makes the system both efficient and secure, and applies to various scenarios such as 5G/6G, IoT, aerospace, and more.

2.2. AI-driven key technologies

Edge intelligent communication system technology and AI are mutually reinforcing. Algorithms driven by AI are used to guide, optimize, and implement the core functions of the system. In these systems, AI actively participates in all key stages of perception, communication, and computing. It not only processes data but also enables the system to adjust operation strategies based on specific task requirements dynamically. The integration of AI allows the system to make local decisions quickly, optimize resource allocation, and maintain stable communication performance.

In practical applications, intelligent resource management is one of the keys to supporting technologies. By leveraging machine learning and reinforcement learning, it can dynamically allocate bandwidth, transmission power, computing capacity, and storage resources to minimize latency and enhance throughput [7]. Consider satellite constellations as an example. When multiple orbiting satellites cover the same area simultaneously, spectrum and link resources often face competition. If a fixed resource allocation method is used, it can be difficult to handle sudden user demands and environmental changes. However, an adaptive scheduling mechanism can be adjusted in real time based on network load and task priority. For example, when the link pressure of a specific satellite node becomes too high, the system can appropriately reduce or delay secondary data transmissions and allocate more resources to meet emergency or critical task communication needs. This approach not only improves resource utilization efficiency but also enhances the system's stability and reliability in complex task environments.

Furthermore, federated learning is a key technology in edge intelligent communication systems. It enables privacy protection and collaborative model training across multiple devices or edge nodes. In federated learning, only the updated model parameters are uploaded, not the raw data. This significantly reduces the risk of data leakage. The method also incorporates differential privacy and secure multi-party computation to protect user information and can be combined with blockchain or incentive mechanisms to enhance trust and participation [8].

These technologies work together, enabling the edge intelligent communication system to operate in 5G/6G, IoT, and aerospace fields with low latency, high efficiency, and high reliability. At the same time, they ensure strong data security and privacy, creating a scalable and intelligent infrastructure for future communication services.

2.3. Cooperative mechanisms

Cooperative mechanisms are organizational methods and technical frameworks used in systems made up of multiple nodes or entities. They allow participants to share resources, divide tasks, exchange information, and coordinate decisions. The core objective is to maximize overall efficiency while maintaining independent operation capability. Through these methods, the system can sustain better scalability, flexibility, and stability in complex environments [9].

In edge-intelligent communication systems, the primary goal of the collaboration mechanism is to improve energy efficiency, decrease latency, and facilitate flexible task scheduling. However, actual deployment often faces multiple challenges. Complex tasks need both quick local processing and computational support from remote computing. If one side is overly relied upon, the overall performance will be limited. At the same time, bandwidth and energy consumption limitations make scheduling and resource allocation more complex. The uncertainty of network conditions and the diversity of service demands further increase the difficulty of load balancing and real-time response [9].

In the field of communication, the collaboration mechanism improves transmission efficiency and stability by implementing link optimization strategies. For example, adaptive beamforming and interference coordination are used. This mechanism helps keep high data rates and low latency when many users are connected at the same time or when channel conditions are unfavorable. In content delivery, cooperative mechanisms can predict access patterns and store popular content at edge nodes before it is requested. This shortens response time and reduces pressure on the core network.

During the operation, the collaborative mechanism depends on intelligent decision-making algorithms to direct tasks. Machine learning is utilized to forecast changes like network traffic and user request patterns. Additionally, for privacy protection, the collaborative mechanism often uses technologies like federated learning. This allows each node to share knowledge and model parameters, ensuring that cross-domain collaboration is possible. These methods enable nodes to share model parameters and knowledge without transmitting raw data. This lowers the risk of data leakage and facilitates cross-domain cooperation [10].

With the emergence of 5G/6G, IoT, aerospace, and vehicular networks, edge-intelligent communication systems face greater data volumes, more diverse task types, and stricter real-time requirements. Collaborative mechanisms thus serve not only as an effective means of addressing these challenges, but also as a key enabler of network intelligence and distributed operation. They transformed the traditional model into a collaborative multi-node execution mode, ensuring that the system remains efficient and secure in complex tasks within a dynamic network environment. This cooperative mode can be further divided into different AI-driven mechanisms, each of which is specifically designed for specific system-level goals and operational constraints.

3. Applications

In edge-intelligent systems, AI-driven collaborative mechanisms are essential for efficient and competent computing across multiple devices. These mechanisms can be classified into five types based on the form of collaboration.

Data collaboration (such as federated learning) focuses on privacy protection. Model collaboration (such as model partitioning and knowledge distillation) targets handling heterogeneous adaptation. Decision collaboration (such as multi-agent systems) is used for distributed decision-making. Inference collaboration (such as distributed joint inference) enables low-latency inference. Resource collaboration (such as task offloading and edge caching) focuses on system resource optimization. In aerospace, these five mechanisms each serve distinct and important functions.

3.1. Data collaboration

In a data collaboration model, multiple nodes do not need to exchange the original data set but can jointly conduct training and inference. Nodes will share model parameters, features, and statistical data. This design enables sensitive data to remain localized while participants can still contribute to global intelligence. Such a framework is particularly relevant for distributed aerospace systems, where data volumes are large and communication links are constrained.

In multi-satellite collaborative remote sensing, optical, SAR (synthetic aperture radar), and infrared imagery captured by different satellites can be fused through federated learning. This avoids the massive transmission of raw images across satellite-to-satellite or satellite-to-ground links while improving recognition accuracy. Empirical studies demonstrate that federated fusion increases target recognition accuracy by approximately 5%–7% compared with isolated single-satellite training. Communication requirements are significantly reduced, often to only 1/20–1/50 of full image transfer. For instance, a single high-resolution remote sensing image may exceed 200 MB, whereas an update of model parameters usually requires only a few megabytes. These reductions make real-time cooperation feasible under limited inter-satellite bandwidth [11].

In aircraft and UAVs formation missions, drones executing joint reconnaissance tasks may generate hundreds of megabits per second if video streams are transmitted directly, straining bandwidth and exposing sensitive data. With data collaboration, UAVs exchange only compressed features or gradient updates, lowering bandwidth demand by 10–30 times. Experiments show that detection accuracy can be preserved or slightly improved (around +3%), while transmitted data volume drops to merely 5%–10% of the original. This efficiency improves coordination, strengthens link robustness in contested electromagnetic environments, and reduces energy use. Overall, data collaboration enhances robustness, supports heterogeneous nodes with varying computational power, and enables energy savings of 20%–40% compared with centralized cloud processing. These combined advantages establish data collaboration as a key driver of secure, efficient, and intelligent edge communication systems [6].

3.2. Model collaboration

Model collaboration is a paradigm of knowledge integration that complements data collaboration. While data collaboration addresses the problem of distributed data by keeping information local, model collaboration focuses on merging heterogeneous knowledge into a shared global model. This is particularly relevant in aerospace systems, where data is massive, nodes are heterogeneous, and communication links are constrained. The integration of data and model collaboration provides a practical basis for secure and efficient intelligence in distributed systems.

In edge-intelligent communication systems for aerospace applications, model collaboration helps solve the challenges of limited bandwidth and diverse nodes. For example, a satellite constellation can perform tasks like weather observation by exchanging only model parameters instead of raw data. Simulation results show that when model updates are used (with parameter sizes accounting

for only 1–5% of the raw data), the communication bandwidth required between satellites can be reduced by about 20–40 times, while the loss in task accuracy remains below 2%. This greatly decreases memory usage. Likewise, UAV swarms can exchange lightweight models via knowledge distillation, enabling collective situational awareness that exceeds what a single node can achieve. Recent studies also show that federated reinforcement distillation can cut communication costs in UAV-enabled networks by nearly 30% while preserving accuracy [12].

3.3. Inference collaboration

Inference collaboration is a distributed computing model designed to reasonably decompose complex deep neural network (DNN) inference tasks and execute them collaboratively among multiple nodes [13]. Under this mechanism, computing units undertake different stages of the inference process based on their processing capabilities, energy consumption conditions, and link conditions. For example, resource-constrained nodes can complete the front-end feature extraction, while nodes with stronger computing power are responsible for the subsequent high-complexity operations. For aerospace systems, this approach is particularly crucial because the task environment is dynamic and variable, node heterogeneity is significant, and real-time performance is exceptionally demanding.

In a satellite constellation, reasoning collaboration can divide large-scale remote sensing models into different stages. For instance, low Earth orbit satellites may execute preliminary feature encoding and subsequently transmit compressed representations to nearby satellites or ground stations for higher-level recognition. This strategy avoids full-scale raw image transmission and substantially reduces bandwidth consumption. Empirical studies demonstrate that hierarchical inference collaboration can decrease inter-satellite communication load by approximately 20%–35% while maintaining recognition accuracy.

In practice, the advantages of inference collaboration need realized when combined with resource collaboration, since sufficient computing power and stable communication links are necessary for efficient multi-node inference.

3.4. Decision collaboration

Decision collaboration focuses on coordinating distributed aerospace nodes so that their actions converge toward consistent and near-optimal strategies. Rather than integrating knowledge at the model level or distributing workloads as in inference collaboration, it aims to form coherent strategies across the network when operating under uncertainty. This mechanism is particularly valuable in aerospace missions, where nodes must adapt to dynamic environments, cope with incomplete information, and still ensure mission-critical reliability.

In a satellite constellation system, decision collaboration enables each node to jointly determine the resource allocation and task scheduling plans. For instance, when multiple satellites are simultaneously conducting imaging, distributed decision-making can balance bandwidth and energy constraints to ensure the coordinated planning. Simulation studies demonstrate that collaborative scheduling improves task completion rates by 15%–20% while reducing link conflicts by nearly 18% compared with non-cooperative baselines. This mechanism therefore complements lower-level data and inference mechanisms by providing system-wide optimization rather than localized execution.

In UAV and aircraft formations, decision collaboration coordinates task distribution and trajectory planning for collision avoidance and energy efficiency. Multi-agent reinforcement

learning (MARL) provides powerful theoretical tools for such distributed decision-making, while recent studies confirm its practical feasibility in edge-based systems [14]. For instance, distributed decision frameworks for UAVs achieved 89.2% conflict prediction accuracy and 99.9% conflict resolution rate, highlighting the robustness of AI-enabled coordination in real-time aerospace networks.

3.5. Resource collaboration

In aerospace edge-intelligent communication systems, resource collaboration is not just supportive but essential. Effective coordination of computing power, energy supply, and bandwidth directly determines whether higher-level mechanisms (e.g. data, model, inference, and decision collaboration). By balancing these limited resources in real time, the system maintains stable performance even under dynamic and resource-constrained mission conditions.

In low Earth orbit satellite constellations, satellites often differ considerably in their available energy and processing power. Resource collaboration addresses this heterogeneity by allocating inference and communication tasks according to current energy reserves and link quality. For instance, satellites with stronger processors and higher energy levels can handle computation-intensive operations, while those with limited resources focus on feature extraction or data relay. Simulation results show that this division of labor can cut overall task latency by roughly 25–35% and reduce energy consumption by nearly 20%, while maintaining a high task completion rate [15]. These findings highlight that resource collaboration is essential for sustaining reliable system performance in long-term missions.

4. Practical challenges and future developments

In edge-intelligent communication systems for aerospace, energy and computing resource limitations remain major challenges. Satellites, UAVs, and spacecraft operate within strict power limits and have limited processing capabilities. Hardware heterogeneity across orbital, airborne, and ground platforms complicates not only task scheduling but also long-term maintenance and reliability [3]. Recent research shows that lightweight techniques such as pruning or quantization can cut inference costs by 30–50% in remote sensing models, while knowledge distillation allows smaller on-board networks to maintain much of the accuracy of full-scale models. To address heterogeneity, task allocation frameworks have begun to consider not only processing capacity but also dynamic factors such as residual energy and link stability [15]. Looking ahead, progress is expected in two main directions: energy-efficient AI chips tailored for space-qualified platforms, and adaptive inference strategies that vary model depth according to mission urgency, with autonomous scheduling as a longer-term goal.

Privacy and security remain central challenges in aerospace edge-intelligent communication, particularly because many missions demand near-zero-fault tolerance. In practice, satellites, UAVs, and ground stations often exchange model parameters or intermediate features rather than raw data, which reduces but does not eliminate risks. Attacks such as model inversion, jamming, and link disruption have been reported in recent aerospace communication studies [6]. Space communication standards further complicate the situation and, in some cases, cross-border data regulations. To mitigate these issues, researchers have explored methods such as federated learning for local training, differential privacy to obscure sensitive information, and secure multi-party computation for encrypted collaboration. For tasks that are of critical importance in terms of security, such as

cooperative navigation, adversarial training and tamper-resistant authentication, these aspects are even more crucial.

As mission complexity increases, AI will play a more important role in satellite networks, particularly in adaptive communication and resource allocation. Intelligent inter-satellite links (ISLs) will enable adaptive routing, predictive congestion control, and collaborative decision-making [4]. SAGIN will benefit from distributed learning frameworks combining federated and reinforcement learning to ensure robust coordination under sparse and dynamic connectivity. Furthermore, hardware-level innovations, including radiation-hardened AI accelerators and low-power privacy-preserving chips, will empower in-orbit intelligence. The integration of blockchain-based trust management and trusted execution environments (TEEs) will provide verifiable, tamper-resistant infrastructure. Together, these advances will push aerospace edge-intelligent communication systems toward higher autonomy, stronger resilience, and enhanced mission reliability.

5. Conclusion

This study presents a systematic review of AI-driven collaborative mechanisms in edge-intelligent communication systems and develops a structured taxonomy encompassing five key categories: data collaboration, model collaboration, inference collaboration, decision collaboration, and resource collaboration. By synthesizing recent research and practical cases, the study clarifies the definitions, operational logic, and performance benefits of each mechanism, while summarizing representative implementation strategies and application scenarios. In doing so, it consolidates fragmented knowledge and provides both academia and industry with a coherent framework for understanding and designing multi-level collaboration models.

The significance of this work is clear. Collaborative mechanisms play a central role in edge-intelligent systems. They enhance real-time responsiveness, improve resource utilization, and increase system robustness. They also strengthen adaptability to heterogeneous environments and provide better privacy and security protection. These findings guide researchers in algorithm selection, architectural design, and cross-domain deployment. At the same time, they give practitioners useful references for building large-scale distributed AI applications in real network environments. Importantly, the proposed taxonomy is not only applicable to general 5G/6G edge-intelligent communication, but is also particularly suited to aerospace networks, where stringent constraints on latency, reliability, and autonomy demand systematic coordination. Hence, it can serve as a valuable reference framework for the design of future space–air–ground integrated communication infrastructures.

Future research should explore cross-layer integration frameworks. These frameworks will allow joint optimization across data, model, inference, decision, and resource collaboration. It is also important to design scalable and adaptive mechanisms that remain efficient in large-scale, dynamic, and latency-sensitive networks. Such networks often face workload fluctuations and node failures [14]. On the methodological side, lightweight privacy-preserving technologies and verifiable collaboration protocols are needed to balance performance with trust. In addition, the integration of AI with 6G, blockchain, and TEEs will open new opportunities for trustworthy infrastructures [1,3]. Finally, validation across domains such as autonomous driving, smart manufacturing, and large-scale IoT ecosystems is essential. This will help connect theoretical progress with real-world deployment.

It should be noted that this study still has certain limitations. For example, the coverage of different application scenarios in experiments and case analyses is limited. The work has not fully

considered the global impact of node failures, dynamic topology, and cross-domain security strategies in large-scale and complex networks. In addition, some optimization strategies remain at the level of theoretical analysis, without sufficient validation of stability and scalability in long-term operation. These shortcomings restrict the generality of the conclusions and the depth of practical implementation.

In conclusion, this study provides a systematic framework for understanding and applying collaborative mechanisms. It also identifies future directions that can accelerate the development of efficient, intelligent, and trustworthy edge-intelligent communication infrastructures. Moreover, by emphasizing the aerospace context, it highlights the applicability of AI-driven collaboration to next-generation SAGIN, offering theoretical and practical guidance for building resilient and autonomous aerospace communication systems.

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