



AI-driven multi-tier aerial communication networks: a review of routing, computing, handover, resource management, and optimization techniques

Shafkat Khan Siam¹ · Muhammad Yeasir Arafat¹ · Muhammad Morshed Alam² · Xu Zhu³ · Ping Yang⁴ · Zilong Liu⁵ · Krishnendu Guha¹ · Md. Noor-A-Rahim¹

Received: 5 November 2025 / Accepted: 9 July 2026
© The Author(s) 2026

Abstract

Multi-tier aerial communication networks (MACNs), integrating satellites, high-altitude platforms, and unmanned aerial vehicles, are emerging as a cornerstone of next-generation global connectivity. Their promise of resilient and ubiquitous coverage, however, is hindered by highly dynamic topologies, severe energy and computational constraints, environment-sensitive channels, diverse quality-of-service requirements, and limited real-world validation. Artificial intelligence (AI) has increasingly been explored as a flexible framework to address these challenges, enabling adaptive routing, distributed computing and task offloading, handover management, intelligent resource allocation, and large-scale network optimization. This survey provides a comprehensive and structured review of methods for MACNs, with particular emphasis on AI-driven solutions and their relationship to classical and hybrid alternatives. We critically evaluate representative approaches in terms of scalability, efficiency, data demands, and practical deployability, and identify emerging trends such as graph neural networks with reinforcement learning for dynamic routing, predictive learning for mobility management, and federated learning for distributed computation. Persistent challenges remain in lightweight edge intelligence, real-world testbeds, reproducible benchmarking, and simulation-to-deployment transfer. To address these issues, we offer a research roadmap emphasizing compressible and interpretable models, standardized benchmarks, realistic validation, and hybrid designs that balance adaptability with computational and energy overhead. Finally, we identify open challenges and future research directions, offering insights into the design of AI-driven MACNs that are efficient, scalable, and adaptive to evolving network and service demands.

Keywords AI-driven networks · UAV communications · Multi-tier aerial communication networks (MACN) · Space-air-ground integrated network (SAGIN) · Routing · Edge computing · Handover · Resource allocation · Optimization techniques.

1 Introduction

The rapid evolution of communication networks that incorporate unmanned aerial vehicles (UAVs), low-altitude platforms (LAPs), high-altitude platforms (HAPs), and satellites has ushered in a transformative era of connectivity known as the multi-tier aerial communication network (MACN). Low earth orbit (LEO) is now populated by numerous commercial constellations; Starlink alone has surpassed 10,000 active satellites in that orbit, with regulatory approval for more than 42,000 (Wang et al. 2024), and other operators such as OneWeb, together with emerging systems like Amazon's Project Kuiper and Telesat's Lightspeed are progressively densifying LEO. This proliferation of LEO constellations, when combined with UAV, LAP and HAP-based tiers, is reshaping MACN design by enabling lower-latency global coverage, new backhaul and relay topologies, and novel cross-tier resource-management and orchestration challenges (Morshed Alam et al. 2026). MACNs promise persistent connectivity for applications ranging from disaster response and remote broadband access to environmental monitoring. However, integrating these heterogeneous tiers into a seamless system raises critical challenges in deployment, resource constraints, dynamic topology management, and real-time adaptation (Sharif et al. 2023).

Prior to the widespread adoption of Artificial Intelligence (AI)-driven techniques, researchers addressed the challenges of MACNs primarily through classical optimization, control-theoretic, and heuristic frameworks. These approaches provided important theoretical foundations and remain valuable under structured and well-characterized conditions. However, their applicability in highly dynamic multi-tier environments is subject to practical limitations. Joint trajectory and communication co-design frameworks for multi-UAV enabled wireless networks employed convex optimization and successive convex approximation to balance throughput and energy consumption. These formulations typically required accurate channel state information (CSI) and relied on deterministic mobility models. While effective for small-scale or quasi-static networks, such methods become computationally expensive as the number of UAVs, users, and tiers increases. MACN architectures integrating aerial and ground coverage relied on geometric analysis and heuristic placement algorithms to extend connectivity. Resource-efficient seamless transition protocols for high-performance multi-hop UAV multicasting utilized game-theoretic formulations and distributed coordination schemes. While these non-AI-based strategies provided foundational insights and remain valuable under well-characterized conditions, they face inherent limitations when confronted with the dynamic, large-scale, and stochastic nature of modern MACNs. Specifically, classical optimization methods often require accurate CSI and stable topology assumptions that are difficult to maintain amid rapid UAV mobility, time-varying interference, and heterogeneous traffic demands. Furthermore, the computational complexity of jointly optimizing trajectory, resource allocation, and handover decisions grows prohibitively with network scale, rendering real-time solutions infeasible.

Classical methods remain indispensable in MACNs and should not be viewed as superseded by AI. Optimization, control-theoretic, graph-theoretic, heuristic, and game-theoretic methods offer strong advantages when the system model is sufficiently accurate, the decision space is moderate, and guarantees on stability, latency, or interpretability are required. In such regimes, simple model-based solutions may remain more attractive than AI because they incur lower training cost, lower inference overhead, and clearer failure modes. However, MACNs also exhibit several forms of dynamicity that challenge purely model-based

operation: (i) topology dynamicity due to fast satellite motion, UAV mobility, and intermittent visibility; (ii) channel dynamicity caused by Doppler, blockage, atmospheric effects, and time-varying interference; (iii) traffic dynamicity arising from bursty arrivals and heterogeneous QoS demands; (iv) resource dynamicity involving changing battery levels, queue states, and onboard compute availability; and (v) cross-tier coupling, where routing, handover, offloading, and resource allocation decisions become interdependent across space, air, and ground tiers. In these settings, AI is not universally superior, but it can become useful when decisions are sequential, partially observed, high-dimensional, and repeatedly re-optimized under nonstationary conditions. The key design question is therefore not whether AI should replace classical methods, but when classical, AI-based, or hybrid solutions are most appropriate for a given MACN operating regime.

Against this background, AI-based and hybrid methods have been explored across multiple MACN functions. In routing, graph neural networks (GNN) and learning-augmented heuristics enable topology-aware and scalable path selection by predicting link quality and capturing mobility patterns. For distributed computing and offloading, data-driven predictors and federated learning support low-latency task placement while limiting raw data movement. In handover and mobility management, predictive models and reinforcement learning (RL) facilitate proactive handover scheduling and joint optimization of trajectory, transmit power, and signaling to meet stringent latency and reliability requirements. In resource management, RL enables online adaptation and allocation policies under nonstationary traffic and interference. For global network optimization, approaches that combine AI and classical optimization methods, for example surrogate models or RL together with established solvers, can offer favorable trade-offs between sample efficiency and solution quality. As shown in Fig. 1, the MACN reference architecture comprises space, aerial, and ground tiers interconnected by heterogeneous link types and layered compute resources. The figure highlights cross-tier roles and indicates typical locations for AI agents that per-

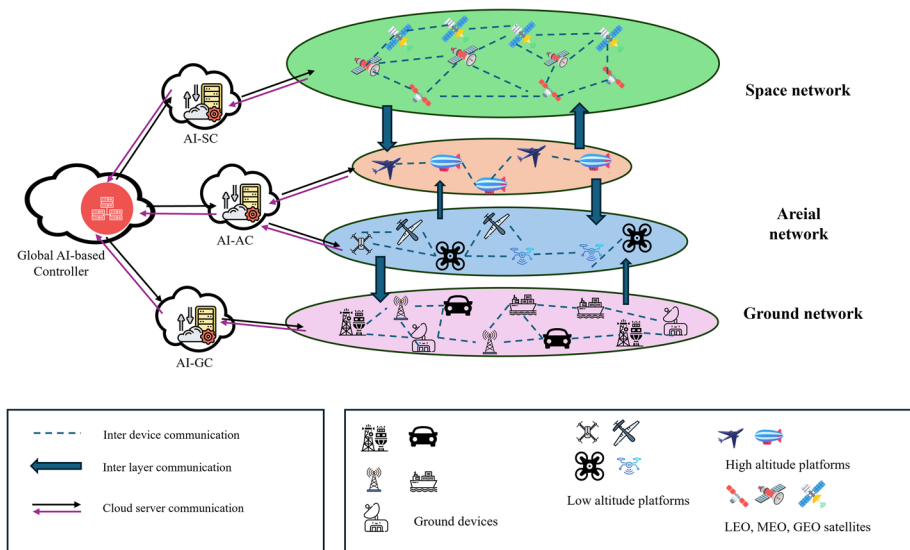


Fig. 1 Architecture of MACN: tiers, principal link types, and placement of intelligence at ground, aerial, and space networks

form inference, aggregation, and model training; the links are idealized for clarity. Here ground, aerial, and space networks are equipped with AI-based controllers (AI-GC, AI-AC, and AI-SC) and a global AI-based controller for all the networks.

Despite these advances, practical limitations persist, including substantial computational and energy footprints at edge tiers, strong dependence on idealized simulations, and a scarcity of real-world datasets, reproducible benchmarks, and testbeds. This survey therefore (i) develops a classification of methods across routing, computing and offloading, handover, resource management, and optimization methods; (ii) critically evaluates representative approaches with respect to scalability, energy footprint, data dependency, and practical readiness for deployment; and (iii) identifies open challenges and proposes a prioritized research agenda that emphasizes lightweight and compressible models, interpretability and robustness for safety-critical control, standardized benchmarks and shared datasets, and realistic testbeds to bridge the simulation-to-reality gap. The remainder of the paper is organized along these five functional axes, namely routing, computing and task offloading, handover management, resource allocation and control, and optimization, and concludes with evaluation best practices and a roadmap for future research.

1.1 Existing survey works and gaps

Table 1 summarizes representative surveys from the literature and the dimensions they cover. Existing surveys have covered important aspects of space–air–ground integrated networks (SAGIN) and aerial networking, but their emphases differ in scope and synthesis style. Some surveys focus on architecture, others on a single function such as routing or handover, and others summarize AI applications without explicitly comparing them against classical baselines. Our contribution is therefore not to claim that prior work ignored cross-tier networking or AI methods, but rather to provide a more decision-oriented synthesis along four specific dimensions.

First, we examine cross-tier and cross-function coupling, that is, how routing, handover, offloading, resource allocation, and optimization interact across space, aerial, and ground segments rather than being treated independently. In this context, the tiers refer to the space segment (LEO/MEO/GEO satellites), the aerial segment (HAPs and UAVs), and the ground segment (terrestrial cellular and edge networks). The functions refer to routing, computing and offloading, handover management, resource allocation, and network-level optimization. The term integration denotes cross-tier coordination and joint optimization across these functions, rather than isolated, single-layer solutions. Many existing surveys analyze these tiers or functions independently, for example focusing solely on satellite routing, UAV trajectory optimization, or terrestrial resource management. Architecture-focused works such as Liu et al. (2018) and Zhang et al. (2020) describe structural designs and capabilities but do not analyze how cross-tier interactions influence resource allocation, mobility management, or the joint optimization of routing and computing. Early routing solutions for UAV and FANET environments (Arafat and Moh 2018; Yeasir and Moh 2019) focused on topology-aware, cluster-based, and hierarchical routing designs to address high mobility, intermittent connectivity, and limited energy resources. However, in practical MACNs, routing paths often span multiple tiers, vertical handovers occur between satellite, air, and ground segments, and resource allocation decisions couple trajectory control, spectrum manage-

Table 1 Coverage of key dimensions across related surveys

References	Year	Core functions				Techniques			
		Network architecture		Computing		Handover technique		Optimization technique	
		6G	SAGIN	Routing	Computing	Handover technique	Resource management	Optimization technique	AI/ML AI comparison
Liu et al. (2018)	2018	×	✓	✓	×	×	×	✓	×
Zhang et al. (2020)	2020	×	✓	×	×	×	×	×	×
Zhang et al. (2020)	2020	×	✓	✓	×	×	✓	×	×
Jiang et al. (2021)	2021	✓	✓	×	✓	×	×	×	×
Guo et al. (2021)	2022	✓	✓	✓	×	×	×	×	✓
Qiu et al. (2022)	2022	✓	✓	×	×	×	×	×	×
Sharif et al. (2023)	2023	✓	✓	×	✓	×	×	×	×
Bakambekova et al. (2024)	2024	✓	✓	×	×	×	✓	✓	×
Wang et al. (2024)	2024	✓	✓	✓	×	×	✓	×	✓
Chen et al. (2024)	2024	✓	✓	×	×	×	✓	×	×
Xiao et al. (2024)	2024	✓	✓	×	✓	×	×	×	×
Meng et al. (2024)	2025	✓	✓	×	✓	×	×	×	×
Fontanesi et al. (2025)	2025	✓	✓	✓	✓	✓	✓	✓	✓
Our work	2025	✓	✓	✓	✓	✓	✓	✓	✓

ment, and inter-satellite scheduling. The lack of explicit cross-tier and cross-function analysis limits understanding of how AI techniques coordinate end-to-end decision making.

Second, we provide MACN-specific method-selection guidance by comparing classical, AI-based, and hybrid solutions under mobility, intermittency, onboard resource limits, and heterogeneous QoS demands. Although some studies discuss AI methods in context, systematic side-by-side evaluations of algorithmic paradigms across core functions are largely absent. There is a need to clearly document when classical approaches outperform learning-based ones, where RL or SL are most appropriate, and how algorithmic complexity and data requirements trade off against performance for routing, edge computing and offloading, mobility management, and resource management. Without such comparative treatments, practitioners lack principled guidance for selecting and adapting AI methods to specific MACN functions and operational constraints.

Third, we review practical readiness by identifying which studies remain simulation-only, which include prototype or emulator-level validation, and what computational or energy assumptions underlie their reported gains. Practical deployment considerations receive insufficient attention. Important aspects for real-world adoption are often only briefly mentioned or omitted, including the computational and energy footprints of candidate AI models, strategies for model compression and on-device inference, interpretability requirements for safety-critical control, and robustness under nonstationary or adversarial conditions. Surveys such as Guo et al. (2021) and Chen et al. (2024) note these topics, but they do not provide detailed, comparative guidance that would help designers evaluate model readiness for constrained aerial and space platforms.

Fourth, we summarize the current state of datasets, simulators, and reproducibility practices, and we outline a minimal set of evaluation dimensions needed for fair comparison across studies. Existing literature heavily relies on simplified simulations and lacks standardized evaluation platforms. This issue directly affects the credibility of AI-based routing, handover, and optimization results, as performance metrics such as delay, handover failure rate, energy consumption, and scalability are often evaluated under idealized topology and traffic assumptions. Shared real-world datasets and open experimental platforms remain scarce, which limits reproducibility and reduces the external validity of performance claims reported in works such as Qiu et al. (2022) and Xiao et al. (2024). Without consistent benchmarks or realistic multi-tier testbeds, it is difficult to assess the practical feasibility of proposed AI solutions.

1.2 Scope and objectives

The primary aim of this survey is to provide a structured and focused review of state-of-the-art methods for multi-tier aerial communication networks, commonly referred to as space, air, and ground integrated networks. The paper concentrates on five functional areas: routing, distributed computation and task offloading, handover management, resource allocation and control, and network-level optimization. Across these areas, we synthesize classical, AI-based, and hybrid methodologies, evaluate their practical suitability with respect to scalability, computational and energy cost, data requirements, and deployment-related trade-offs, and identify research directions that can accelerate the transition from simulation to operational deployment.

The objectives of this survey are threefold. First, we synthesize and consolidate recent research across the MACN stack, covering terrestrial networks, LAPs, HAPs, and satellite systems, to present a coherent account of multi-tier design challenges and cross-tier interactions. Second, we critically assess classical, AI-based, and hybrid methods with respect to their suitability for different MACN operating conditions, paying particular attention to mobility, intermittency, onboard resource limitations, computational and energy cost, and heterogeneous QoS requirements. Third, we identify open problems and propose a prioritized research agenda to guide future work toward seamless, scalable, and deployable connectivity in next-generation aerial communication networks.

1.3 Contributions of the survey

This survey provides a holistic account of how AI shapes the design and operation of different tiers of aerial networks within the broader MACN framework. We examine the multiple roles that AI techniques play in addressing core challenges such as routing, task offloading, resource allocation, and network level optimization in heterogeneous and highly dynamic aerial environments. By systematically organizing recent advances and synthesizing findings from the literature, the survey offers an integrative perspective intended to inform and guide future research and development in this rapidly evolving field. Our key contributions are as follows.

- **We provide a comprehensive and unified analysis of AI based methodologies.** Specifically, we categorize and evaluate a broad spectrum of AI techniques applied to routing, distributed computing, resource management, and optimization. Our analysis spans different network layers and emphasizes the interdependencies and functional overlaps that affect overall performance of MACN.
- **A critical evaluation of existing AI solutions.** We evaluated the strengths, limitations, and applicability of a range of AI paradigms, including supervised learning (SL), RL, deep learning (DL), and hybrid methods, within the context of MACN. This assessment offers insights into the effectiveness, scalability, and operational constraints of current approaches under diverse network conditions.
- **Identification of leveraged opportunities between network tiers.** We examine how AI can facilitate effective cooperation among space-based, aerial, and ground-based network components. The survey highlights recurring design patterns and coordination mechanisms through which inter-tier collaboration can increase system resilience, reduce end to end latency, and improve overall resource utilization.
- **A forward-looking roadmap for research and development.** Drawing on observed trends and identified gaps, we outline future directions to guide researchers and practitioners toward more scalable, deployable, and context-aware aerial networking systems. The roadmap emphasizes open challenges in scalability, real-time decision-making, cross-layer optimization, and resource-aware deployment, and highlights opportunities for standardized evaluation, realistic testbeds, and methods that balance performance gains against computational and energy overhead.

1.4 Organization of the paper

To situate our work within the existing literature, Table 1 presents a comparative overview of related surveys published over the last ten years. Each surveyed paper is evaluated across dimensions that are pertinent to MACN research, including routing protocols, computing paradigms, handover techniques, resource management strategies, optimization methods, and the application of AI methodologies. Most prior surveys address only a subset of these topics, leaving gaps in integration, comparative analysis, and AI specific evaluation. Our survey differs by providing a comprehensive review that spans all major technical domains and includes a focused comparison of AI techniques, thereby offering readers a broader and more coherent account of the current state of the art. The remainder of the paper is organized as follows.

- **Section II:** This section provides essential background on MACN architectures and a systematic classification of core network functions by AI technique. It introduces the foundational concepts required to understand the integration of artificial intelligence into hierarchical network systems, including architectural structure, layered organization, and inter-layer communication models. Building on this background, the section maps AI paradigms such as machine learning, deep learning, and reinforcement learning to representative networking tasks, and it explains typical objectives, evaluation metrics, and practical deployment considerations for each mapping. The goal is to give the reader both the conceptual grounding and the applied perspective needed to follow the technical discussions that follow.
- **Section III:** This section reviews state of the art AI enabled routing protocols designed to address the challenges of dynamic aerial topologies, including node mobility and intermittent connectivity. The discussion emphasizes adaptability, latency reduction, and improvements in data throughput, and highlights representative algorithms and evaluation methods that demonstrate these benefits.
- **Section IV:** This section examines distributed computing frameworks in which aerial platforms serve as mobile processing units, enabling real time data analytics and edge intelligence (EI). It discusses architectural designs, task scheduling mechanisms, and the integration of AI models to support efficient and resilient workload distribution across heterogeneous computing and communication resources.
- **Section V:** This section examines handover techniques in MACN, starting with a concise classification into horizontal, vertical, and predictive handovers. It then provides a comprehensive review of AI-based solutions, including RL, multi-agent reinforcement learning (MARL), lightweight bandit methods, and hybrid as well as emerging paradigms. The discussion addresses key design objectives, evaluation metrics, and practical implementation considerations, and it identifies open challenges for ensuring robust and scalable handover in MACN.
- **Section VI:** This section analyzes resource management strategies that are specifically tailored to the physical and operational constraints of MACN. It addresses key aspects such as energy efficiency, spectrum allocation, and bandwidth management, and examines the application of predictive artificial intelligence models for proactive and optimized resource allocation.
- **Section VII:** This section examines optimization techniques aimed at enhancing net-

work performance across the layers of MACNs. It reviews both classical and AI-driven optimization frameworks, highlighting how AI-based methods complement traditional approaches in addressing multi-objective optimization challenges and achieving real-time adaptability.

- **Section VIII:** This section synthesizes and compares the AI-enabled routing, computing, handover, resource management, and optimization methods reviewed in the preceding sections. We extract and organize the core open challenges, evaluate current solutions with respect to representative performance metrics, and identify methodological and deployment gaps to guide future research directions.
- **Section IX:** This concluding section synthesizes the paper's main findings and contributions. It emphasizes the transformative potential of AI for MACNs, discusses the practical and theoretical implications of the surveyed techniques, and outlines concrete research directions and deployment challenges.

2 Background and multi-tier aerial communication network

To fully appreciate the role of AI in MACNs, it is necessary to understand the foundational aspects of this heterogeneously connected architecture. This section presents background on software defined networking (SDN) in multi layered aerial networks, emphasizing structural components and operational principles. It focuses on the constituent sub-networks, describing their communication models and routing strategies, and examines how these diverse layers interact. Common communication challenges are identified, and the obstacles that arise in dynamic environments are outlined. Section 2.2 provides a concise classification of network functions in relation to AI methods, while Sects. 3 through 7 review ongoing research trends and developments in MACNs, with particular emphasis on the integration of AI techniques for routing, computing, handover, resource management, and optimization.

2.1 Multi-tier aerial network architecture

The multi-tier architecture of SAGIN comprises three principal segments which include space, aerial, and ground. Each segment provides distinct capabilities that collectively enable seamless global connectivity and support a broad spectrum of applications, ranging from high-speed broadband access to real time Earth observation and emergency response systems. By leveraging the complementary strengths of these layers while compensating for their individual limitations, the hierarchical architecture establishes a robust and adaptable communication ecosystem.

2.1.1 Space segment

The space segment of an MACN primarily comprises satellites, which are conventionally classified by orbital altitude into geostationary earth orbit (GEO), medium earth orbit (MEO), and LEO. Each class exhibits distinct operational characteristics determined by its altitude, and together these classes form hierarchical, multi-layer satellite constellations that support diverse service requirements Chen et al. (2024). This section examines the space segment as the foundational infrastructure of space-air-ground integrated networks, with an

emphasis on its role in providing extensive coverage and high-capacity long-range communication links.

- **GEO satellites:** Positioned at an altitude of approximately 35,786 km, GEO satellites, exemplified by the Inmarsat constellation, maintain a fixed position relative to earth because their orbital period matches the planet's rotation. This characteristic enables extensive coverage; in theory, as few as three satellites can provide near-global communication services outside the polar regions. The geostationary configuration also simplifies link maintenance and ground station operations. However, the high altitude yields significant propagation delays of approximately 250 to 280 ms round trip and increased path loss, both of which can constrain data throughput and increase system complexity. Moreover, the finite number of geostationary orbital slots, which are internationally regulated, poses a growing challenge given the rising demand for satellite deployments (Network 2011).
- **MEO satellites:** MEO satellites, exemplified by systems such as Inmarsat-P, Odyssey, MAGSS-14, and O3b, operate at altitudes ranging from 7,000 km to 25,000 km (Network 2011). They support critical services including positioning, navigation, and timing, as well as international search and rescue. By occupying an intermediate altitude between the GEO and LEO satellites, MEO constellations offer a balance of advantages, notably reduced latency relative to GEO and broader coverage than LEO. Furthermore, orbital slots in the MEO band are comparatively more available owing to less stringent allocation constraints, which makes MEO attractive for enhancing mid-layer capabilities.
- **LEO satellites:** Recent advances in aerospace engineering and electronic systems have markedly reduced the cost of satellite design, manufacture, and launch. Concurrently, the increasing demand for ubiquitous Internet access and IoT services, particularly in areas with limited terrestrial infrastructure, has driven the rapid deployment of large-scale LEO constellations (Chen et al. 2024). Operating at altitudes of approximately 300 to 1,500 km, LEO satellites offer substantially lower propagation delays and reduced path loss compared with GEO and MEO platforms, making them well suited for latency-sensitive services. At the same time, LEO architectures introduce significant technical challenges due to high relative motion, including pronounced Doppler effects and frequent topology changes that complicate inter-satellite and ground link design.

A notable trend in LEO systems is the shift from transparent signal forwarding to on-board data processing, which enables more intelligent and efficient satellite operations. For example, SpaceX's Starlink project incorporates approximately 32,000 Linux based computing nodes and more than 6,000 micro-controllers in orbit (Spacex 2020), demonstrating the practical feasibility of satellite edge computing. These capabilities necessitate careful architectural consideration of heterogeneous satellite functionalities when developing integrated communication protocols across orbital layers (Chen et al. 2024).

2.1.2 Air segment

The air segment of SAGINs constitutes a critical tier, employing aerial platforms such as UAVs, airships, and balloons for data acquisition, transmission, and processing. Situated

between the space and ground segments, it enhances network flexibility, enables rapid deployment, and extends coverage to regions lacking terrestrial infrastructure (Liu et al. 2018). These capabilities render the air segment indispensable in scenarios such as disaster recovery and battlefield communication, where timely and reliable data exchange is of paramount importance (Qiu et al. 2022).

- **LAP:** Aerial platforms are diverse and are primarily classified according to their design and operational altitude. UAVs, or LAPs, include fixed-wing, rotary-wing, such as quadcopters and hexacopters, and hybrid configurations (Liu et al. 2018). Fixed-wing UAVs provide long-range capabilities owing to their speed and endurance, whereas rotary-wing UAVs offer superior maneuverability and the ability to hover, making them well suited for precision tasks (Zhang et al. 2020).
- **HAP:** HAPs, such as balloons and airships, operate at substantially higher altitudes and can interconnect with multiple UAVs. They often function as aggregation points, charging stations, or edge and cloud computing nodes, thereby compensating for the limited energy and computational resources of LAPs (Chandrasekharan et al. 2016). This functional diversity enables the aerial segment to support services such as broadband delivery and to serve as aerial base stations.

The performance of aerial platforms is governed by several key factors: payload, range, altitude, speed, and endurance (Zhang et al. 2020). The payload determines the weight capacity available for onboard systems, such as sensors and transceivers. Range and altitude influence operational coverage, with higher altitudes enabling broader service areas. Speed affects mission responsiveness and overall efficiency, which is particularly important for time-critical operations. Endurance, as determined by energy sources such as batteries or solar panels, restricts the duration a platform can remain operational without recharge.

Each aerial platform comprises several core components: a body frame; a flight control unit, which includes electronic speed controllers, inertial measurement units, and microcontrollers; communication modules; power systems; payloads; and onboard computers (Qiu et al. 2022). These components enable coordinated and autonomous operations and allow the air segment to interconnect the space and ground layers, forming a heterogeneous network with overlapping coverage areas. UAVs and HAPs integrate with terrestrial communication systems and employ air-to-air links. This capability is essential in high-demand or complex environments, where aerial platforms relay data between ground sensors and satellites to preserve seamless connectivity (Chandrasekharan et al. 2016).

2.1.3 Ground segment

The ground segment constitutes the terrestrial layer of the MACN and forms the foundational communication infrastructure. It encompasses a broad array of terrestrial systems, including cellular networks, local area networks, and various ad hoc configurations that support both civilian and industrial services (Conti and Giordano 2014; Aalamifar et al. 2014). Collectively, these technologies enable extensive connectivity and serve as the core substrate for terrestrial data transmission within the integrated network architecture (Liu et al. 2018).

The ground segment is characterized by a progressive evolution of cellular technologies. Beginning with first-generation 1 G systems, terrestrial networks have advanced through 2 G, 3 G, 4 G and long term evolution advanced (LTE-A) (Demestichas et al. 2013). Current efforts concentrate on the deployment and optimization of fifth generation 5 G networks and on the preliminary exploration of sixth generation 6 G systems (Conti and Giordano 2014; Aalamifar et al. 2014). These developments aim to satisfy increasing demands for ultra-reliable, high-speed, and low-latency services across a wide range of applications. Standardization is coordinated by the third generation partnership project (3GPP), which issues technical specifications governing network architecture, radio access, and service provisioning (Aalamifar et al. 2014; Demestichas et al. 2013; Xiao et al. 2024). Despite these advancements, the ground network faces several limitations.

- **Limited coverage and environmental constraints:** One of the principal challenges is inadequate coverage in rural and remote areas, where infrastructure deployment is either economically infeasible or logistically constrained (Aalamifar et al. 2014; Demestichas et al. 2013). Moreover, complex terrain and natural obstructions degrade signal penetration and undermine network stability, further exacerbating connectivity gaps in these regions.
- **Communication efficiency and service diversity:** Traditional ground-based systems face challenges in maintaining communication efficiency when supporting multiple heterogeneous services. These systems must concurrently process diverse data types while meeting stringent requirements for low latency and high throughput, a demand that strains existing architectures and resource management mechanisms (Yuhui 2020).

To address these challenges, researchers have explored architectural and technological innovations.

- **Heterogeneous network fusion:** One promising solution is the integration of heterogeneous networks to achieve functional complementarity. For example, converging LTE-R networks with ad hoc networks can improve coverage reliability in ground environments where conventional LTE-R infrastructure exhibits gaps (Zhang 2020). Such heterogeneous integration enhances fault tolerance, capacity, and resilience, particularly in dynamic or harsh environments (Sheng et al. 2021).
- **Ground communication enhancements:** In domain-specific applications such as high-speed railways, dedicated systems such as GSM-R and train dispatch communication have long been employed (Zhang 2020). With the deployment of 5 G networks, railway private networks and bus communication systems have increasingly incorporated features such as service oriented architecture and network slicing, enabling tailored deployments and improved support for transportation operations (Zhang 2020; Yuhui 2020).

The ground segment continues to advance through both the evolution of cellular technologies and the integration of domain-specific networks. Although it remains the principal layer for high throughput terrestrial communication, its limitations in coverage and adaptability underscore the necessity of seamless integration with aerial and space-based systems within SAGIN.

2.2 Multi-tier aerial communication network

In this review, Fig. 2 presents a comprehensive taxonomy that organizes the surveyed literature according to core MACN functionalities: routing protocols, computing paradigms, handover mechanisms, resource management, and optimization techniques. The taxonomy emphasizes AI driven solutions tailored for dynamic, multi-layered environments. For each functionality, approaches are classified by AI technique. SL, which typically relies on labeled data for predictive tasks such as classification or regression and is well suited to static pattern recognition; RL, in which agents learn via interaction and reward signals, and which is particularly appropriate for sequential decision making under uncertainty; unsupervised learning (UL), which seeks to discover latent structures without labels and is less common in this domain; and hybrid methods that combine evolutionary algorithms, generative models, or multiple AI paradigms to address complex, multi-objective problems. We briefly justify the placement of papers within categories and subcategories and include one or two representative examples per grouping to illustrate prevailing trends, notably the prevalence of RL in adaptive scenarios.

2.2.1 Routing protocols

Routing protocols in MACNs handle data path selection across dynamic topologies, positions, and cross-layer adaptations, with AI enhancing resilience in SAGINs' heterogeneous environments.

Routing in MACNs presents unique challenges arising from the interplay of dynamic, heterogeneous, and resource-constrained network components. The rapid mobility of LEO satellites, with orbital cycles on the order of 90 to 120 min, together with the movement of UAVs, produces frequent topology changes that necessitate real-time route recalculation (Chen et al. 2025; Zhang et al. 2025; Jiang et al. 2023). Satellites and UAVs operate under stringent bandwidth, energy, and computational constraints, with substantial variation in platform capabilities across tiers (Chen et al. 2025; Hu et al. 2023; Guo et al. 2024).

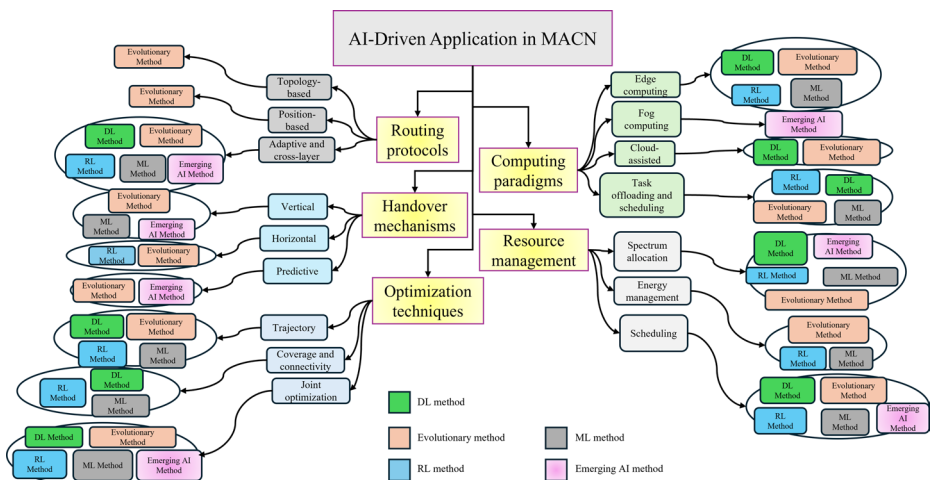


Fig. 2 Classification of AI applications in MACN: mapping functions to AI paradigms

MACNs support a wide spectrum of applications ranging from ultra-low-latency emergency communications to energy-efficient IoT connectivity, requiring routing protocols to reconcile competing QoS requirements (Hu et al. 2023; Cui et al. 2022). Environmental factors, particularly rain attenuation at frequencies above 20 GHz, can substantially degrade signal quality and necessitate predictive routing strategies (Yuan et al. 2022). Mega-constellations comprising thousands of satellites together with massive IoT deployments place stringent demands on routing scalability, while the explosive growth of data traffic produces severe congestion (Chen et al. 2025; Park et al. 2023; Zhang et al. 2025). The heterogeneous composition of MACNs also increases protocol and coordination complexity across tiers, which can affect reliability, robustness, and end-to-end service continuity (Li et al. 2022; Conti et al. 2024). Finally, coordinating space, aerial, and ground layers requires interoperability across diverse technologies, complicating protocol design and network management (Yuan et al. 2025; Cui et al. 2022). These challenges underscore the limitations of conventional routing protocols and motivate the development of AI-driven approaches capable of adapting to real-time fluctuations in topology, resources, and demand.

In supervised learning, approaches often use machine learning or deep learning models trained on historical data to predict optimal routes, fitting adaptive and cross-layer routing sub-categories due to their focus on pattern-based signal prediction. For instance, Yuan et al. (2022) employs extended extreme machine learning to predict rain-induced signal blockages, enabling reliable path selection in SAGIN IoT networks by anticipating environmental disruptions.

In reinforcement learning, methods learn routing policies through trial and error, making them well suited to adaptive and cross-layer routing, where real-time decisions respond to network dynamics. Examples include the study in Chen et al. (2025), which employs graph-based DRL for routing in LEO mega-constellations under service constraints and optimizes paths under highly dynamic conditions; and the work in Guo et al. (2024), which applies a generative attention network augmented DRL approach to infer network states and select routes, thereby improving efficiency in data-scarce SAGIN scenarios.

Hybrid approaches combine evolutionary and other emerging AI methods to achieve robust, multifaceted routing, and are commonly applied in position-based or topology-based categories to manage optimization trade-offs. For position-based routing, Hu et al. (2023) optimize UAV trajectories and resource allocation using evolutionary algorithms in MACNs, treating UAVs as edge relays for task routing. In the domain of adaptive and cross-layer routing, Park et al. (2023) employ evolutionary methods to design random access protocols with virtual deadlines, thereby directing Internet of Things traffic across layers according to urgency.

2.2.2 Computing paradigms

Computing paradigms distribute processing across edge, fog, and cloud layers in MACNs and incorporate mechanisms for task offloading, with AI used to optimize resource-constrained and time-sensitive computations.

Designing robust computing architectures in MACNs requires addressing several critical challenges arising from heterogeneous network layers and dynamic operating conditions. Computational tasks must be distributed across edge, fog, and cloud tiers according to task complexity, data volume, latency sensitivity, and available resources, where lightweight

latency-critical tasks are typically executed at the edge while data-intensive operations can be offloaded to the cloud (Li et al. 2025). Time-sensitive applications such as disaster response and autonomous navigation require low-latency processing, necessitating intelligent task offloading and proximity-based computing (Zhu et al. 2025). The high mobility of aerial platforms introduces variability in connectivity, link stability, and resource availability, requiring real-time adaptability in workload distribution and dynamic network management (Lan et al. 2024; Tang et al. 2022a). The system must scale to accommodate increasing numbers of connected devices and evolving network topologies through distributed computing paradigms and load-balancing mechanisms (Gu et al. 2021; Li and Chen 2023). Data exchange across tiers, particularly over wireless links, must remain reliable and efficient despite intermittent connectivity, heterogeneous protocols, and limited resource budgets (Lan et al. 2024). Energy optimization is critical for battery-constrained edge devices and aerial platforms, necessitating energy-aware scheduling and offloading strategies (Xia et al. 2022). Finally, seamless integration across heterogeneous computing tiers requires adherence to standardized protocols and data formats to ensure coordination among diverse components (Li and Chen 2023). These challenges motivate the application of AI-driven approaches capable of adaptive resource management under dynamic and heterogeneous conditions.

SL is particularly well suited to task offloading and scheduling problems, where models trained on labeled data such as task complexity and device capability metrics predict optimal task placement and scheduling. For example, the study in Li et al. (2022) employs DL to hierarchically offload DL tasks across SAGIN layers, reducing latency by aligning tasks with the computational capabilities of available devices.

RL is particularly effective in dynamic environments for edge computing and task offloading, as it learns policies that minimize latency or energy consumption through reward-driven interaction. For task offloading, the study in Zhu et al. (2025) employs deep Q-network (DQN) based RL to jointly optimize computation and communication resources in 6 G SAGIN MEC, balancing energy and delay through problem decomposition. In the context of edge computing, the work in Li et al. (2025) applies a DQN approach to IoT task offloading within MACNs, intelligently selecting communication links to prolong device lifetime. These examples illustrate how RL can adaptively manage scarce resources under changing network conditions and heterogeneous device capabilities.

Hybrid methods combine evolutionary and other emerging AI techniques to address the complexities and uncertainties inherent in heterogeneous computing environments, and they are frequently applied within cloud and edge subcategories. For task offloading, Tang et al. (2022a) integrate blockchain with FRL in a hybrid framework to enable secure traffic offloading in MACNs, thereby mitigating threats while preserving user privacy. In the domain of cloud computing, Zhang et al. (2024) adopt a quantum-inspired evolutionary optimization within Com²Net to unify cross-domain resources for large-scale AI training, demonstrating the potential of hybrid optimizers to coordinate diverse computing assets efficiently.

2.2.3 Handover mechanisms

Handover mechanisms ensure seamless connectivity during link or node transitions in MACNs, with AI used to predict or adapt to mobility induced changes across vertical, horizontal, and predictive handover categories.

Handovers in MACNs present unique challenges arising from high mobility and constantly changing network topologies. LEO satellites complete an orbit in approximately 90 min and traverse specific ground areas in less than 10 min, requiring handover frequencies three to five times higher than conventional terrestrial cellular networks Tong et al. (2025); Lv et al. (2022); Niu et al. (2024). Seamless transitions across heterogeneous tiers, such as from satellites to HAPs or UAVs and further to terrestrial base stations, require harmonized protocols that consider differing communication standards, latency profiles, and mobility patterns, and can suffer high failure rates when handover thresholds or trajectory prediction are inadequate (Zhang et al. 2024; Guo et al. 2022; Morshed et al. 2024). Environmental factors pose significant challenges, particularly for optical inter-satellite links that may experience 15 to 25 dB signal attenuation from cloud scattering and atmospheric turbulence, while high-frequency radio channels are susceptible to Doppler shifts reaching up to 100 kHz (Niu et al. 2024; Mahboob and Liu 2024). The finite onboard resources of aerial nodes must be shared among increasing numbers of users, intensifying contention in high-density scenarios and leading to handover access failures or degraded quality of service (Tong et al. 2025; Lv et al. 2022). Practical applications further illustrate these challenges: disaster response scenarios require predictive handover strategies within satellite visibility windows often limited to less than 60 s per pass (Mohamed et al. 2024), commercial aircraft undergo handovers approximately every 90 s within LEO constellations (Lv et al. 2022), and remote IoT devices must incorporate delay-tolerant networking principles to manage intermittent coverage (Han et al. 2024). These challenges motivate the development of AI-driven handover mechanisms capable of adaptive decision-making under dynamic and heterogeneous conditions.

RL is particularly prominent for real time decision-making in horizontal and vertical handovers, as it learns switching policies from environmental feedback. For example, researchers in Tong et al. (2025) apply an advantage A2C RL algorithm to optimize LEO satellite handovers based on signal strength and link duration. In the vertical handover context, authors in Tao et al. (2025) employ MAPPO augmented with generative models to minimize jitter in SAGIN IoT deployments, adapting to integrated sensing and communication dynamics. These learning based approaches illustrate how adaptive policies can enhance continuity and QoS under highly dynamic mobility and channel conditions.

Hybrid approaches employ evolutionary and other emerging AI techniques to support predictive and complex handover decision making, thereby managing uncertainties such as topology changes. For predictive handover, authors of Kim et al. (2025) propose a quantum-MARL framework for coordinating CubeSats, HAPs, and UAVs, balancing energy consumption and service requirements in MACNs. In the vertical handover context, researchers in Mohamed et al. (2024) integrate multi-armed bandit RL with evolutionary components for UAV and LEO selection in disaster scenarios, optimizing trajectories and resource allocation under uncertain conditions.

2.2.4 Resource management

Resource management in MACN encompasses the allocation of spectrum, energy, bandwidth, and scheduling resources, and AI is increasingly employed to address scarcity and temporal dynamics.

The complexity of multi-tier systems, in which LEO, MEO, and GEO satellites, HAP stations, UAV swarms, and terrestrial nodes interact over heterogeneous links, produces tightly coupled trade-offs across spectrum, energy, and compute resources. Prior studies have characterized uplink and downlink performance and weather-driven switching between FSO and RF links in hybrid MACN configurations; however, these works typically assume simplified, static networks with single ground receivers and fixed routes (Singh and Swaminathan 2023; Swaminathan et al. 2021; Altubaishi and Alhamawi 2019; Zhang et al. 2009). Practical deployments require resource control that scales to many concurrently served ground users and responds to rapidly varying channel, traffic, and mobility conditions. Jointly exploiting direct satellite-to-user links and HAPS-assisted relays through dynamic adjustment of coverage footprints, relay selection, and routing promises substantial performance gains but introduces challenges in cross-layer optimization, real-time decision latency, and coordination among distributed controllers. The physical placement of high altitude platform stations is a decisive design variable because both relay capacity and effective coverage expansion depend strongly on satellite-HAPS geometry and user demand distribution; nevertheless, systematic strategies that jointly consider HAPS positioning, coverage control, and AI-driven resource allocation across diverse operational scenarios remain largely unexplored (Mashiko et al. 2025). These challenges motivate the application of AI methods such as DRL for sequential decision problems, GNN for topology-aware reasoning, and FL for privacy-preserving distributed model training to enable adaptive, data-driven resource management.

SL is well suited to predictive allocation tasks within dynamic scheduling and spectrum management subcategories, where models are trained on historical demand and channel state data to anticipate resource requirements. For example, Dahrouj et al. (2023) applied an ensemble of deep neural networks to assign users to integrated networks, thereby maximizing throughput subject to power constraints. RL, particularly DRL, predominates in adaptive resource allocation tasks, where agents learn policies for energy and bandwidth management from reward signals under varying network conditions. For dynamic scheduling, the study in Jia et al. (2025) formulates service function chaining (SFC) scheduling in SAGIN as a DRL problem over time-extended graphs to maximize deployment efficiency. For energy management, the work in Zhang et al. (2024) combines DRL with graph convolutional networks (GCN) to orchestrate MACN resources, minimizing energy consumption while maximizing revenue. These examples illustrate how RL-based methods can adaptively optimize scarce resources in highly dynamic, multi-tier environments.

Hybrid methods combine evolutionary and other emerging AI techniques to address multi-objective resource management problems, particularly those that involve trade-offs between energy and bandwidth. For dynamic scheduling, the study in Li and Shang (2025) employs evolutionary optimization to enhance multi-connectivity in MACNs, thereby improving coverage in remote regions. For energy management, the work in Zhi et al. (2024) proposes a self-powered reconfigurable intelligent surface (RIS) scheme to strengthen MACN security and sustainability by jointly optimizing amplitude and phase control.

2.2.5 Optimization techniques

This section examines optimization techniques that maximize trajectory efficiency, coverage, and joint control objectives in MACNs, wherein AI addresses complex multiobjective problems.

AI-driven optimization in MACNs addresses several critical challenges arising from the integration of satellites, UAVs, HAPs, and terrestrial infrastructure. Ensuring seamless connectivity across diverse environments, including urban, rural, and remote regions, remains a central objective, with civil aircraft-assisted SAGINs and UAV deployments adapting dynamically to variations in population density (Li et al. 2022; Mohamed et al. 2023). Efficient placement of network nodes is essential to balance resource utilization with coverage, particularly given high node density and dynamic satellite mobility (Chen et al. 2022). Optimizing UAV trajectories is crucial for achieving both energy efficiency and spectral efficiency in highly dynamic environments, requiring coordination of flight paths, power control, and user association (Liu et al. 2025; Nguyen et al. 2023; Ding et al. 2021). Interference resulting from heterogeneous devices and dynamic network topologies poses significant obstacles to reliable communication, motivating the use of reconfigurable intelligent surfaces and non-orthogonal multiple access schemes to dynamically manipulate electromagnetic wave propagation and enable frequency resource sharing (Bariah et al. 2022; Khoshafa et al. 2025; Zhou et al. 2023). These optimization objectives are frequently formulated as multi-objective problems that balance competing requirements such as latency, energy consumption, throughput, and security, highlighting the need for integrated design frameworks that jointly address cross-layer trade-offs (Wang et al. 2023; Tu et al. 2024). These challenges motivate the application of AI-driven optimization approaches capable of learning adaptive policies under dynamic and heterogeneous conditions.

SL is commonly applied to joint optimization and coverage tasks by training predictive models on labeled datasets to inform resource allocation and deployment decisions. As an example within distributed supervised settings, Jing et al. (2025) employ FL for online model training across SAGIN nodes with unreliable links, using sample selection strategies to reduce communication overhead while maintaining model performance. RL is particularly well suited to trajectory and coverage optimization in dynamic MACNs because it learns sequential decision policies from reward signals. MARL enables cooperative policy learning among multiple aerial nodes, facilitating coordinated path planning and resource allocation under changing topology and channel conditions. For trajectory optimization, Liu et al. (2025) apply a MARL framework to plan UAV paths in MIMO-enabled networks, balancing energy consumption with operational efficiency. In the joint communication, computing, and control domain, Cheng et al. (2025) employ MARL to develop cooperative transmission strategies that jointly optimize routing and resource allocation across tiers. These RL based approaches illustrate how sequential learning can adapt policies to evolving network states, thereby improving coverage, resilience, and overall performance.

Hybrid approaches combine generative, evolutionary, and multiple AI techniques to address complex optimization problems, and are particularly suitable for trajectory and coverage optimization under uncertainty. For joint communication, computing, and control, Tao et al. (2025) employ diffusion based generative AI to support handover decision making, thereby improving robustness in space air ground integrated network Internet of Things deployments. For trajectory optimization, Zhou et al. (2023) integrate evolutionary

optimization with non orthogonal multiple access (NOMA) for energy efficient data collection in SAGIN, demonstrating reduced energy consumption while maintaining coverage and throughput.

3 AI-driven routing in multi-tier aerial networks

MACNs are central to the realization of 6 G systems by integrating LEO satellites, UAVs, and terrestrial infrastructure to deliver seamless global connectivity. The heterogeneous, multi-tier, and highly dynamic character of SAGINs creates complex routing challenges that conventional protocols are ill equipped to resolve, owing to frequent topology changes, constrained resources, and diverse service requirements. AI, with its capacity for online adaptation and data-driven optimization, offers transformative approaches for routing under these conditions. This section examines the principal routing challenges, surveys AI-based routing protocols, and presents a comparative evaluation informed by recent advances in MACN research. Our analysis focuses on how ML and optimization techniques can meet ambitious 6 G performance objectives which includes high throughput, low latency, and strong reliability, while accommodating mobility, energy, and spectrum constraints inherent to multi-tier deployments.

The explosive growth of massive machine type communication devices (MTCs) has spurred extensive research into random access mechanisms that mitigate congestion at the access layer and thereby affect link availability, reliability, and routing in aerial networks. Representative access layer solutions include grant-free random access frameworks (Srinath et al. 2022), time alignment control for NB IoT (Zhang et al. 2020), probabilistic user activity models based on multivariate Bernoulli distributions (Liu et al. 2022), and analyses of retransmission limits (Zhan et al. 2021). Additional approaches address Age of information (AoI) through collision resolution protocols (Pan et al. 2022), exploit directional beam-based cell zoning (Pei et al. 2021), and employ group-based random access that combines preamble and data or uses two phase group access (Choi and Ding 2021; Wang et al. 2021). Non orthogonal random access schemes (Khairy et al. 2021), downlink congestion controllers that classify preamble collisions (Jang et al. 2021), and MARL methods for preamble selection and congestion control (Bai et al. 2021; Huang et al. 2020; Lee et al. 2022) further broaden the design space. These mechanisms modify collision patterns, retransmission dynamics, beam and zone allocations, and user activity characteristics, which in turn alter link stability and latency profiles; consequently, they must be explicitly considered when designing routing strategies for MACN.

MACNs present tightly coupled routing challenges, including high mobility, rapidly varying topologies, intermittent links, stringent latency requirements, and limited onboard computation and storage, all of which render classical routing protocols inadequate. This section reviews AI driven routing methods that adapt to the spatio-temporal dynamics of MACNs and that can operate in concert with the access level mechanisms cited above (Srinath et al. 2022; Lee et al. 2022).

3.1 Topology-based routing

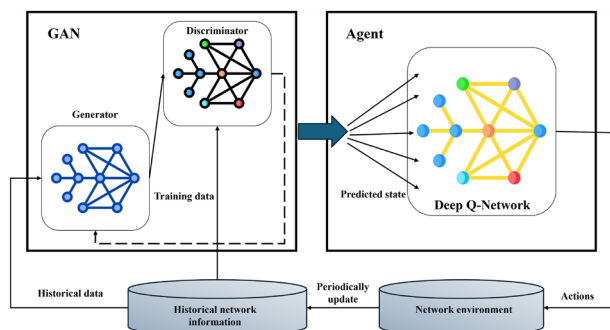
Topology-based routing methods explicitly represent the network as a time-varying graph and employ AI to infer link quality, predict topology evolution, or directly learn routing policies over graph structures. These techniques are particularly well suited to LEO constellations and scenarios dominated by inter-satellite links, where the connectivity graph exhibits a regular structure but changes rapidly in time (Chen et al. 2025).

Relevant routing challenges. Rapid mobility of LEO satellites and UAV movement produce frequent topology changes that necessitate near real-time route recalculation and robust topology forecasting. Scalability is a central concern: mega-constellations and large device populations create very large graphs that are costly to manage in real time (Chen et al. 2025; Park et al. 2023). Resource constraints on many aerial nodes further limit the feasibility of heavy in-node computation, motivating tier-aware solutions that exploit ground or cloud resources for training or inference when available.

Representative AI techniques. Supervised learning techniques and Bayesian estimators supply lightweight predictors for short-term link availability and uncertainty quantification, which can feed classical heuristics. Deep learning on graphs, and in particular GNN, provide a natural framework for representing evolving neighborhood structures and link attributes; when combined with deep reinforcement learning (DRL), the resulting GNN-DRL paradigm can proactively select routes in anticipation of topology changes rather than reacting after failures (Chen et al. 2025). RL and multi agent RL (MARL) formulations cast routing as a sequential decision problem, enabling agents to learn forwarding policies that optimize long-term metrics such as throughput and delay. GAN-augmented DRL can mitigate data scarcity by synthesizing plausible topology or state samples for training; Fig. 3 illustrates such a pipeline (Guo et al. 2024). Federated learning and distributed graph representation learning offer privacy-preserving, scalable training alternatives by aggregating model updates rather than raw telemetry across tiers (Chen et al. 2025).

Practical trade-offs. GNN-DRL methods scale well to large LEO constellations but demand substantial compute and memory resources, typically requiring offloading or ground assistance for training and inference. Lightweight predictors, including extended ELM, provide rapid edge-suitable inference for blockage or link-quality prediction but can be sensitive to noisy or scarce data (Yuan et al. 2022). Topology-based approaches must also address environmental and security concerns because link availability is affected by atmospheric events and because attacks on critical graph nodes can severely degrade end-to-end connectivity.

Fig. 3 GAN-augmented DRL pipeline for topology inference and sample augmentation in routing Guo et al. (2024)



3.2 Position-based routing

Position-based routing leverages node locations, predicted trajectories, and motion dynamics to inform forwarding decisions. This approach is especially relevant for UAV swarms, cooperative aerial relays, and scenarios in which geographic information and mobility models are available and reliable.

Relevant routing challenges. High mobility and trajectory uncertainty in aerial platforms produce intermittent links and variable link quality that position-aware predictors must accommodate. Service function constraints and QoS heterogeneity require position-based policies to balance hop count, stability, latency, and energy consumption. Resource limitations of smaller UAVs impose strict processing and energy budgets, constraining the complexity of on-node models and decision rules.

Representative AI techniques. Classical machine learning methods such as clustering and density estimation reduce routing overhead by grouping nodes with similar mobility or spatial locality. Time-series predictors based on recurrent neural networks and convolutional architectures consume sequences of location and sensor measurements to produce short-term trajectory forecasts that inform next-hop selection. MARL enables decentralized learning of forwarding and motion policies, where agents optimize jointly for connectivity, energy efficiency, and latency using local observations and limited neighbor exchange (Yuan et al. 2025). Swarm intelligence algorithms such as ant colony optimization and particle swarm optimization provide simple, local-rule-based mechanisms that are compatible with resource-constrained UAV implementations. Explainable AI (XAI) techniques and federated training further support transparency and privacy in civilian airspace operations.

Practical trade-offs. Position-based solutions can be lightweight and interpretable, which is advantageous in safety-critical missions. However, their performance degrades when positional measurements are noisy or unavailable, and they must be complemented with topology or cross-layer information for robust operation in complex environments.

3.3 Adaptive and cross-layer routing

Adaptive and cross-layer routing exploits metrics and control signals from the physical, MAC, network, and application layers to make routing decisions that account for both instantaneous link conditions and long-term service requirements. This paradigm explicitly recognizes that access layer mechanisms and traffic dynamics directly alter link availability and must therefore be integrated into routing logic.

Relevant routing challenges. Access-layer dynamics such as grant-free random access, time alignment control, group-based access, non-orthogonal schemes, retransmission behavior, and preamble collisions modify collision patterns and retransmission dynamics, which in turn affect link stability and latency profiles. Designing cross-layer routing must therefore reconcile random access behavior, Age of Information objectives, energy budgets, and application-specific QoS. Heterogeneous tier capabilities and integration complexity across space, aerial, and ground domains further complicate unified cross-layer control (Srinath et al. 2022; Lee et al. 2022).

Representative AI techniques. Probabilistic graphical models and Bayesian networks integrate cross-layer indicators such as random access success probability, retransmission statistics, and queue states to estimate end-to-end performance and guide routing decisions.

Representation learning methods, for example autoencoders, produce compact features from heterogeneous telemetry that feed supervised predictors or RL agents, thereby enabling faster adaptation under noisy measurements (Guo et al. 2024). DRL is especially suited to long-horizon trade-off optimization among latency, energy, and reliability and can naturally incorporate access-layer dynamics within reward formulations. Hybrid frameworks that combine digital twins, blockchain, and AI facilitate safe offline testing and policy optimization at the expense of increased computational cost. Satellite-terrestrial fog networks (STFN) provide a practical partitioning in which intensive learning tasks execute on more capable edge or ground nodes while lightweight inference runs on aerial devices (Yuan et al. 2025). RL has been increasingly adopted for topology-aware and adaptive routing in UAV networks, enabling agents to learn optimal forwarding policies based on observed mobility, link quality, and network dynamics (Arafat and Moh 2021).

Practical trade-offs. Cross-layer AI solutions can achieve superior end-to-end performance by explicitly coordinating access and network behaviors. Their principal limitations are increased model complexity, elevated data requirements for reliable cross-layer estimation, and the need for standardized telemetry and interfaces to enable effective information exchange across tiers.

3.4 Comparison and evaluation

A comparative analysis of these AI-based routing protocols assesses their performance in terms of adaptability, resource efficiency, data requirements, security, and other key metrics, providing insights into their suitability for MACN applications. Table 3 presents a focused comparison of representative AI routing protocols, highlighting performance metrics, principal strengths, and practical limitations.

GNN-DRL and GAN-DRL exhibit strong adaptability in highly dynamic environments. These methods can learn and adjust to satellite and UAV mobility patterns, rendering them particularly effective for large-scale, time-varying topologies (Chen et al. 2025; Guo et al. 2024). In contrast, the VDI approach achieves adaptability through selective layer engagement to accommodate IoT scenarios (Park et al. 2023), while ELM provides lightweight environmental adaptability suitable for resource-constrained nodes (Yuan et al. 2022). Quantum routing methods, although still in an early stage, offer potential for future dynamic networks in which fundamentally different communication primitives are available (Conti et al. 2024).

Resource efficiency represents a key differentiator among these approaches. ELM is computationally lightweight, making it suitable for resource-constrained nodes such as small satellites or edge IoT devices (Yuan et al. 2022). In contrast, GNN-DRL, GAN-DRL, and STFN require substantial computational and memory resources, limiting their direct deployment on small UAVs or CubeSats without offloading or specialized accelerators (Chen et al. 2025; Guo et al. 2024; Yuan et al. 2025). The VDI approach occupies an intermediate position by balancing complexity and effectiveness for massive IoT connectivity (Park et al. 2023).

Data dependency and training requirements further influence applicability. Methods such as ELM and maritime deep learning rely on large, labeled datasets for tasks including blockage prediction or maritime routing, which can be challenging in data-scarce environments (Yuan et al. 2022; Liu et al. 2022). DRL schemes mitigate some of this limitation by

learning directly from environmental interactions rather than depending solely on precollected datasets (Chen et al. 2025; Guo et al. 2024). However, approaches that explicitly model transmission dynamics or topology evolution often require comprehensive topology and channel datasets to achieve robust and reliable performance (Zhang et al. 2025).

Security constitutes an additional axis of comparison. ESMD-Flow enhances security by employing dynamic protocol switching, which mitigates eavesdropping risks at the expense of increased retransmissions and potential packet reordering (Li et al. 2022). Quantum routing provides the theoretical advantage of unconditional security based on quantum mechanical principles; however, practical deployment is constrained by current hardware limitations (Conti et al. 2024). Most other routing protocols require supplementary security mechanisms to satisfy the demands of high-assurance applications.

When evaluated across performance metrics, these methods exhibit distinct strengths and trade-offs. GNN-DRL optimizes the SFC score, average network load, path delay, capacity, and runtime, making it particularly suitable for large LEO constellations (Chen et al. 2025). The SFC score quantifies the success rate and efficiency of service function chain deployment, typically computed as the ratio of successfully deployed service chains to total requested chains weighted by resource utilization and path delay (Chen et al. 2025). Readers seeking detailed mathematical formulations should consult the original works. ELM achieves high predictive performance, with reported accuracy, precision, recall, and F1 scores near 91%, thereby enhancing link reliability with minimal computational overhead (Yuan et al. 2022). VDI improves the random access success rate, AoI, and energy efficiency in IoT connectivity scenarios (Park et al. 2023), while ESMD-Flow enhances path reliability and throughput at the expense of additional retransmissions (Li et al. 2022). Maritime DL approaches balance delay, throughput, and path lifetime in seaborne networks (Liu et al. 2022). ME-SAGIN increases the content delivery ratio but incurs additional routing computation overhead, STFN demonstrates improvements in latency, throughput, and resource utilization, although detailed metrics remain limited (Yuan et al. 2025), and quantum routing optimizes entanglement generation rates and channel loss characteristics for long-term quantum-enabled networks (Conti et al. 2024).

In practice, GNN-DRL and GAN-DRL are most suitable for large, dynamic deployments such as mega-constellations, whereas ELM and VDI are well suited for resource-constrained IoT and edge scenarios. ESMD-Flow is particularly appropriate in environments where security is critical, and maritime DL approaches address domain-specific requirements in seaborne networks. ME-SAGIN and STFN offer practical frameworks for edge processing and experimental evaluation of novel routing strategies, while quantum routing represents a promising but still aspirational direction.

Looking ahead, advances that enhance distributed optimization (Chen et al. 2025; Hu et al. 2023; Li et al. 2022), energy, and security-aware designs, and scalability will be critical (Jiang et al. 2023; Conti et al. 2024). The integration of AI with network slicing, block-chain-based trust mechanisms, and quantum error-correction techniques has the potential to further improve both performance and trustworthiness. Crucially, addressing computational overhead and improving data efficiency will determine whether these methods can evolve from promising research findings to practical, deployable solutions.

AI-based routing protocols provide transformative solutions for MACNs in 6 G networks by addressing dynamic topologies, resource constraints, and diverse QoS requirements. Challenges such as computational overhead and data dependency remain; however, ongoing

research continues to advance scalability, security, and efficiency. Continued development in this field is essential to fully realize the potential of MACNs. Collectively, Tables 2 and 3 reveal several important patterns across AI-based routing protocols in MACNs. Graph-based deep reinforcement learning approaches such as GDRL-SFC (Chen et al. 2025) and GAN-DRL (Guo et al. 2024) demonstrate strong performance in handling dynamic topologies, achieving 32% reduction in average delay and 28% reduction in packet loss respectively, though they incur high computational loads and data-intensive training requirements. Lightweight approaches such as Extended ELM (Yuan et al. 2022) offer edge-suitable implementations with 91% accuracy for blockage prediction but exhibit sensitivity to data noise. Scalability varies significantly, with probabilistic methods (Park et al. 2023; Guo

Table 2 Summary of routing methods in MACN

References	AI model	Dataset and simulator	Scalability	Robustness
Chen et al. (2025)	Graph DRL with GNN	Python	Medium (Handles massive networks but resource-heavy)	High (Robust to SFC constraints and dynamic topology)
Hu et al. (2023)	Optimization with Dinkelbach Algorithm and Block Coordinate Descent	Python	Medium (Scales to multi-layer SAGIN but assumes perfect conditions)	Medium (Energy/security issues in dynamic scenarios)
Yuan et al. (2022)	Extended ELM	N/A	Low (Data-hungry, shaky with noisy data)	High (91% accuracy for blockage prediction)
Park et al. (2023)	Bayesian Estimation and VDI Shifting Algorithm	N/A	High (Handles massive IoT with probabilistic adjustments)	Medium (Assumes accurate device estimation)
Guo et al. (2024)	GAN-Powered DRL	N/A	High (Scales to dynamic SAGIN with GAN predictions)	High (Beats traditional methods in speed/balance)
Jiang et al. (2023)	DSTMR Algorithm with Dijkstra	N/A	Medium (Complex for real-time but reliable paths)	High (Guarantees deterministic delivery)
Zhang et al. (2025)	Transmission Dynamics Theory	N/A	Low (Heavy theory, light on practical details)	Medium (Handles congestion but dynamic topologies challenging)
Liu et al. (2022)	Deep Learning for Pareto-Optimal Routing	N/A	High (Uses local info for moving networks)	High (Balances delay/throughput/lifetime)
Li et al. (2022)	Graph Theory for Multipath Routing	Mininet, Python	Medium (Higher retransmission/out-of-order issues)	High (Mimic Defense for security)
Yuan et al. (2025)	Not AI-Specific (AI-Driven Optimization)	N/A	Medium (Complexity of integration)	Medium (Latency/throughput focus)
Conti et al. (2024)	Not AI-Specific	N/A	Low (Quantum memory/scalability issues)	Medium (Coherence time/channel loss)
Cui et al. (2022)	Not AI-Specific (MILP for Mobility)	N/A	Medium (High latency/protocol complexity)	High (Improved latency/flexibility)

Table 3 Comparison of AI routing protocols in MACN

Protocol	AI technique	Key metrics	Strengths	Limitations
GDRL-SFC (Chen et al. 2025)	Graph DRL with GNN	SFC score, avg. delay (↓ 32%)	Handles dynamic topologies	High computational load
GAN-DRL (Guo et al. 2024)	DRL with GAN	Packet loss (↓ 28%), queue utilization	Robust to partial observability	Data-intensive training
Extended ELM (Yuan et al. 2022)	ELM with SMOTE	Blockage prediction (91% accuracy)	Lightweight, edge-suitable	Sensitive to data noise
VDI-Based RA (Park et al. 2023)	Bayesian Estimation	Age of Information, energy efficiency	Scalable for massive IoT	Assumes perfect coordination
ESMD-Flow (Li et al. 2022)	Mimic Defense	Eavesdropping success (↓ 41%), path reliability	Endogenous security	Retransmission overhead

“↑” indicates improvement or increase and “↓” indicates reduction. Metrics are representative values reported in the cited works

et al. 2024) effectively handling massive IoT deployments, while graph DRL and optimization-based methods (Chen et al. 2025; Hu et al. 2023) become resource-intensive as network size increases. Most protocols achieve high robustness against dynamic conditions, with security-focused approaches such as ESMD-Flow (Li et al. 2022) reducing eavesdropping success by 41% through mimic defense mechanisms; however, several methods assume ideal operating conditions that may compromise robustness in practical deployments. The analysis demonstrates a fundamental trade-off between model complexity and deployment feasibility, suggesting that no single protocol universally dominates across all criteria and that the selection of an appropriate method depends on specific deployment requirements including network scale, computational resources, and security considerations.

A broader comparison of the surveyed routing methods suggests that the main advantage of AI in MACN routing does not lie in replacing all classical protocols, but in improving adaptability when network conditions vary too quickly or too irregularly for fixed rules to remain effective. In relatively structured settings, lightweight geographic, topology-based, or heuristic routing strategies may still offer an attractive balance between simplicity, interpretability, and low overhead. However, as topology changes become more frequent, link availability becomes less predictable, and routing decisions must jointly account for mobility, congestion, and heterogeneous service requirements, AI-based methods become more compelling because they can learn decision policies from data or interaction rather than relying on repeated manual redesign. This benefit, however, comes at the cost of increased training complexity, data dependence, and computational burden, particularly for graph-based deep learning and DRL approaches. Therefore, the practical value of AI-driven routing in MACN is strongest in highly dynamic and large-scale scenarios, whereas classical or lightweight hybrid solutions may remain preferable in constrained deployments that prioritize simplicity, explainability, and low runtime cost.

4 AI for computing and task offloading

Researchers have investigated the use of satellites and UAVs within MACNs as traffic offloading points. For instance, the authors in Du et al. (2018) proposed an SDN-based auction mechanism for STNs that facilitates both cooperation and competition among the system's beam groups. Considering energy constraints, Li et al. (2020) introduced a transmission scheme that offloads base station traffic through satellite broadcast to achieve a more energy-efficient RAN. Several studies have proposed architectures for space-0terrestrial integrated networks (STINs). For example, Li et al. (2017) introduces SERVICE, an SDN framework for integrated satellite communications leveraging SDN and network function virtualization (NFV). To enhance connectivity and improve delay and reliability, Dai et al. (2021) proposes an intelligent gateway-placement strategy. Addressing the time-varying behavior of STINs, Dai et al. (2020) presents a dynamic user association mechanism with task classification to support load balancing and user task processing. Finally, Chen et al. (2022) develops a LEO-based STIN framework for crowded and underserved areas and recommends the application of federated learning in LEO satellite communications. A concise summary of the surveyed computation and task-offloading methods, along with their simulators, scalability, and robustness considerations, is provided in Table 4.

4.1 Edge, fog, and cloud computing models

In MACNs, multi-tier computing architectures are fundamental for enabling efficient communication, computation, and coordination across diverse and geographically distributed network segments. SAGIN integrates three hierarchical layers, space (satellites), aerial (UAVs or HAPs), and ground (terrestrial networks), into a unified framework that provides seamless end-to-end connectivity and computational intelligence (Wu et al. 2025; Xu et al. 2023; Xie et al. 2025; Yoo and Lee 2021).

This integrated, multi-tier architecture overcomes many limitations of traditional single-tier or isolated computing approaches, particularly in scenarios requiring real-time responsiveness and adaptability to dynamic network conditions. By distributing computation across the different layers, MACNs enable efficient task offloading, robust resource management, and scalable service delivery in environments characterized by mobility, latency sensitivity, and heterogeneous infrastructure. Communication in MACNs extends beyond simple data transfer to encompass a wide range of interactions, including human-to-human communication and machine-to-machine exchanges involving IoT devices, mobile terminals, and autonomous agents. Within such a dynamic ecosystem, real-time decision-making is critical. This includes determining optimal communication paths, prioritizing sensor data, adapting to fluctuating bandwidth, and managing computational loads across tiers. Consequently, integrating computational intelligence into network nodes is no longer optional but a fundamental requirement.

Nodes within the SAGIN architecture frequently perform multifunctional roles. Beyond basic data transmission, they are increasingly responsible for localized computing, routing optimization, and intelligent decision-making. For instance, a UAV node may simultaneously act as a data relay, an edge server, and a sensor data filter, depending on the operational context. To accommodate these evolving demands, multi-tier computing models comprising edge, fog, and cloud layers have been adopted to distribute computation intelligently across

Table 4 Summary of computation and task offloading methods in MACN

References	AI model	Dataset or simulator	Scalability	Robustness
Zhu et al. (2025)	DQN for Task Offloading	N/A	Low (High DQN complexity, simplified mobility)	Medium (27–53% cost reduction)
Wu et al. (2025)	Graph Theory-Based Iterative Optimization (GIO)	MATLAB	Medium (Simplified mobility/energy)	High (Reduced latency)
Li et al. (2025)	D3QN for Task Offloading	Python	Medium (No mobility, scalability issues)	High (20–30% energy reduction)
Li et al. (2022)	Hierarchical Task Offloading	Python	Medium (Limited testbed and mobility)	High (1.5× latency reduction)
Wang et al. (2022)	Queue-Aware Deep Actor-Critic	N/A	Medium (Incomplete information/dimensionality)	High (33–44% reductions in energy/delay)
Gu et al. (2021)	Coded Storage-and-Computation (CSC)	N/A	Medium (Latency/fault tolerance issues)	High (18–59% delay reduction)
Zhang et al. (2024)	Quantum Genetic Algorithm (QGA)	N/A	High (Quantum advantage for diversity)	High (>90% accuracy, 54% faster convergence)
Gong et al. (2024)	AI-Driven S3C Framework	N/A	Medium (Complex topology/privacy risks)	High (Improved transmission rate)
Zhang et al. (2024)	Not AI-Specific (QoS Calculation)	Monte Carlo Simulations	Medium (Hardware/protocol mismatch)	Medium (Optimized handover latency)
Tang et al. (2022b)	FRL with A2C	N/A	Medium (High heterogeneity/privacy)	High (11% packet drop rate)
Morshed et al. (2024)	Knapsack-Modeled Predictive Algorithm	NS-3	Medium (ACC scalability/simplified mobility)	High (84% lower timeout rates)
Peng et al. (2025)	Not AI-Specific (DCI for Time-Sensitive)	N/A	Medium (Cross-domain/mobility challenges)	High (Latency/reliability focus)
Xu et al. (2023)	RL with PPO	Python	Medium (Limited scope/prediction errors)	High (Improved inference throughput)
Tang et al. (2022a)	Blockchain-Enabled FRL	N/A	Medium (Computational overhead/mobility simplification)	High (Packet drop rate ↓37%)
Gong et al. (2022)	LMAPPO (Lyapunov-Based MARL)	N/A	Medium (Complexity/assumptions)	High (Improved sum-rate)

Table 4 (continued)

References	AI model	Dataset or simulator	Scalability	Robustness
Xie et al. (2025)	CPODQN (Cache-Pool-Optimized DQN)	Python	Medium (Energy constraints/scalability)	High (29–49% delay variance reduction)
Xia et al. (2022)	Distributed AI (MARL, Federated Learning)	N/A	Medium (Scalability/privacy-utility tradeoff)	High (Improved security/decision making)
Li et al. (2024)	Dual-Net-work DRL Offloading (DRLO)	N/A	Low (Limited scalability/static weights)	High (80–90% pseudo-packet loss reduction)
Yoo and Lee (2021)	FRL with PPO	Python	Medium (Simplified mobility/perfect links)	High ($3.25 \times$ throughput gain)
Mao et al. (2020)	Block Coordinate Descent (BCD) with SCA	MATLAB	Low (Static IoT/no trajectory)	High (30% delay reduction)
Lin et al. (2024)	PSO with Simulated Annealing (PSP)	N/A	Medium (Buoy deployment costs/complexity)	High (Reduced energy consumption)
Fang et al. (2022)	Olive Branch Learning (OBL) with CNASA	N/A	Medium (Offline assignment/limited mobility)	High (CNASA balances accuracy/time)
Li et al. (2025)	Bi-Level RL with Adaptive Transfer Learning	Python	Medium (Extreme distribution shifts)	High (95% accuracy, 65% lower time)
Li and Chen (2023)	Risk-Aware Distributionally Robust Optimization (RADROO)	MATLAB	Medium (High computational time)	High (Balanced cost/robustness)
Lan et al. (2024)	Proximal Policy Optimization (PPO)	Python	Medium (Static security levels/scalability)	High (15–30% cost reduction)

the network. The edge layer provides immediate, localized processing close to the data source. The fog layer serves as an intermediate platform for aggregating and analyzing data from multiple edge devices. The cloud layer offers centralized resources for large-scale processing, storage, and long-term analytics. Collectively, these layers establish a hierarchical yet flexible framework that supports latency-sensitive services, optimizes network performance, and enhances the overall intelligence of MACN systems. Table 5 complements this taxonomy by consolidating task allocation and offloading approaches, including high-level strategies such as load balancing and energy-aware offloading, alongside their principal methods, strengths, and limitations.

Table 5 Comparison of task allocation and offloading approaches in MACN

Approach	Objective	Methods	Strengths	Weaknesses
RL (Zhang et al. 2024; Tang et al. 2022b; Li et al. 2025; Xie et al. 2025)	Learn adaptive task-allocation policies that optimize long-term metrics in dynamic environments	MARL, single-agent RL, policy-gradient, actor-critic	Adapts to uncertainty and non-stationarity, Good for real-time decisions and online adaptation	High training overhead, and Computationally intensive; requires environment interaction
Heuristic algorithms (Mao et al. 2020; Lin et al. 2024; Wu et al. 2025)	Fast, rule-based allocation for low-latency/low-complexity needs	Greedy, thresholding, priority queues	Simple and lightweight, Low runtime cost	Limited adaptability, may converge to suboptimal local solutions
Metaheuristics (Mao et al. 2020; Lin et al. 2024)	Solve complex, constrained offloading problems (near-optimal solutions)	Genetic algorithms, particle swarm, ant colony, simulated annealing	Effective for NP-hard formulations, Handles multi-objective constraints	Computationally heavy, parameter tuning required, runtime may limit real-time use
SL (Morshed et al. 2024; Peng et al. 2025; Xu et al. 2023)	Predict resource demand, channel/task completion time to enable proactive offloading	Regression, tree-based models, neural nets for prediction/preprocessing	Enables proactive allocation and load forecasting, Low-cost inference once trained	Requires labeled data; not a direct allocation solver
UL (Morshed et al. 2024; Peng et al. 2025)	Discover node clusters and latent structure for hierarchical assignment	Clustering, dimensionality reduction, anomaly detection	Useful for node grouping and reducing scheduling overhead, Reveals hidden patterns	Indirect for allocation; requires downstream policy
Load balancing (Wang et al. 2022; Gu et al. 2021)	Evenly distribute tasks across tiers to reduce hotspots and latency	MARL, heuristics, ML-driven prediction with scheduler	Reduces latency and improves utilization in multi-tier settings	Trade-off between global optimality and communication and coordination overhead
Energy-aware offloading (Gong et al. 2022; Li et al. 2024)	Minimize energy consumption while respecting latency constraints (extend UAV endurance)	RL, convex and nonconvex optimization, energy-aware schedulers	Extends UAV operation time, Can meet strict latency budgets when tuned	May sacrifice throughput; requires energy models and accurate estimates
Mobility-aware computing (Morshed et al. 2024)	Account for UAV and satellite motion in scheduling and task placement	Trajectory prediction, mobility-aware optimization, cooperative offloading	Improves task continuity and reduces offload failures in mobile scenarios	Requires reliable trajectory prediction and tighter coordination

4.1.1 Definitions of each tier

The multi-tier computing architecture in MACN is organized into three distinct layers, which are edge, fog, and cloud. Each layer is optimized for specific computational roles and is situated at different physical locations within the network. These tiers operate in coordi-

nation to enable intelligent task distribution, efficient resource utilization, and low-latency communication across heterogeneous network environments.

- **Edge-tier:** The edge tier is situated at the ground level and encompasses end-user devices, sensors, actuators, and terrestrial edge servers. Devices such as smartphones, connected vehicles, IoT sensors, and smart city infrastructure generate and process data at or near the source. This tier is responsible for real-time data acquisition, initial filtering, and preprocessing, making it essential for latency-sensitive applications such as autonomous driving, industrial automation, and emergency response systems (Wang et al. 2022). To maintain time determinism in next-generation 6 G networks, particularly those incorporating multiple TSN clusters, edge devices can collaboratively offload and process data to mitigate congestion and minimize delays (Peng et al. 2025). By keeping computation close to the data source, the edge tier significantly reduces the need for long-distance communication and supports rapid, context-aware decision-making.
- **Fog-tier:** The fog tier functions as an intermediate computational layer, typically comprising aerial platforms such as UAVs and HAPs. Strategically positioned between the edge and cloud, fog nodes provide enhanced processing capabilities while remaining geographically closer to edge devices. This proximity enables the fog tier to support latency-sensitive tasks, including distributed inference, local data aggregation, and temporary data storage (Li et al. 2022). It plays a critical role in balancing workloads between edge and cloud resources, particularly in scenarios with fluctuating connectivity or mobile nodes. By offloading intermediate processing to the fog layer, SAGIN systems can optimize energy consumption, reduce network congestion, and enhance service continuity.
- **Cloud-tier:** The cloud tier consists of satellite-based infrastructure, including LEO, MEO, and GEO satellites. This tier provides global coverage and centralized computing resources capable of supporting large-scale, resource-intensive operations. Typical applications include big data analytics, long-term data storage, and training of complex ML models (Tang et al. 2022b). Although cloud-based processing introduces higher latency due to the physical distance of satellites from ground nodes, it remains essential for applications that prioritize computational depth over immediacy.

The definitions of edge, fog, and cloud-tiers align with current literature. Edge computing manages real-time data at the source, including IoT sensors and terrestrial edge servers, and is critical for latency-sensitive applications such as autonomous driving (Wang et al. 2022). Fog computing, consisting of UAVs and HAPs, provides intermediate processing to support latency-aware tasks (Li et al. 2022). Cloud computing, implemented via satellites across LEO, MEO, and GEO orbits, offers global coverage for large-scale analytics (Tang et al. 2022b). These characterizations are consistent with recent SAGIN studies, confirming their accuracy and applicability.

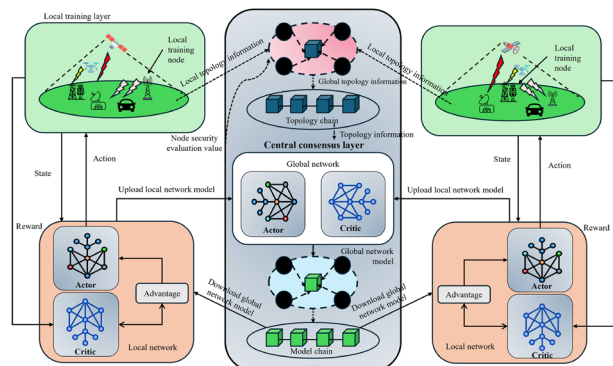
4.1.2 Key design considerations in a multi-tier setting

Designing a robust multi-tier computing architecture in MACN requires careful consideration of several critical factors to ensure optimal performance, high reliability, scalability, and efficient resource utilization across heterogeneous network layers. The integration of

edge, fog, and cloud computing within SAGIN necessitates a holistic design approach that accounts for architectural diversity and dynamic operating conditions.

- **Resource allocation:** Computational tasks should be distributed across the edge, fog, and cloud tiers according to factors such as task complexity, data volume, latency sensitivity, and available computational resources. Effective resource allocation enhances task execution efficiency and prevents overloading of any specific tier. For instance, lightweight tasks with stringent latency requirements are typically executed at the edge, whereas data-intensive or delay-tolerant operations can be offloaded to the cloud (Li et al. 2025).
- **Latency management:** Time-sensitive applications, such as disaster response, autonomous navigation, and real-time surveillance, require low-latency processing and are often executed at the edge or fog tiers to minimize transmission delays. To satisfy strict latency requirements, intelligent task offloading and proximity-based computing are essential. In contrast, less urgent tasks can be deferred to the cloud, where abundant computational resources can be leveraged (Zhu et al. 2025).
- **Mobility and dynamics:** The high mobility of aerial platforms, such as UAVs and satellites, introduces variability in connectivity, link stability, and resource availability. These dynamic conditions necessitate real-time adaptability in workload distribution, routing protocols, and connectivity management to ensure continuous service delivery. Consequently, adaptive task scheduling and dynamic network management strategies are essential for maintaining service continuity (Lan et al. 2024; Tang et al. 2022a). As illustrated in Fig. 4, the BFA3C offloading framework places lightweight actor modules on UAVs and edge nodes while asynchronous aggregation occurs at fog nodes for scalable policy updates. The figure clarifies latency versus centralization trade-offs and the flow of model updates from local devices to fog and cloud.
- **Scalability:** The system must be capable of scaling to accommodate an increasing number of connected devices, users, and services, as well as dynamically evolving network topologies. Scalability is facilitated through distributed computing paradigms and load-balancing mechanisms that adapt to shifting demand patterns in real time. This approach mitigates congestion at the cloud layer and enhances responsiveness throughout the network (Gu et al. 2021; Li and Chen 2023).
- **Energy efficiency:** Energy optimization is critical, particularly for battery-constrained edge devices and aerial platforms with limited energy reserves. Strategies such as ener-

Fig. 4 BFA3C offloading architecture: on-device actors with asynchronous aggregation at fog nodes (Tang et al. 2022a)



gy-aware scheduling, sleep mode operation, and offloading tasks to energy-rich nodes are essential to prolong system lifetime. Moreover, efficient resource allocation and lightweight processing models help extend operational periods while minimizing energy consumption (Xia et al. 2022).

- **Interoperability:** Seamless integration across heterogeneous computing tiers requires strict adherence to standardized protocols and data formats. Interoperability is essential for ensuring consistency, coordination, and compatibility among diverse components operating across the ground, aerial, and space segments. Middleware solutions and interface abstractions facilitate this integration by enabling uniform data handling and communication (Li and Chen 2023).

The considerations outlined, including resource allocation, latency management, mobility, scalability, energy efficiency, and interoperability, reflect the current challenges in MACN. Resource allocation is critical for distributing tasks based on complexity and latency requirements (Li et al. 2025), while mobility management addresses the dynamic behavior of UAVs and satellites (Lan et al. 2024; Tang et al. 2022a). These challenges are supported by recent research, ensuring the relevance and applicability of the proposed solutions.

4.1.3 AI implementation in multi-tier computing

AI plays a transformative role in enhancing multi-tier computing within MACN by enabling intelligent optimization, automation, and adaptability across network layers. Given the highly dynamic and heterogeneous nature of SAGIN, traditional static algorithms are often insufficient. AI techniques provide the flexibility and learning capability necessary to address real-time operational challenges effectively. For a concise mapping of AI paradigms to implementation roles, including task offloading, resource management, and predictive analytics, refer to the approach-oriented entries in Table 5.

- **Task offloading:** AI techniques, such as RL, enable dynamic decision-making to select the optimal tier, edge, fog, or cloud for task execution. These models continuously learn from the environment and adapt their offloading strategies according to evolving conditions, including network load, device energy levels, and latency requirements (Li et al. 2025).
- **Resource management:** ML algorithms can accurately predict resource demand patterns and allocate computational power across the tiers accordingly. This predictive capability prevents resource bottlenecks, optimizes bandwidth utilization, and ensures energy-efficient operation. Such intelligent management is particularly critical when handling constrained edge or aerial platforms (Mao et al. 2020; Li et al. 2025; Zhu et al. 2025).
- **Predictive analytics:** AI leverages both real-time and historical data from edge devices to anticipate future network states, user behavior, and potential equipment failures. By detecting trends and anomalies at an early stage, the system can enable proactive reconfiguration, preventive maintenance, and intelligent rerouting to ensure sustained performance and service continuity (Morshed et al. 2024; Zhang et al. 2024; Gong et al. 2024).
- **Autonomous operation:** Integrating AI capabilities directly into edge and fog nodes facilitates decentralized decision making. This localized autonomy reduces reliance on

cloud-based control, thereby lowering latency, enhancing resilience, and improving responsiveness in highly dynamic MACN environments (Peng et al. 2025).

- **Operational robustness:** AI-based monitoring and anomaly-detection mechanisms can help identify abnormal traffic conditions, unstable links, or unexpected workload behavior across tiers, thereby improving service continuity and system responsiveness under dynamic operating conditions (Lan et al. 2024; Tang et al. 2022a; Li et al. 2025).

The integration of AI into SAGIN's multi-tier computing framework markedly enhances adaptability, resource efficiency, and operational intelligence. AI enables the system to manage complexity autonomously, increasing resilience and supporting the fulfillment of mission-critical requirements in real time. The discussion of AI's role in task offloading, resource management, predictive analytics, autonomous operations, and operational robustness is consistent with current research. RL for dynamic task offloading and ML for resource demand prediction are particularly emphasized (Li et al. 2025; Mao et al. 2020).

4.2 AI-based task allocation and scheduling

In MACN, task allocation and scheduling are critical for optimizing resource utilization and meeting stringent performance requirements. AI techniques, including RL, SL, and UL, as well as heuristic and metaheuristic algorithms, play a central role in addressing these challenges. These techniques provide a unifying framework for managing heterogeneity, network dynamics, and the stringent performance constraints of multi-tier aerial networks. Rather than relying on static heuristics, learned models and adaptive policies can predict resource availability, estimate offloading gains, and make scheduling decisions that jointly optimize latency, energy consumption, and reliability. AI-driven solutions span a spectrum from ultra-lightweight on-device predictors to large-scale cloud-based training and policy distillation. They are organized here according to operational tier which are edge, fog, and cloud, and AI paradigm, including classical ML, DL, RL, evolutionary and swarm intelligence, and emerging approaches. Collectively, these methods enable continuous adaptation to fluctuating link quality, mobility-induced topology changes, and variable workload characteristics, while supporting privacy, energy efficiency, and real-time performance requirements (Li et al. 2025; Zhang et al. 2024). Table 5 provides a consolidated view of task-allocation techniques and their operational objectives, which is referenced when discussing trade-offs at the edge, fog, and cloud tiers.

4.2.1 Edge computing in aerial networks

At the edge, where UAVs, sensors, and small terrestrial devices operate under stringent energy and computational constraints, AI emphasizes compact and responsive models and procedures. Lightweight supervised models and small ensemble learners are employed to prioritize tasks, detect anomalies, and provide short-term load forecasts using modest local telemetry, enabling rapid evaluation and incremental updates. Compact deep architectures, including MobileNet-like networks, pruned or quantized convolutional neural networks, and other compression techniques, perform on-device perception and feature extraction, ensuring that only compressed representations or event triggers are transmitted upward, thereby conserving bandwidth and reducing end-to-end latency. RL at the edge, imple-

mented using sample-efficient QL variants or small actor-critic agents, supports localized decision making for resource allocation and adaptive offloading under non-stationary conditions. These approaches require careful reward shaping and often leverage simulator-to-real transfer to contain training costs. Evolutionary and swarm-inspired heuristics provide additional lightweight optimization tools for rapid, decentralized task partitioning in scenarios where centralized coordination is infeasible (Arafat and Moh 2019). Emerging paradigms such as TinyML and federated on-device updates further reduce power consumption and preserve data locality by enabling microcontroller class inference and collaborative model improvement without sharing raw observations (Wang et al. 2022; Xu et al. 2023).

4.2.2 Fog computing for mid-tier processing

Fog or LAP nodes offer greater computational power and temporary storage compared with edge devices and are therefore well suited to host more sophisticated AI capable of coordinating multiple edge nodes. Classical ML ensembles and advanced predictive models are practical at the fog layer, where aggregated telemetry enables robust load forecasting and user association prediction to inform short-term scheduling. Temporal deep models, including recurrent neural networks and temporal convolutional networks, provide effective time series forecasting for link quality and demand, allowing fog nodes to provision resources and orchestrate flows over brief horizons. MARL facilitates the development of cooperative policies for caching, cooperative inference, and load balancing among multiple LAPs or UAVs whose actions are interdependent, while population-based metaheuristics such as particle swarm optimization and genetic algorithms offer rapid, near-optimal solutions to constrained resource-distribution problems (Alam et al. 2025). Federated fog learning and split inference further address privacy and bandwidth concerns by enabling model training and inference partitioning that preserves local data while leveraging the fog layer's greater computational capabilities (Gu et al. 2021; Lin et al. 2024).

4.2.3 Cloud-assisted aerial networks

At the cloud tier, where satellites and remote data centers provide abundant computational and storage resources, AI techniques are primarily applied to large-scale model training, global optimization, and the synthesis of cross-mission knowledge. Classical ML remains relevant for global classification and decision tasks, whereas the cloud excels at heavy-weight DL, including large transformers and deep convolutional networks (DCN) that aggregate heterogeneous data sources for global traffic modeling, predictive maintenance, and the generation of training data for downstream tiers. RL executed in cloud environments, whether offline, in simulation, or in batches, produces complex policies that can be compressed and deployed to fog and edge actors for real-time operation. Evolutionary multi-objective optimization at the cloud evaluates trade-offs among latency, energy, coverage, and cost at scale, generating candidate operating points that inform local heuristics. Serverless AI and model as a service paradigms provide elastic scaling to accommodate training bursts and inference demand, enabling centralized policy evaluation, long-horizon planning, and knowledge consolidation (Tang et al. 2022b; Li et al. 2025).

4.2.4 Task allocation in a UAV network

Task allocation in a UAV network involves distributing computational tasks, including data processing, inference, and real-time analytics, across network nodes such as UAVs, ground stations, and satellites to optimize objectives such as latency, energy consumption, and resource utilization. The decision to execute a task locally or offload it to another node depends on factors including node capabilities, energy levels, communication delays, and UAV mobility. For instance, in a disaster response scenario, a UAV may need to determine whether to process sensor data locally or offload it to a satellite for faster analysis (Xie et al. 2025). Cross-tier task offloading and scheduling mechanisms integrate capabilities across layers to deliver end-to-end performance. Predictive regressors and lightweight classifiers estimate expected latency, energy cost, and accuracy trade-offs for offloading decisions, providing interpretable signals to schedulers. Deep models and generative architectures can learn mappings from high-dimensional system states to scheduling actions and synthesize realistic traces for rare-event training; however, such approaches must be made practical for real-time deployment through compression, distillation, or surrogate modeling. RL provides a powerful framework for adaptive offloading, where policy gradient and A2C algorithms manage continuous action spaces, such as allocation fractions and compression levels, and optimize multi-objective rewards encompassing latency, energy, and fairness. Evolutionary and swarm intelligence approaches generate robust heuristic schedules when exact optimization is infeasible within operational timescales, while neuro-symbolic and hybrid rule-learning methods combine interpretable constraint handling with learned adaptability to ensure safety and quality-of-service requirements are maintained (Zhang et al. 2024; Li et al. 2025).

4.2.5 Reinforcement learning approaches

RL is widely employed for task allocation because of its ability to adapt to dynamic environments. An RL agent, which may be a UAV, learns optimal allocation policies by observing the network state, including node load and energy levels, taking actions such as offloading tasks to a specific tier, and receiving rewards that reflect objectives such as reduced delay. For example, Li et al. (2025) employs a dueling double D3QN to optimize task offloading in Industrial IoT, achieving reductions in energy consumption and a delay of 20 to 30%. Similarly, Xie et al. (2025) utilizes a cache-pool-optimized DQN (CPODQN) for vehicle networks, improving delay and fairness by 29 to 49%.

4.2.6 Supervised or unsupervised learning approaches

SL can be employed to predict resource availability or task execution times based on historical data, thereby supporting proactive allocation decisions. UL techniques, such as clustering, can group tasks or nodes according to similarity to streamline allocation processes. Although these methods are less commonly used than RL for direct task allocation, they complement RL by providing predictive insights. For instance, Xu et al. (2023) integrates a predictive DNN with RL to enhance inference offloading in UAV-satellite networks.

4.2.7 Heuristic and metaheuristic algorithms

Heuristic algorithms implement simple decision rules, such as allocating tasks to the nearest available node, whereas metaheuristic approaches, including genetic algorithms and particle swarm optimization (PSO), explore the solution space to identify near-optimal allocations in complex scenarios. For example, Wu et al. (2025) proposes a graph theory based Iterative optimization (GIO) scheme to minimize delay in maritime task offloading, while Lin et al. (2024) integrates PSO with simulated annealing to achieve energy-efficient offloading in maritime IoT networks.

4.2.8 Discussion of strengths and weaknesses

RL provides strong adaptability in dynamic environments and enables continuous improvement of policies through interaction and experience. However, it often requires substantial training data and can exhibit instability during learning (Li et al. 2025). Heuristic and metaheuristic algorithms are appealing due to their simplicity and low computational cost, making them suitable for rapid online decision-making; however, they are prone to becoming trapped in local optima and do not guarantee globally optimal solutions (Li and Chen 2023). SL and UL methods are generally not applied directly to task allocation; instead, they play complementary roles, such as prediction, feature extraction, and clustering, to inform allocation policies, as their direct applicability to allocation problems is limited (Fang et al. 2022).

4.3 Load balancing and data aggregation

Load balancing, data aggregation, mobility, and energy-aware computing constitute an integrated set of concerns that are effectively addressed through the multi-tier AI taxonomy. Learning-based load-balancing schemes leverage fog-level coordination and MARL to dynamically redistribute tasks across UAVs and HAPs, preventing hot spots, reducing end-to-end delay, and maintaining fairness. Mobility-aware approaches incorporate trajectory prediction and time-series forecasting, enabling offloading decisions to anticipate topology changes rather than react, thereby ensuring smoother service continuity in highly mobile aerial networks. Energy-aware offloading integrates battery-aware cost models with AI policies to jointly optimize UAV lifetime and mission objectives. In practice, this integration employs edge TinyML for local energy savings, fog-assisted preprocessing to reduce communication overhead, and cloud-driven policy distillation to produce lightweight onboard controllers. FFog-level data aggregation reduces redundant transmissions and supports efficient local analytics, while cloud-level analysis informs long-term scheduling strategies and model updates that progressively enhance system performance across missions (Wu et al. 2025; Xia et al. 2022).

4.3.1 Load balancing in multi-tier UAVs

Load balancing is a critical aspect of multi-tier UAV networks to ensure that no single tier or node becomes overloaded, which could lead to bottlenecks, increased latency, or system failure. By distributing computational tasks and data processing across the edge, fog, and

cloud tiers, load balancing enhances overall system performance, efficiency, and reliability. It maximizes resource utilization and minimizes energy consumption, which is particularly important in scenarios where UAVs operate under limited computational and energy constraints (Wu et al. 2025; Li et al. 2022).

4.3.2 Learning-based load balancing techniques

Learning-based approaches, particularly RL, are increasingly employed to achieve effective load balancing in UAV networks. These techniques enable UAVs to learn optimal strategies for task distribution based on the network state, including task loads, UAV positions, and communication conditions. By adapting to dynamic environments, RL can reduce latency and maximize throughput. For instance, DRL has been applied to jointly optimize UAV trajectories, user association, and resource allocation for load balancing in multi-UAV systems (Wang et al. 2022; Gu et al. 2021).

4.3.3 Mobility-aware computing

Mobility-aware computing in UAV networks accounts for the dynamic movement of UAVs and other mobile entities when making decisions regarding task allocation, resource management, and communication. This consideration is particularly important in mobile edge computing systems, where UAVs act as mobile edge servers, and their positions continuously change, impacting the efficiency of task execution and data transmission. Mobility-aware algorithms leverage trajectory prediction to adjust offloading decisions proactively, ensuring seamless service continuity (Xie et al. 2025; Xia et al. 2022).

4.3.4 Energy-aware offloading

Energy-aware offloading involves transferring computational tasks from UAVs to edge or cloud servers in a manner that minimizes energy consumption while accounting for the limited battery capacity of UAVs. This strategy is essential for extending operational time and ensuring mission success. Techniques including RL, optimization algorithms, and heuristic methods are applied to achieve energy-efficient offloading while satisfying performance objectives such as latency and task completion rates (Gong et al. 2022; Li et al. 2024).

4.3.5 Summarizing load based approaches

Table 5 provides a concise summary of load balancing and energy-aware offloading approaches, highlighting the primary strategies, operational tiers, and key performance outcomes based on the referenced studies and recent literature.

4.3.6 Critical observations and gaps

Current methods for load balancing and task offloading in UAV networks often assume predictable mobility, which limits their applicability in real-world scenarios characterized by highly uncertain trajectories and link dynamics (Morshed et al. 2024). Furthermore, integrated approaches that simultaneously address load distribution, mobility management,

and energy efficiency remain scarce, leaving critical trade-offs unresolved. Reliability and deployment-oriented considerations in load balancing have also received limited attention, particularly under highly dynamic and resource-constrained operating conditions (Lan et al. 2024). Figure 5 sketches the canonical PPO training loop used as a stable policy-gradient baseline for resource allocation and mobility control.

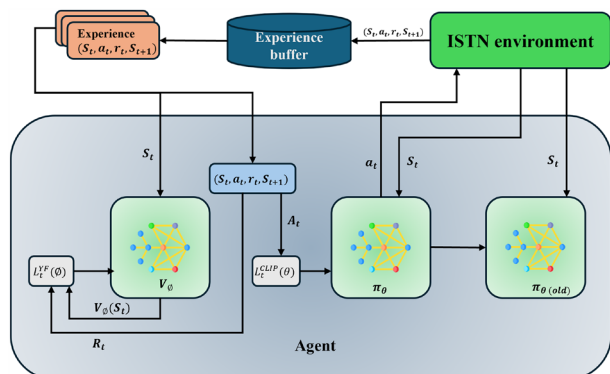
Several key observations emerge from recent studies. First, AI, particularly RL, has demonstrated significant value in optimizing load balancing and energy-aware offloading due to its adaptability to dynamic environments. Mobility-aware strategies are essential for maintaining reliable performance, as exemplified in (Xie et al. 2025; Xia et al. 2022), where dynamic network conditions are explicitly incorporated. The integration of AI techniques not only enhances adaptability, but also improves system efficiency and resilience. For instance, blockchain-enhanced frameworks illustrate how distributed coordination mechanisms can support more reliable load balancing operations in decentralized aerial networks (Tang et al. 2022a).

Despite these advances, several research gaps persist. There is limited exploration of real-time decision making frameworks capable of handling highly dynamic and uncertain environments. Existing solutions often struggle to integrate multiple objectives, such as balancing network load, minimizing energy consumption, and ensuring service continuity, within a unified optimization framework. Furthermore, the scalability challenge of managing large UAV swarms remains underexplored, with most studies focused on small-scale scenarios. This gap is particularly significant given the growing interest in large-scale multi-UAV operations for disaster management, surveillance, and 6 G-enabled services (Peng et al. 2025; Li and Chen 2023). Addressing these challenges is critical to advancing practical and robust load balancing solutions in multi-tier aerial computing networks.

4.4 Summary of approaches

The presented taxonomy highlights the complementary strengths of different computing tiers. Edge methods provide the lowest latency and highest responsiveness, but are limited in model capacity and energy. Fog methods balance latency with richer models and coordination capabilities, supporting cooperative schemes and short-horizon forecasting. Cloud methods offer unparalleled computational resources for global optimization and large-scale training, although they incur higher latency and require effective policy transfer to lower tiers. AI paradigms naturally align with these roles, TinyML and lightweight ML are suited

Fig. 5 PPO training loop: trajectory collection, surrogate objective computation, and policy update (Lan et al. 2024)



to latency, and energy-sensitive edge tasks, temporal DL and MARL address fog-level coordination and prediction, and transformers, evolutionary multi-objective optimization, and offline RL facilitate complex, global-level reasoning in the cloud. Promising research directions include multi-objective RL for joint optimization of latency, energy, and robustness; efficient policy transfer and distillation pipelines from cloud to fog to edge; realistic mobility models and real-world validation of learned schedulers on large UAV swarms; and improving the reliability and deployability of learning-based schedulers. Addressing these avenues requires cross-tier co-design that jointly considers model complexity, communication cost, and mission constraints to deliver robust, scalable, and energy-efficient task allocation and scheduling for MACN (Peng et al. 2025; Li and Chen 2023). Tables 4 and 5 reveal distinct trade-offs across AI-based computing and task offloading approaches in MACNs. Reinforcement learning methods, including DQN (Zhu et al. 2025; Li et al. 2025), PPO (Xu et al. 2023; Yoo and Lee 2021; Lan et al. 2024), and MARL variants (Gong et al. 2022; Xia et al. 2022), demonstrate strong adaptability to dynamic environments with reported improvements of 20–53% in cost and energy reduction, though they incur high training overhead and computational complexity. Federated reinforcement learning approaches (Tang et al. 2022a, b; Yoo and Lee 2021) reduce raw-data exchange while achieving notable performance gains, including 37% reduction in packet drop rate and 3.25x throughput improvement, but face challenges related to heterogeneity and communication overhead. Heuristic and metaheuristic methods (Mao et al. 2020; Lin et al. 2024; Wu et al. 2025) offer lightweight alternatives suitable for low-latency requirements but may converge to suboptimal solutions in complex scenarios. Supervised learning approaches (Morshed et al. 2024; Xu et al. 2023) enable proactive offloading through demand prediction, achieving 84% lower timeout rates, yet require labeled data and serve primarily as preprocessing rather than direct allocation solvers. The majority of surveyed methods exhibit medium scalability, with simplified mobility assumptions and energy constraints remaining common limitations across approaches. Notably, quantum-inspired methods (Zhang et al. 2024) demonstrate high scalability potential with greater than 90% accuracy and 54% faster convergence, suggesting promising directions for addressing the computational complexity inherent in large-scale MACN deployments.

The reviewed literature on multi-tier computing in UAV networks highlights the following approaches:

4.4.1 High-level comparison

The reviewed studies collectively underscore the central role of AI, particularly RL and ML, in optimizing computing within MACN environments. These approaches primarily aim to reduce delay, conserve energy, and improve resource utilization across diverse application domains, including maritime, vehicular, and IoT networks (Zhu et al. 2025; Lin et al. 2024). Several thematic directions emerge from a closer examination.

First, edge, fog, and cloud computing paradigms are widely employed to distribute computation hierarchically, thereby reducing latency and improving overall resource efficiency. Such frameworks enable mission-critical tasks to be processed closer to the end devices while offloading more complex workloads to higher-tier nodes, as demonstrated in Wu et al. (2025); Li et al. (2022). Building on this foundation, AI-based task allocation has emerged as a key strategy for dynamic resource management. RL, heuristic methods, and optimiza-

tion models are applied to determine optimal task assignments under fluctuating network and resource conditions (Zhang et al. 2024; Mao et al. 2020).

Load balancing is another recurring theme, emphasizing the distribution of computational workloads across UAVs and aerial tiers to prevent bottlenecks and maintain fairness. These strategies are critical for sustaining performance in dense or heterogeneous networks (Wang et al. 2022; Gu et al. 2021). Mobility-aware computing further incorporates UAV movement and trajectory prediction into offloading and allocation decisions, ensuring that resource management aligns with the dynamic topology of airborne platforms (Xie et al. 2025; Xia et al. 2022). Energy-aware offloading strategies address the dual challenge of conserving limited UAV or satellite energy while maintaining task reliability and timely execution. Optimization frameworks in this area minimize energy expenditure without compromising service quality (Gong et al. 2022; Li et al. 2024).

In general, high-level comparisons indicate that AI-based approaches, particularly RL, dominate due to their adaptability in dynamic and uncertain environments. Heuristic and metaheuristic algorithms remain valuable as simpler, lightweight alternatives that are effective in resource constrained or application specific scenarios (Li et al. 2025; Li and Chen 2023). This contrast highlights a key trade-off between adaptability and complexity. Advanced AI provides superior flexibility and robustness, while heuristic methods are attractive for practical deployments with limited computational capacity. Collectively, Tables 4 and 5 summarize the principal trade-offs between adaptability, computational cost, and data dependence across tiers, serving as a reference for selecting methods appropriate to edge, fog, or cloud deployments.

4.4.2 Common themes and divergences

Common themes across the literature include AI-driven resource management and the adoption of MACN spanning space, air, and ground segments. Many studies leverage RL and DL to optimize offloading, scheduling, and routing decisions under uncertainty, underscoring the value of data-driven adaptation in complex MACN scenarios (Li et al. 2025; Mao et al. 2020). Mobility awareness is repeatedly emphasized as a critical design requirement for UAV and aerial operations, since trajectory dynamics and intermittent links significantly impact offloading and scheduling performance (Xie et al. 2025; Xia et al. 2022). Energy efficiency constitutes another prevalent concern, driven by UAV battery limitations and satellite power constraints, motivating energy-aware offloading and joint energy-delay optimization frameworks (Gong et al. 2022; Li et al. 2024).

Substantial divergences are also observed in methodological approaches and evaluation priorities. Studies differ in the AI techniques employed, such as value-based methods such as DQN versus policy gradient approaches such as proximal policy optimization, each associated with distinct trade-offs in sample efficiency, stability, and computational cost. Some works favor classical heuristics or metaheuristics due to their low complexity and predictability, whereas RL-based methods are valued for adaptability, but often require greater computational resources and interaction data (Zhang et al. 2024; Mao et al. 2020). Performance metrics also vary widely, including latency, throughput, energy consumption, fairness, and robustness, reflecting the heterogeneity of application scenarios from disaster response to persistent surveillance (Morshed et al. 2024; Peng et al. 2025). Concrete examples include space-air-ground edge computing frameworks that prioritize minimizing the

overall task completion delay (Yu et al. 2021) and energy-efficient offloading and resource allocation algorithms for satellites and ground terminals (Song et al. 2021).

A notable gap across these studies is the relative neglect of fairness in onboard terminal offloading. While many approaches optimize aggregate delay or energy, they often overlook equitable resource allocation for heterogeneous, delay-sensitive tasks, such as real-time navigation, remote vehicle control, or vehicle detection, where prioritization is essential to preserve safety and service quality (Du et al. 2023). Collectively, these commonalities and divergences highlight promising directions for future research, including the development of hybrid methods that balance adaptability and efficiency, the extension of performance metrics to incorporate fairness and quality-of-service differentiation, and the design of scalable solutions capable of operating under realistic mobility and energy constraints.

4.4.3 Takeaways and research opportunities

AI techniques, particularly RL, have demonstrably enhanced computing efficiency in MACNs by enabling adaptive task allocation, load balancing, and energy-aware offloading. Mobility-aware and energy-efficient strategies are especially critical for UAV operations, where trajectory dynamics and limited battery life directly influence offloading and scheduling decisions (Xie et al. 2025; Xia et al. 2022; Gong et al. 2022). Despite these advances, significant challenges remain. Many existing schemes struggle to scale to large networks, rely on idealized mobility models that reduce real-world applicability, and insufficiently integrate deployment-oriented constraints into resource management decisions.

Several concrete research directions appear particularly promising. First, the development of MARL frameworks that jointly optimize latency, energy, and fairness can address the trade-offs highlighted in recent studies (Li and Chen 2023). Second, closer integration of real-time decision making with predictive analytics and mobility forecasting, using sequence models or physics-informed predictors, can enable more effective proactive offloading and handover strategies (Morshed et al. 2024). Third, achieving scalability for large UAV swarms necessitates hierarchical or distributed learning architectures, potentially leveraging FL or transfer learning, to reduce communication overhead and improve generalization across heterogeneous environments (Peng et al. 2025). Finally, bridging the simulation-to-reality gap through deployment on experimental testbeds and standardized benchmarks, while embedding robustness and deployment-aware objectives into optimization routines, is essential to transition AI methods from research prototypes to robust, operational solutions. Integrating these approaches with emerging 6 G and MACN capabilities, accompanied by rigorous real-world validation, will be critical for realizing resilient and efficient aerial computing infrastructures.

Across the surveyed studies, a clear pattern emerges that no single task offloading or computing paradigm is universally optimal for MACN environments. AI-based approaches, particularly RL and MARL, are most beneficial when offloading decisions are sequential, strongly coupled with mobility and channel variability, and must adapt continuously to changing workload and resource conditions. In contrast, optimization-based and heuristic methods remain attractive when low-complexity, fast, and predictable decisions are required, especially for platforms with limited onboard energy or processing capability. Supervised learning methods are often most useful as supporting tools for prediction and estimation rather than as complete decision engines. These observations suggest that the

most promising direction is not a strict choice between classical and AI-based computing control, but rather the careful matching of method complexity to operating conditions, with lightweight solutions favored in stable or resource-constrained settings and more adaptive learning-based methods reserved for highly dynamic and uncertain scenarios.

5 AI-driven handover mechanisms in multi-tier aerial networks

MACNs enable ubiquitous connectivity, facilitate human–machine interaction, and provide foundational support for intelligent systems and societal advancement (Kato et al. 2019; Zhang et al. 2020; Liu et al. 2019). This integration connects a vast array of hardware devices; however, traditional networks are constrained by tight hardware–software coupling, deployment challenges, and dependence on costly proprietary equipment. NFV decouples hardware from software, reducing deployment costs and enabling flexible, software-defined services (Ferrús et al. 2016). Similarly, software-defined networking separates centralized control from distributed data forwarding, providing programmability and reducing maintenance costs for global MACN interconnectivity (Gardikis et al. 2017; Wang et al. 2017).

Resource scheduling and transmission control are critical for improving network performance (Du et al. 2017). Software-defined networking addresses hardware limited resource utilization bottlenecks in SAGINs (Kak et al. 2018; Cui et al. 2016; Xu et al. 2019). In SDN-enabled MACNs, controllers consolidate functions such as routing, resource allocation, and mobility management for satellite operations (Shi et al. 2019, 2018). By decoupling the control and data planes, SDN optimizes resource allocation, reduces load on the forwarding nodes, and enhances overall network performance.

The inherent complexity of SAGINs challenges traditional transmission control protocols (TCP) in traffic management and resource allocation (Shi et al. 2018). To enable efficient data transmission, schemes emphasizing control, optimization, and load balancing have gained prominence (Sheng et al. 2017; S. K. Siam et al. 2026). These approaches leverage SDN characteristics and employ game-theoretic models that account for bandwidth, power, delay, and user demands (Pietrabissa et al. 2018).

In MACNs, controllers and switches perform core transmission functions; overload from switch requests can result in congestion. Existing schemes often target generic or specific traffic types and may not scale effectively for SAGIN environments. To address these limitations, this work introduces a dynamic handover software-defined transmission control (DHSTC) scheme for heterogeneous users. The DHSTC is based on queuing game theory and incorporates user diversity and variable controller arrival rates. Key parameters include the value of user service, modeled as a random variable to capture heterogeneity, and associated waiting costs. The queuing model operates in observable and unobservable modes. Given the high delay and jitter typical in MACNs, minimizing switch-controller interactions through the unobservable mode enhances efficiency. By comparing social welfare across both modes, the DHSTC identifies optimal strategies to improve network performance. Handovers in multi-tier aerial networks, particularly within MACNs, are essential for maintaining seamless connectivity in dynamic environments where network nodes, such as LEO satellites, HAPs, UAVs, and ground devices, are constantly in motion. The high mobility of these nodes leads to frequent handovers, which can result in service disruptions, increased latency, and deterioration of QoS.

5.1 Handovers in aerial networks

Handovers in MACNs, encompassing LEO satellites, UAVs, and HAPs, are critical for maintaining uninterrupted connectivity in environments characterized by high mobility and constantly changing network topologies. These networks must address rapid node movements, varying coverage footprints, and fluctuating link quality, all of which necessitate sophisticated handover mechanisms to prevent service disruptions. For instance, in LEO satellite constellations, user terminals must frequently re-establish connections as satellites orbit the Earth at speeds exceeding 27,000 km/h, resulting in brief visibility windows and the need for proactive beam steering or satellite selection algorithms (Tong et al. 2025). In SAGINs deployed for IoT applications or emergency response operations, handover complexity increases due to dual mobility dynamics, where both end users, such as autonomous vehicles or portable drones, and infrastructure nodes, including satellites and UAVs, are in motion, potentially causing alignment mismatches or signal handoff failures (Tao et al. 2025). These challenges are especially pronounced in specialized environments, such as aeronautical corridors where commercial aircraft rely exclusively on LEO satellites for broadband access, or in underserved regions lacking ground-based infrastructure, where reliable handovers are essential for applications such as real-time disaster forecasting, environmental monitoring, and bridging the digital divide in rural communities (Lv et al. 2022; Han et al. 2024).

- **Orbital dynamics:** LEO satellites, including those in the Starlink mega-constellation, complete an orbit in approximately 90 min and traverse specific ground areas in less than 10 min, requiring handover frequencies three to five times higher than those in conventional terrestrial cellular networks. This rapid traversal necessitates frequent beam switches and inter-satellite link adjustments to maintain session continuity, with polar orbital configurations adding complexity through overlapping coverage zones that can induce interference or redundant handovers if not managed optimally (Tong et al. 2025; Lv et al. 2022; Niu et al. 2024).
- **Vertical handover complexity:** Seamless transitions across heterogeneous tiers, such as from satellites to HAPs or UAVs and further down to terrestrial base stations, require harmonized protocols that consider differing communication standards, latency profiles, and mobility patterns. Vertical integration often relies on multi-layer decision-making frameworks to evaluate link quality metrics, including signal-to-noise ratio (SNR) and handover latency. For example, UAVs operating in offshore environments may need to switch from ground-based relays to satellite backhauls during extended missions, but such transitions can result in failure rates up to 40% due to mismatched handover thresholds or inadequate prediction of node trajectories (Zhang et al. 2024; Guo et al. 2022; Morshed et al. 2024).
- **Atmospheric interference:** Environmental factors pose significant challenges to handover reliability, particularly for optical inter-satellite links that may experience 15 to 25 dB signal attenuation from cloud scattering, atmospheric turbulence, or aerosol absorption, potentially disrupting handover signaling. High-frequency radio channels, such as those in the Ka-band (26–40 GHz), are susceptible to Doppler shifts reaching up to 100 kHz due to relative velocities between nodes, requiring adaptive equalization and robust channel estimation to mitigate handover interruptions and maintain link stability (Niu

et al. 2024; Mahboob and Liu 2024).

- **Resource contention:** The finite onboard resources of aerial nodes, including limited channel capacity, typically around 200 channels per satellite, must be shared among an increasing number of users, intensifying contention in high-density scenarios such as European airspace corridors, where more than 500 aircraft may simultaneously seek connectivity. This can lead to handover access failures, increased queuing delays, or degraded quality of service, highlighting the necessity for intelligent resource orchestration algorithms that prioritize critical traffic during handoffs (Tong et al. 2025; Lv et al. 2022).

In real-world deployments, handover mechanisms in MACNs must be adapted to specific application domains, where environmental constraints, user mobility patterns, and mission-critical requirements shape the design of adaptive strategies. These scenarios illustrate the practical implications of handover challenges, demonstrating how theoretical models translate into operational necessities across diverse sectors, including emergency management, aviation, and remote sensing.

- **Disaster response:** In emergency scenarios such as wildfires or earthquakes, UAV swarms are deployed to collect and relay survivor locations, sensor readings, or video feeds through LEO satellites. Given that satellite visibility windows are often limited to less than 60 s per pass, predictive handover strategies leveraging orbital ephemeris data and AI-based trajectory forecasting are essential to preemptively select the next serving node and minimize data loss during transitions (Mohamed et al. 2024).
- **Aeronautical communications:** Commercial aircraft cruising at altitudes around 11 kilometers in densely trafficked airspace undergo handovers approximately every 90 s within large-scale LEO constellations. Low-latency handover mechanisms are required to maintain in-flight entertainment, cockpit communications, and telemetry links without interruptions that could compromise safety or passenger experience (Lv et al. 2022).
- **Remote IoT:** IoT devices deployed in isolated environments, such as deserts, oceans, or polar regions, rely on sporadic satellite overpasses for connectivity. Handover mechanisms in these settings must incorporate delay-tolerant networking principles, including store-and-forward buffering, to manage intermittent coverage and ensure reliable data delivery for applications such as wildlife tracking, oceanographic monitoring, and remote asset management (Han et al. 2024).

5.2 AI techniques for handover decision making

The inherent complexity and high dynamism of MACNs, characterized by rapid node mobility, fluctuating channel conditions, and heterogeneous resource constraints, have motivated the integration of advanced AI techniques to enhance handover decision making processes. Methods such as RL, DRL, MARL, and generative AI enable these networks to adapt dynamically to real-time environmental variations, including signal degradation, orbital shifts, and load imbalances. By learning from interactions with the environment, these AI approaches facilitate proactive handover strategies that reduce service disruptions, optimize resource utilization, and improve overall network performance. For instance, in LEO satellite constellations where handovers occur frequently due to orbital speeds exceed-

ing 27,000 km/h, AI algorithms such as advantage A2C allow user terminals to select optimal satellites based on metrics including signal strength, remaining service time, and predicted visibility windows. This approach reduces the handover frequency and enhances signal stability (Tong et al. 2025). Similarly, generative AI models, including diffusion-based approaches, synthesize realistic network states to manage uncertainties in SAGINs, supporting robust handover decisions for IoT devices with integrated sensing and communication capabilities (Tao et al. 2025). These advancements are particularly critical in applications such as disaster response, aeronautical communications, and remote IoT deployments, where seamless connectivity is essential for mission-critical operations. Table 6 provides a summary of representative AI techniques for handover optimization, detailing their operating mechanisms, principal advantages and limitations, and the performance gains reported in the literature.

The hybrid combinations discussed below build on the baseline properties listed in Table 6, which should be consulted when evaluating computational and measurement trade-offs for each fusion. A growing trend in handover optimization involves hybrid AI methodologies that combine complementary techniques to address the multifaceted challenges of MACNs. These fusions leverage the strengths of individual approaches, such as the explor-

Table 6 Comparison of AI techniques and representative metrics for handover optimization in MACN

Method	Mechanism	Key advantages	Key limitations	Representative metrics & measurement
RL (A2C, MAPPO) (Tong et al. 2025; Tao et al. 2025)	Model handover as a multi-agent MDP; agents learn node and satellite selection via reward shaping that balances signal stability, handover rate and throughput	Fewer handovers; adapts to dual mobility patterns; improved convergence and predictability	High training latency and compute needs; sensitive to imperfect position	↓37% handovers (simulation); measured with network simulators and SNR traces
Quantum Multi-Agent RL (Q-MARL) (Kim et al. 2025)	Quantum circuits, compressed action-space representations for joint scheduling (CubeSats, HALE-UAVs) using QoS energy rewards	Faster convergence; scalable in simulation; energy-efficiency gains for constrained agents	Requires mature, fault-tolerant quantum hardware; limited by current quantum technology	×50% faster convergence (reported in study); simulation/experimental traces
Generative AI (Tao et al. 2025)	Generate synthetic 3D SAGIN states (positions, signal and load) to enable robust VHO under missing or uncertain data	Robust to missing observations; improves Pareto efficiency for multi-objective trade-offs	High GPU memory and training cost; scalability limits in ultra-dense settings	↑25% Pareto coverage; reduced handover failures (multi-objective eval.)
Multi-Armed Bandit (BC-UCB, LinUCB) (Mohamed et al. 2024)	Online contextual bandits for LEO selection and budgeted UCB for UAV trajectory planning using features (elevation, visible time, bandwidth)	Real-time adaptation; large energy gains in disaster scenarios; simple online updates	Sensitive to context estimation errors; often ignores explicit handover delay modeling	×15 energy-efficiency in scenario studies; measured via UAV telemetry/simulated traces
Graph-based MADM (coverage graphs with CRO) (Lv et al. 2022)	Time-evolving coverage graphs plus MADM or CRO using ADS-B and channel reservation for aeronautical handovers	Lower access failures; near-zero handover blocking; incorporates real traffic density	$O(n^3)$ complexity for large networks; centralized decision-making limits scalability	↓20% access failures; handover blocking ≈ 0 (ADS-B trace/simulator evaluation)

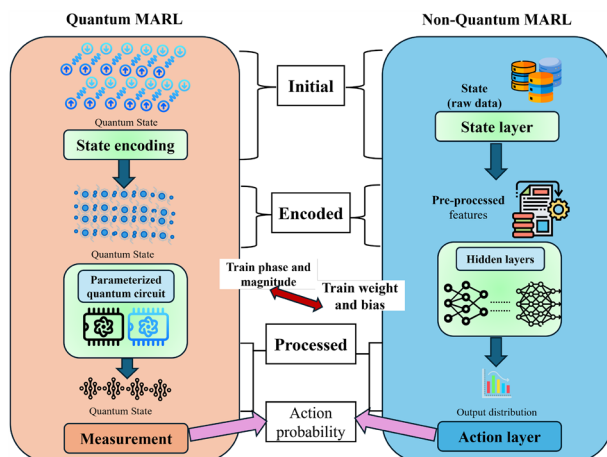
atory capabilities of RL with the predictive power of generative models or quantum-inspired enhancements, to achieve superior performance in dynamic environments.

The QMARL-A2C fusion (Kim et al. 2025; Tong et al. 2025) combines quantum-inspired MARL for action-space compression with advantage A2C policy learning for adaptive satellite selection in LEO constellations. Figure 6 contrasts conventional multi-agent RL with quantized or compressed action representations, referred to here as QMARL. The figure highlights the primary trade-off that reducing action dimensionality can improve scalability and convergence but may reduce action fidelity and fine-grained control. By formulating joint CubeSat-UAV scheduling as a quantum-enhanced multi-agent Markov decision process, this hybrid reduces handover latency by approximately 52 % while preserving high signal stability of around 99.5%. It is particularly suited for MACN deployments requiring global access in remote or polar regions where energy efficiency and quality of service are critical. The main limitation lies in the gap between algorithmic potential and practical quantum hardware; advances in fault-tolerant, high-throughput quantum processors or efficient classical approximations are required for scalable deployment.

Generative RL (Tao et al. 2025) employs diffusion-based generative models to synthesize diverse network states for pretraining MAPPO agents tasked with vertical handovers in IoT- integrated sensing and communication (ISAC) enabled MACNs. Pretraining on these synthetic trajectories accelerates convergence by approximately 63% and improves robustness to dual mobility and constrained resources, thereby reducing handover jitter in dense IoT and industrial scenarios. However, this approach increases GPU and dataset requirements, as wider trajectory diversity and larger synthetic datasets are necessary for generalization. Without model compression or distillation, the method may be limited for real-time or on-edge deployment.

Channel-aware RL integration (CAHM) (Nuo et al. 2025) enhances RL-based handover managers with physical channel features, including satellite-ground distance, doppler-aware channel gain models, and historical quality-of-experience telemetry, to inform context-rich decisions. In dynamic MACN scenarios, such as disaster relief or tactical operations, CAHM reduces interruption ratios and end-to-end latency by explicitly incorporating propagation and mobility effects into the state representation. Future work should focus on reducing

Fig. 6 Comparison of MARL and QMARL: trade-off between action dimensionality and fidelity (Kim et al. 2025)



computational demands for resource-constrained platforms and extending the model to incorporate direct UAV-satellite link options with their associated signaling constraints.

MAB-Graph fusion (Mohamed et al. 2024; Lv et al. 2022) integrates lightweight multi-armed bandit online learners with graph-based environmental modeling to guide UAV trajectories and satellite selection in disaster response applications. By prioritizing energy-efficient paths and reserving channels using coordinated reservation operators, this approach yields higher sustained data rates and fewer access failures in small-scale deployments. Scaling to larger multi-UAV fleets will require explicit modeling of handover delays, inter-UAV coordination overhead, and contention effects. Augmenting the bandit layer with multi-agent coordination or hierarchical control could help manage these complexities.

Collectively, these hybrid approaches illustrate a continuum of trade-offs. Quantum and generative hybrids enhance performance and robustness at the expense of hardware and data demands. Channel-aware RL grounds decisions in physical reality, but increases computational requirements. Bandit-graph fusions offer lightweight, online adaptability, but require additional coordination logic for scalability. Future research should emphasize complexity reduction through model compression and hierarchical control, realistic channel and mobility modeling, and end-to-end evaluation on emulators or testbeds to validate these promising approaches under operational constraints.

Innovative parameters, such as the channel reservation order in graph-based methods, prioritize channel allocation based on signal quality, throughput, and reservation urgency, achieving near zero handover blocking rates in high-traffic aeronautical scenarios (Lv et al. 2022). Complementary AI-driven strategies, including predictive decision making in UAV communications (Morshed et al. 2024) and dynamic handover control in MACNs (Guo et al. 2022), further demonstrate the importance of queuing models and SDN in minimizing latency and maximizing social welfare. Despite promising results, challenges such as high computational overhead, scalability limitations, and the need for real-world validation remain. Addressing these issues through energy-aware optimization, multi-orbit integration, and O-RAN frameworks represents a critical avenue for future research (Mahboob and Liu 2024). Collectively, these AI-driven techniques, evidenced by metrics such as reduced handover failure rates, enhanced energy efficiency, and improved quality of service, hold transformative potential for handover decision-making, enabling resilient and adaptive multi-tier aerial networks in 6 G and beyond.

5.3 Handover execution and management

Effective handover execution and management in MACNs require sophisticated strategies to ensure seamless transitions, minimize service disruptions, and optimize resource utilization across heterogeneous network layers. These strategies exploit real-time data, predictive analytics, and advanced network architectures to address the inherent dynamism of MACNs. Table 7 provides implementation details for representative studies, including AI models, simulation environments, and remarks on scalability and robustness, complementing the mechanism-oriented comparisons presented in Table 6.

Table 7 Summary of methods in handover and channel management of MACN

References	AI model	Simulator	Scalability	Robustness
Tong et al. (2025)	Advantage actor-critic (A2C)	N/A	Medium (Computational power struggles)	High (Improved convergence/signal stability)
Kim et al. (2025)	Quantum multi-agent reinforcement learning (QMARL)	Python	Medium (Action space complexity)	High (Improved QoS/energy efficiency)
Nuo et al. (2025)	Channel-aware Handover management (CAHM)	N/A	Medium (N/A)	High (Improved delivery ratio)
Zhang et al. (2024)	Not AI-specific (QoS Calculation)	Monte Carlo simulations	Medium (Hardware heterogeneity)	Medium (Optimized handover latency)
Yao et al. (2021)	Identity-based mutual authentication scheme (IMAS)	N/A	Low (High complexity/poor scalability)	High (Reduced authentication delay)
Morshed et al. (2024)	Knapsack problem for predictive decision	N/A	Medium (Complexity of ACC)	High (Reduced delay/loss rate)
Niu et al. (2024)	HZAO and HTWO algorithms	N/A	Medium (Latency/power consumption)	High (37% fewer handovers)
Tao et al. (2025)	Diffusion model with MAPPO	Python	Medium (Computational overhead)	High (Reduced handover failure)
Lv et al. (2022)	MADM with channel reservation order (CRO)	N/A	Medium (Simplified mobility)	High (Reduced access failure)
Han et al. (2024)	Adaptive data offloading and seamless handover	MATLAB	Medium (Limited UAV mobility)	High (15–30% faster convergence)
Guo et al. (2022)	Queueing game theory for DHSTC	OMNeT++ 5.5.1	Medium (Limited scalability/latency simplification)	High (Reduced interaction overhead)
Mohamed et al. (2024)	Two-stage MAB (BC-UCB and LinUCB-VA)	N/A	Medium (Handover impact ignored)	High (Improved data rate/energy efficiency)
Mahboob and Liu (2024)	ML/DL/RL for optimization	OAI	Medium (Onboard limitations/scalability)	High (Improved Doppler/handover)

5.3.1 Vertical handover techniques

The rapidly changing topology and traffic conditions in MACNs induce frequent vertical handovers across heterogeneous wireless tiers, which can compromise service continuity and QoS. The handover decision problem is inherently online, high-dimensional, and complex, rendering classical rule-based or low-dimensional methods insufficiently adaptive. Recent studies indicate that diffusion models, due to their strong adaptability to dynamic, high-dimensional environments, are well suited to learn robust handover policies that reduce interruptions and maintain service reliability (Tao et al. 2025). Sensing plays a critical role in applications such as intelligent transportation, environmental monitoring, and virtual reality by enabling action recognition, status acquisition, and geolocation. Traditional designs separate radar sensing and communication, resulting in increased cost and reduced efficiency (Zhang et al. 2023). By contrast, ISAC unifies the mmWave radar and communication functions, leveraging shared array antennas, RF transceivers, and DSP chains to reduce hardware redundancy while enabling advanced features and new services (Cui et al. 2021). In SAGINs with ISAC deployment, all three RAN tiers (GN, HN, SN) can perform concur-

rent sensing and communication. GN and HN generally achieve higher perception accuracy due to propagation or beam characteristics, creating opportunities for sensing-assisted communications and networked sensing that enhance cross-tier coordination and improve user experience (Zhang et al. 2024). Framed as a time-varying, resource-constrained distributed optimization problem, FL over SAGINs requires hierarchical and asynchronous algorithms, connectivity, and compute-aware client scheduling, and provable convergence analyses under intermittent links. This setting provides fertile ground for AI-driven orchestration and control techniques that jointly optimize learning performance and multi-tier network resources (Han et al. 2024). Representative metric improvements reported by the surveyed methods, including handover failure rate, interruption ratio, energy per handover, Pareto coverage, and signaling overhead are summarized in Table 6, while Table 7 cross-references these metrics with simulator and platform information.

5.3.2 Horizontal handover techniques

Conventional LEO handover methods rely on single-attribute, multi-attribute weighted, or prediction-aware schemes, which depend on prior measurements, fixed thresholds, and static knowledge. These methods are time-consuming to implement and prone to errors when network information becomes outdated, often causing frequent handovers and load imbalance (Liu 2021). Given the dynamic, unpredictable, and high-dimensional nature of LEO handovers, DRL, implemented via an A2C framework, models the problem as a multi-agent markov decision process (MAMDP) to provide a scalable, data-driven approach for learning multi-factor handover policies. These policies jointly optimize access selection, continuity, and service quality without heavy reliance on static prior knowledge (Tong et al. 2025; Liu 2021; Ferreira et al. 2019; Wu et al. 2021). Physical layer channel modeling, such as channel capacity estimation, has been explored to support real-time handovers, but such methods often fail under rapid network dynamics and typically ignore historical interaction data. The channel-aware handover management (CAHM) strategy addresses these limitations by evaluating satellite-to-ground channel quality using distance, channel gain, and free-space path loss while augmenting these metrics with user-computed remaining service time. To further optimize handovers, CAHM incorporates inter-satellite link conditions, including signal-to-noise ratio, link duration, and buffer queue states, providing a holistic view of end-to-end connectivity. Additionally, a novel service pause penalty leverages historical quality-of-experience data to reward or penalize candidate handovers, improving decision quality over time and reducing disruptive switches (Nuo et al. 2025). Another horizontal handover strategy leverages HAPs to create a reliable network that facilitates data transfer between satellites, UAVs, and ground users (Niu et al. 2024).

5.3.3 Predictive handover techniques

QMARL scheduling and predictive, graph-based handover designs together illustrate a powerful, data-driven approach to managing the extreme dynamics and constraints of MACN. The proposed QMARL scheduler compresses action dimensions via quantum-inspired measurement (PVM) and learns QNN-based policies to reduce the effective action space to logarithmic scale, enabling coordinated access scheduling among multiple ground stations while jointly optimizing residual energy and service performance; validated on a realistic

testbed using CubeSat TLEs, HALE-UAV aerodynamic data, and photovoltaic charging models, the scheduler sustains performance at very large action sizes ($|A| = 2^n$) where conventional MARL degrades (Kim et al. 2025). Complementary handover solutions use GNNs combined with high-temporal-resolution traffic maps, GBH prediction models, and CRO-augmented MADM to produce data-driven, predictive handover decisions that integrate naturally with learning-based predictors or optimization engines for improved QoS in aeronautical LEO SatCom (Sharma et al. 2018; Lv et al. 2022). These techniques are critical because satellite orbital motion, solar vector changes, radiation damage, and atmospheric gusts create highly uncertain scheduling and handover conditions, and swarm missions impose divergent traffic requirements, from ultra-reliable, low-latency CNPC flows (tens of milliseconds) to high-bandwidth payload streams, that must be served across three complementary link types (U2S, U2U, and U2G) with both vertical and horizontal handover protocols (Zeng et al. 2019; Zhu et al. 2019; Mozaffari et al. 2019).

Cross-layer solutions further enhance end-to-end continuity by integrating learning, control, and data management across tiers. FL continuity techniques enable seamless transfer of model parameters during satellite handovers (Han et al. 2024), while adaptive data offloading distributes non-sensitive data to UAVs for local preprocessing and model watermarking preserves model integrity during multi-satellite transfers. UAV-satellite joint control formulations, such as air control center optimization, coordinate scheduling and control objectives across platforms (Lin et al. 2024). Despite these advances, challenges remain. Authentication and control-plane mechanisms can introduce significant delays; for instance, IMAS reports up to a 300% increase in authentication latency during polar handovers, complicating the integration of quantum key distribution in real-time settings (Yao et al. 2021). Additionally, mobility prediction remains brittle in complex environments, with kalman filter predictors reporting approximately 35% RMS error in urban-canyon UAV-satellite links, highlighting the need for robust trajectory-aware forecasting and lightweight, fault-tolerant implementations for quantum-inspired schemes (Mohamed et al. 2024; Kim et al. 2025).

5.3.4 Software-defined control and predictive resource orchestration

Software-defined control and predictive orchestration techniques collectively provide a flexible control plane and proactive resource allocation strategy that are particularly suitable for the high-latency and heterogeneous links of MACN. The DHSTC protocol (Guo et al. 2022) illustrates a software-defined approach by dynamically alternating controller queues between two operating modes. In the observable mode, high-priority traffic (such as emergency UAV command-and-control) benefits from active congestion feedback and fine-grained scheduling. In the unobservable mode, best-effort flows (such as bulk sensor telemetry) are admitted probabilistically, thereby reducing control-plane signaling. By adapting its mode based on traffic composition and link conditions, DHSTC achieves approximately 40% lower interaction overhead, which is particularly significant for satellite environments where round-trip controller delays are non-negligible.

Complementary to software-defined control, predictive resource orchestration schemes proactively reserve and schedule radio and optical resources to mitigate access failures and enhance link reliability. The channel reservation order (CRO) mechanism (Lv et al. 2022) prioritizes aircraft handovers according to link quality and system load. For example, when satellite elevation exceeds 30° and SNR is greater than 15dB, CRO pre-allocates chan-

nels and reserves preemption capacity for emergency flights. Under heavy system loads (utilization exceeding 80%), it employs a knapsack-based allocation strategy to maximize aggregate throughput. This predictive allocation reduces aeronautical access failures by approximately 22% compared with FIFO baselines. In the optical domain, HAP-assisted FSO relaying (Niu et al. 2024) enhances the stability of free-space optical links through networked high-altitude platforms. The HZAO algorithm minimizes zenith angles to reduce atmospheric loss, while the HTWO scheduler classifies HAPs as idle or congested in order to extend satellite visibility windows and improve link continuity.

Tables 7 and 6 illustrate the diversity of AI-driven handover mechanisms in MACNs and their associated trade-offs. Reinforcement learning approaches, including A2C (Tong et al. 2025) and MAPPO (Tao et al. 2025), effectively model handover as multi-agent Markov decision processes, achieving 37% reduction in handover frequency and improved signal stability, though they require substantial training latency and computational resources. Quantum multi-agent reinforcement learning (Kim et al. 2025) demonstrates promising scalability with 50% faster convergence and enhanced energy efficiency, but remains constrained by the maturity of fault-tolerant quantum hardware. Generative AI methods (Tao et al. 2025) enable robust vertical handover under missing or uncertain data by synthesizing 3D SAGIN states, achieving 25% improvement in Pareto coverage, yet incur high GPU memory and training costs that limit deployment in ultra-dense settings. Multi-armed bandit approaches (Mohamed et al. 2024) offer real-time adaptation with significant energy efficiency gains, particularly in disaster scenarios, but are sensitive to context estimation errors and often neglect explicit handover delay modeling. Graph-based multi-attribute decision making methods (Lv et al. 2022) achieve near-zero handover blocking and 20% reduction in access failures by leveraging time-evolving coverage graphs, though their cubic computational complexity limits scalability for large networks. The majority of surveyed methods exhibit medium scalability with high robustness, indicating that while current approaches effectively handle moderate network sizes, addressing computational overhead and simplified mobility assumptions remains essential for practical deployment in large-scale MACN environments. Taken together, SDN mechanisms such as DHSTC provide low-overhead, policy-driven control, while CRO and HAP-enabled optical relaying contribute predictive, link-aware resource management necessary for resilient MACN operation. The primary trade-offs lie in control-plane complexity and the requirement for accurate link and state estimation. Specifically, SDN controllers must limit excessive signaling on high-latency links, and predictive schemes depend on sufficiently reliable telemetry (including elevation, SNR, and system load) to support effective pre-allocation. Future research directions include hybrid controllers that adapt DHSTC mode transitions using CRO-style predictions and the extension of HAP scheduling strategies to jointly consider both RF and optical link multiplexing.

5.4 Performance metrics for handover evaluation

Evaluating the performance of handover mechanisms in MACN requires a comprehensive set of metrics that collectively capture reliability, efficiency, and user satisfaction. These metrics are essential for addressing the diverse requirements of MACNs, which range from minimizing service disruptions to optimizing resource utilization.

The performance evaluation of handover schemes in MACN typically relies on a suite of complementary metrics that together reflect reliability, effectiveness, and operational efficiency. The handover failure rate and interruption probability quantify the likelihood of unsuccessful switches or service disruptions and are therefore central to reliability assessments. For instance, HAP networking (HAPN) reports an approximately 80% reduction in interruption probability compared with RF-based MACNs by exploiting stable FSO links (Niu et al. 2024), while the GBH framework explicitly seeks to minimize access-failure probability for aeronautical traffic (Lv et al. 2022). The average number of handovers is another important indicator, as fewer handovers reduce signaling overhead and lower the risk of transient outages. A2C-based schedulers extend satellite dwell time, thereby reducing handover counts and improving link stability in LEO constellations (Tong et al. 2025).

Latency and delivery delay remain critical for time-sensitive applications such as autonomous systems and disaster response. Channel-aware and SDN schemes, including CAHM and DHSTC, mitigate end-to-end delay by incorporating context-aware decision making and reducing control-plane signaling (Nuo et al. 2025; Guo et al. 2022). FL architectures further reduce training latency by approximately 15–30% through adaptive offloading (Han et al. 2024). Throughput and data rate are key metrics for data-intensive payloads such as remote sensing and video streaming. HAPN's FSO deployment achieves a reported 38.25% throughput gain, while UAV trajectory-aware schemes enhance payload link rates through joint planning (Niu et al. 2024; Morshed et al. 2024; Mohamed et al. 2024).

Signal stability and QoS, measured through indicators such as SNR and QoE, ensure persistent connectivity. Frameworks such as GBH prioritize SNR for aeronautical flows, QMARL explicitly optimizes QoS in CubeSat-HALE networks, and CAHM incorporates QoE penalties to better align handover decisions with user satisfaction (Kim et al. 2025; Lv et al. 2022; Nuo et al. 2025). For AI-driven methods, convergence speed and training reward provide valuable indicators of learning efficiency and adaptability. Approaches such as DGHD and QMARL demonstrate faster convergence and higher training rewards relative to baseline RL methods, thereby enabling quicker adaptation to nonstationary network conditions (Kim et al. 2025; Tao et al. 2025).

Energy efficiency is particularly important for UAVs and small satellites with limited power budgets. Joint trajectory optimization and MAB-based strategies report up to fifteen-fold improvements in energy utilization, while QMARL frameworks explicitly trade off energy consumption against service quality in scheduling decisions (Mohamed et al. 2024; Kim et al. 2025). Finally, system-level metrics such as social welfare and interaction overhead provide a holistic view of performance in SDN-based control. For example, DHSTC improves social-welfare metrics while simultaneously reducing controller interaction overhead in heterogeneous SAGINs (Guo et al. 2022).

It is important to emphasize that these metrics interact in nontrivial ways. Reducing the frequency of handovers may inadvertently increase latency or lower throughput, while aggressive throughput maximization can significantly raise energy consumption. As a result, evaluations should report multi-metric trade-offs under realistic mobility and traffic models. Moreover, validation on emulators or testbeds is recommended to capture cross-layer effects and control-plane delays that are often overlooked in simulation-only studies. Taken together, Tables 6 and 7 provide a compact reference for selecting handover strategies. Specifically, Table 6 characterizes mechanisms and performance gains across metrics,

while Table 7 records implementation and validation details necessary for reproducibility and deployment assessment.

5.4.1 Trade-off analyses

CAHM (Nuo et al. 2025) illustrates a latency reliability trade off in harsh environments such as disaster zones: the scheme deliberately accepts small latency increases on the order of milliseconds to secure very high delivery ratios of approximately 99.9%. The delivery ratio represents the proportion of data packets successfully delivered to their intended destination relative to the total packets transmitted, serving as a fundamental measure of communication reliability under handover conditions (Nuo et al. 2025). Detailed mathematical definitions and measurement methodologies are provided in the cited references. Energy throughput trade offs are apparent in BC UCB based schemes for UAV trajectory and access planning (Mohamed et al. 2024), which report substantial energy savings on the order of $\sim 89\%$ reduction in UAV energy consumption compared with greedy baselines while preserving a large fraction of peak throughput (roughly 80% of greedy data rates). These results underscore a practical compromise between endurance and instantaneous capacity. At the opposite extreme of the design space, MARL solutions handle dynamics and cooperation in dense non terrestrial networks effectively (Kim et al. 2025; Han et al. 2024), but conventional approaches suffer from severe convergence and scalability limitations as the number of agents and the dimensionality of actions increase. QMARL mitigates this problem by compressing action dimensionality, achieving logarithmic scaling thorough projection valued measures, at the cost of reduced classical implementability and maturity while improving convergence in very high dimensional action spaces (Kim et al. 2025). DRL and generative hybrids, including A2C, MAPPO, and diffusion model based methods, yield adaptive and high performance handover policies (Tong et al. 2025; Tao et al. 2025); however, they impose greater training and inference demands and often rely on centralized or cloud based training, which can limit real time on board deployment unless accompanied by model compression or edge offloading. Finally, system level design choices exhibit throughput robustness cost trade offs: high altitude platform networking with free space optical relays attains large simulated gains in throughput and interruption reduction but increases deployment cost and sensitivity to weather (Niu et al. 2024), whereas CRO augmented multi attribute decision making for aeronautical traffic improves aggregate throughput and reduces access failures at the expense of additional computation on aircraft or edge nodes (Lv et al. 2022).

5.4.2 Validation gaps

Across the surveyed works there is substantial heterogeneity in validation platforms and a persistent scarcity of hardware validation. Many studies perform algorithmic evaluation in Python or MATLAB (Kim et al. 2025; Tao et al. 2025; Han et al. 2024), OMNeT++ is employed in at least one investigation (Guo et al. 2022), Monte carlo experimentation appears in others (Zhang et al. 2024), and OAI based emulation or hardware like testbeds are relatively rare but notable in survey level contributions (Mahboob and Liu 2024). True hardware or emulation based end to end demonstrations remain exceptional rather than typical, although some works incorporate real world datasets such as ADS B flight snapshots (Lv et al. 2022) or TLE traces and HALE UAV aerodynamic logs to increase real-

ism (Kim et al. 2025). Reporting practices further limit reproducibility: roughly half of the papers do not consistently report their simulation platforms, and many omit complete simulator configurations, parameter sets, and computational cost metrics including training time, inference time, memory, and energy, despite the centrality of these metrics for assessing on board feasibility in non terrestrial network contexts (Tong et al. 2025; Tao et al. 2025; Kim et al. 2025). Moreover, several contributions rely on idealized channel, mobility, or energy models, while only a minority evaluate algorithms under high fidelity traces or realistic flight dynamics (Kim et al. 2025; Lv et al. 2022), which raises questions about the extent to which reported gains will transfer to operational environments.

To strengthen validation practices we recommend adopting shared benchmark scenarios and datasets, for example ADS B snapshots, TLE traces, and HALE aerodynamic logs; increasing the use of hardware in the loop and real emulation studies; mandating comprehensive reporting of simulator, platform, and configuration details; and requiring publication of computational and energy cost metrics. Encouraging open source releases would further enable independent replication and fair comparison. As Table 7 demonstrates, simulator platforms and reporting practices vary widely across studies, which complicates direct comparison and underscores the need for standardized benchmarks and openly available datasets.

Taken together, the handover literature indicates that the value of AI depends strongly on the degree of mobility uncertainty, cross-tier heterogeneity, and the extent to which handover decisions require prediction rather than simple thresholding. In comparatively regular settings, conventional handover mechanisms based on signal strength, hysteresis margins, dwell time, or lightweight predictive rules may still achieve acceptable performance with lower complexity and clearer operational behavior. AI-based methods become more useful when handover decisions must simultaneously account for multiple time-varying factors such as node mobility, channel fluctuations, traffic load, and service continuity across heterogeneous tiers. Under such conditions, RL, MARL, and hybrid predictive approaches can reduce unnecessary handovers and improve robustness, but they also introduce higher computational cost, training overhead, and implementation complexity. This trade-off suggests that future handover design in MACN should focus not only on improving AI performance, but also on clarifying when simpler model-based approaches remain sufficient and when the added complexity of learning-based control is operationally justified.

6 AI-enabled resource management

The integration of AI into MACN is transforming resource management from static, rule based control to adaptive, data driven decision making. The complexity of multi tier systems, in which LEO, MEO, and GEO satellites, HAP stations, UAV swarms, and terrestrial nodes interact over heterogeneous links, produces tightly coupled trade offs across spectrum, energy, and compute resources. Consequently, AI methods such as DRL for sequential decision problems, GNN for topology aware reasoning, and FL for distributed model training with reduced raw-data exchange have emerged as powerful enablers for optimizing allocation policies that jointly satisfy quality of service and user quality of experience metrics. This section surveys recent AI driven solutions organized into four focal areas: (i)

spectrum and bandwidth allocation, (ii) energy and battery aware management, (iii) QoS or QoE aware resource allocation, and (iv) learning based adaptive resource policies (Fig. 7).

Prior studies have characterized uplink and downlink performance and weather driven switching between FSO and RF links in hybrid MACN configurations composed of LEO satellites, HAP, and ground stations; however, these works typically assume a simplified, static network with a single ground receiver and fixed routes (Singh and Swaminathan 2023; Swaminathan et al. 2021; Altubaishi and Alhamawi 2019; Zhang et al. 2009). Practical deployments will require AI enabled resource control that scales to many concurrently served ground users and that responds to rapidly varying channel, traffic, and mobility conditions. In particular, jointly exploiting direct satellite to user links and HAPS assisted relays through dynamic adjustment of coverage footprints, relay selection, and routing promises substantial performance gains but also introduces new challenges in cross layer optimization, real time decision latency, and coordination among distributed controllers. The physical placement of high altitude platform stations is a decisive design variable because both relay capacity and effective coverage expansion depend strongly on satellite HAPS geometry and on the spatial distribution of user demand; nevertheless, systematic strategies that jointly consider HAPS positioning, coverage control, and AI driven resource allocation across diverse operational scenarios remain largely unexplored (Mashiko et al. 2025).

In the remainder of this section we highlight AI approaches that address these challenges, including MARL for coordinated coverage and handover control, GNN based models for rapid inference on network graphs, and FL schemes that enable collaborative model training across nodes with constrained backhaul. We also identify open problems such as the design of safe and explainable policies, transfer learning across operational environments, and the joint optimization of communication, computation offloading, and energy management in large scale, dynamic MACN. Table 8 summarizes representative AI and non AI methods for resource management in MACN together with their evaluation platforms, remarks on scalability, and observations on robustness; the table is intended as a concise mapping from algorithmic families to practical deployment trade offs.

6.1 Spectrum and bandwidth allocation

Spectrum scarcity and the heterogeneity of MACN, including LEO satellites, HAPS, UAV, and terrestrial systems, make real time, cross tier spectrum and bandwidth management indispensable. A SDN control plane that provides a global network view can enable flexible orchestration and network slicing, yet the extreme dynamism, scale, and heterogeneous

Fig. 7 Joint perception, communication, computing, and actuation framework illustrating cross-layer coupling (Meng et al. 2024)

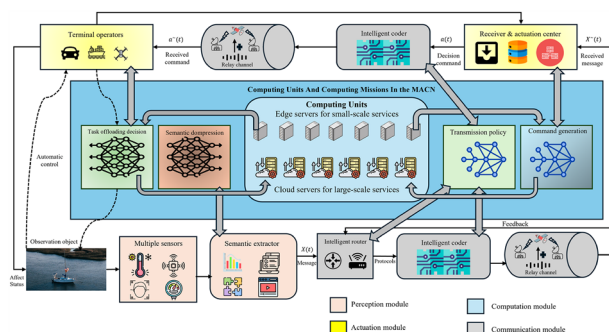


Table 8 Summary of methods for resource management in MACN

References	AI model	Simulator	Scalability	Robustness
Li and Shang (2025)	Not AI-Specific (Stochastic Geometry)	N/A	Medium (Latency and coordination complexity)	High (Improved SINR and coverage)
Mashiko et al. (2025)	Not AI-Specific (FSO or RF Models)	N/A	Medium (Lack of coordination)	High (Improved spectral efficiency)
Jia et al. (2025)	DRL for SFC Scheduling	Python	Medium (Complexity and scalability)	High (Improved SFC deployment)
Tianhao and Zhiyong (2024)	Self-Attention Based DRL	N/A	Medium (Rapid changes and computational overhead)	High (Reduced energy and delay)
Meng et al. (2024)	Not AI-Specific (SCol Metric)	N/A	N/A	Medium
Dahrouj et al. (2023)	Ensembling Deep Neural Networks (EDNN)	Python	Medium (Dynamic challenges and interference)	High (Improved sum-rate)
Wu et al. (2021)	SDN with AI Algorithms	STK, Didi Chuxing Dataset	Medium (Signaling overhead and dynamic resources)	High (Improved throughput)
Zhi et al. (2024)	Not AI-Specific (Graph Theory)	N/A	Medium (Optimization complexity)	High (Improved secrecy rate)
Jia et al. (2024)	DRL for Resource Allocation	Python	Medium (Radiation vulnerability and unreliable links)	High (Reduced system cost)
Ding et al. (2024)	Endogenous AI with RASAR	N/A	Medium (AI overhead and deployment complexity)	High (Improved user serviceability)
He et al. (2022)	Reliable transport system (RTS)	Real SGIN Prototype, Virtual SGIN	Medium (Caching and control packet overhead)	High (>66% delay reduction)
Wu et al. (2024)	PPO for load balancing	Mininet, BMV2 P4 Switches, Python	Medium (AI interpretability and telemetry overhead)	High (40–50% lower queue imbalance)
Lins et al. (2021)	SI/EI with DNN Partitioning	OAI, free5GC, Docker/ Kubernetes, Matlab, Mininet	Medium (Standards rigidity and UAV limits)	High (Reduced latency and jitter)
Peng et al. (2024)	MAPPO with LSTM	N/A	Medium	High (Improved hit ratio and delivery delay)
Li et al. (2021)	MILP with tabu search (TS)	N/A	Medium (Link capacity or latency constraints)	High (Improved profit and acceptance ratio)
Zhang et al. (2022)	FL with Q-Learning	N/A	Medium (Complexity and resource load)	High (12.9–33.1% revenue improvement)
Cao et al. (2021)	Improved Two_Arch2 Algorithm	N/A	Medium (Multi-level control and scalability)	High (Improved HV for multi-objective)
Zhang et al. (2024)	GCN with DRL	Python	Medium (Static topology and limited attributes)	High (Improved revenue-cost ratio)

Table 8 (continued)

References	AI model	Simulator	Scalability	Robustness
Li et al. (2022)	SN-LSTM for Navigation	ROS-GA-ZEBO, UUV Simulator	Medium (Simulation-only)	High (0.26 km error reduction)
Ivanov et al. (2022)	GNN for Graph-Based RA	N/A	Medium (Complexity and assumptions)	High (3–46 kb/s/J EE)
Ozturk et al. (2025)	Multi-Attention for Latency-Aware Switching	N/A	Medium (Interference and AI privacy)	High (Reduced power consumption)
Alam and Song (2024)	GNN with DDPG	BRITE, ns-3	Medium	High (Improved VNR acceptance and QoS)
Wang et al. (2018)	Lagrange dual decomposition with CCP	N/A	Medium (Perfect information and heavy computing)	High (Improved throughput)
Jiang et al. (2023)	Multi-sided ascending-price auction	N/A	Medium (N/A)	High (Improved admission ratio)
Zhou et al. (2023)	CDMADDPG	N/A	Medium (Simplified assumptions and complexity)	High (Balanced throughput)
Cai et al. (2024)	MAPPO	N/A	Medium (Complexity and security limits)	High (Reduced system cost)
Sun et al. (2024)	Auction with DRL	N/A	Medium	High (Improved system profit or load balance)
Hassan et al. (2022)	MINLP with BD/DA/ADMM	Python	Medium (Simplified scenarios or fixed network)	High (Improved EE/SE)
Zhang et al. (2021)	DRL for multi-domain VNE	N/A	Medium (Offline testing and simplified mobility)	High (Improved revenue and acceptance rate)

QoS requirements of MACNs demand AI augmented decision engines for fast, adaptive allocation and sharing decisions (Di et al. 2019; Cheng et al. 2020; Zhang et al. 2017). In practice, an effective spectrum controller must reconcile competing objectives such as spectral efficiency, latency, reliability, fairness, and energy consumption under stringent constraints including limited onboard power, long satellite propagation delays, and rapidly evolving aerial topologies (Wang et al. 2020; Zhuang et al. 2019; Zhang et al. 2020). Table 8 lists representative spectrum allocation and graph based studies, for example EDNN and GNN entries, and summarizes the platforms and scalability assumptions that underlie their reported gains.

SL and imitation learning methods often serve as a first step in converting historical or simulated traces into fast, low complexity decision rules for user scheduling and initial allocation. For example, EDNN can learn high quality mapping policies that assign users to satellites, HAPS, UAVs, or ground base stations to maximize aggregate throughput subject to power or association constraints; these learned schedulers are particularly effective in environments with predictable traffic patterns or where labeled data from simulations or logs are available (Dahrouj et al. 2023). Lightweight sequence models, such as compact long short term memory (LSTM) networks, can be deployed on resource constrained edge platforms to reduce signaling and offloading demands. By performing localized inference, these models lower the bandwidth and energy required for centralized coordination and thereby alter the effective spectrum demand profile (Li et al. 2022).

Graph based AI methods offer a topology aware paradigm for spectrum allocation and interference management in MACN. Representing heterogeneous elements and their interference relationships as graphs or hypergraphs enables the use of GNN to capture spatial and relational structure, generalize across varying network sizes, and produce fast inference when mobility changes link connectivity. Frameworks such as GRIST employ hypergraph formulations and GNN to jointly reason about inter subnetwork interactions, including cellular, device to device, satellite, and aerial relays, and to generate interference aware channel assignments and reuse patterns that adapt to evolving topology and traffic mixes (Ivanov et al. 2022). Graph based approaches further support transferability. Policies trained on one constellation or regional topology can be fine tuned or transferred to another constellation with similar graph statistics, which reduces the need for expensive retraining.

For sequential, long horizon control problems in which actions have delayed or cumulative effects, DRL and multi agent variants are particularly well suited. RL agents can jointly optimize band allocation, power control, UAV hovering altitude, and handover thresholds to maximize long term capacity while suppressing cross tier interference and satisfying latency and reliability constraints (Wang et al. 2018). In multi agent formulations, individual aerial platforms or SDN sub controllers learn coordinated policies via centralized training with decentralized execution or via communication aware MARL, thus supporting large scale coordination without excessive signaling overhead. Hybrid architectures that combine RL for high level policy decisions with low complexity learned heuristics or supervised models for rapid local actions provide a pragmatic balance between optimality and run time responsiveness.

Data heterogeneity, administrative separation, and limited backhaul motivate distributed learning paradigms, most notably FL. FL enables geographically distributed SDN controllers, satellite gateways, and aerial nodes to jointly refine models for demand forecasting, interference prediction, or price dynamics without requiring centralized raw-data collection across domains. Model compression, quantization, and knowledge distillation are often necessary to make FL feasible over constrained links such as satellite uplinks or underwater acoustic channels, and these edge-oriented design choices directly affect spectrum utilization and control-plane overhead.

Economic and market based mechanisms complement data driven AI by embedding fairness and incentive compatibility into allocation. Auction based designs, for example multi sided ascending price auctions for network slicing, provide provable efficiency and fairness guarantees while enabling heterogeneous providers, including satellite operators and radio access network operators, to coordinate bandwidth sharing and latency sensitive slice tenancy across domains (Jiang et al. 2023). These mechanisms can be augmented with learning modules that predict demand, estimate willingness to pay, or adapt reserve prices, thus increasing spectral utilization while mitigating strategic behavior.

Domain specific constraints illustrated by maritime and other specialized scenarios must inform algorithm design. Maritime and low gain user settings shift demand toward aerial relaying links and impose strict energy and antenna gain constraints that affect scheduling and spectrum sharing policies (Hassan et al. 2022; Li et al. 2020; Zhou et al. 2017). UAV relays serving low earth users through air to satellite and air to ground links change interference footprints and require dynamic, energy aware, and delay sensitive reallocation strategies (Sun et al. 2018; Motlagh et al. 2016). Likewise, deployments that mix radio and underwater acoustic modalities must treat channel capacities, latencies, and energy costs as

modality specific resources, which motivates cross domain schedulers that jointly optimize when to communicate, when to compute locally, and when to defer or compress data.

From a systems perspective, hierarchical SDN architectures that combine local fast loop controllers for low latency, safety critical actions with higher level global orchestrators for strategic slice reconfiguration are a promising approach to couple AI models operating at different granularities. In these architectures, lightweight edge inference handles rapid link level adaptations while periodic global updates, possibly informed by FL or offline RL retraining, adjust slicing and spectrum reservations to reflect evolving traffic patterns. Critical performance metrics for evaluation should therefore include not only throughput and spectral efficiency but also control plane overhead, decision latency, fairness across users and slices, energy per bit for battery operated nodes, and robustness to topology shifts and adversarial conditions.

In the context of bandwidth management within AI enabled resource allocation frameworks for MACN, (Shang et al. 2021) propose an EI driven SAGIN architecture that leverages DRL to optimize communication resources, including bandwidth, together with computing and storage capabilities. By integrating software defined networking and NFV with microservices (Bao et al. 2019), this architecture enables the decomposition of delay sensitive services, for example Internet of Vehicles (IoV), augmented reality (AR), or virtual reality (VR), into independent microservices for distributed processing across satellites, aerial nodes, and ground stations. This approach addresses bandwidth constraints in resource limited environments by dynamically allocating spectrum under time varying channel conditions and satellite dynamics. The RASAR and DRCAM style architectures and their comparative platforms and limitations are summarized in Table 8, which readers may consult to compare bandwidth management trade offs and reported performance.

A central contribution is the DRL based resource allocation and computation offloading algorithm for microservices, DRCAM, which minimizes a weighted sum of latency and energy consumption while explicitly accounting for bandwidth constraints. Building on prior DRL and RL works for storage and bandwidth optimization in MACNs (Wang et al. 2021; Zhang et al. 2022), DRCAM incorporates knowledge graphs for context aware decision making and demonstrates pervasive bandwidth efficiency for massive service requests in full coverage 6 G scenarios (Li et al. 2023). Simulations indicate lower system cost relative to cloud centric paradigms (Xie et al. 2021) and improved performance for user constrained environments (Hassan et al. 2020). Notable challenges include inefficiencies arising from centralized optimization and high development overhead; possible remedies include deeper AI integration for real time sensing and orchestration (Xu et al. 2023; Lin et al. 2023; Yang et al. 2022). Overall, this EI strategy complements existing AI techniques by extending bandwidth management across space, air, and ground tiers to promote ubiquitous access and quality of experience guarantees in remote or harsh environments (Jia et al. 2024).

Authors in Ding et al. (2024) introduce the RASAR architecture for autonomous resource management in MACNs, embedding endogenous AI in a closed loop hierarchy of three levels and optimizing bandwidth through federated learning at the access level and RL at the service level. By slicing the network to separate delay tolerant and delay sensitive users, RASAR improves slice reconstruction latency, burst service response time, user serviceability, and resource efficiency in simulated LEO or MEO setups with busy traffic, outperforming benchmarks such as CDA and NCS. The framework nevertheless faces AI overhead and

deployment complexity, and future work should address joint data and service management as well as optimal AI placement. Related efforts target reliable transport and caching to indirectly improve bandwidth efficiency. For example, a distributed caching design with hop by hop acknowledgments demonstrated substantial end to end delay reduction and lower resource consumption in a prototype involving the Qilu 1 satellite and virtual simulations, although caching overhead motivates further on orbit evaluation (He et al. 2022). Other works advocate full dimensional programmability for self driving 6 G networks, employing RL methods such as proximal policy optimization for load balancing and in band telemetry to monitor bandwidth states; Mininet and P4 switch emulations report marked reductions in queue imbalance compared with equal cost multipath, while highlighting the need for explainable AI and enhanced edge intelligence to address interpretability and hardware constraints (Wu et al. 2024).

Additional AI enabled strategies include MAPPO with LSTM for collaborative content caching, which clusters satellites to improve hit ratio and reduce delivery delay in dynamic networks though real world scalability remains an open issue (Peng et al. 2024), and intent based orchestration that combines GNN with DDPG based RL to satisfy low latency and high bandwidth virtual network requests in BRITE and ns-3 simulations (Alam and Song 2024). Economic mechanisms also contribute to bandwidth allocation: a multi sided ascending price auction allocates bandwidth across satellite, RAN, and WAN domains to maximize gain from trade while preserving truthfulness and budget balance, with performance assessed by admission ratio and served bandwidth per user and with natural extensions to include delay and energy considerations (Jiang et al. 2023). Modeling resource orchestration as a virtual network embedding problem, other studies use DRL to optimize bandwidth and node embedding for intelligent transportation scenarios, achieving higher long term revenue and acceptance rates in Python simulations, though the lack of real world testing constrains external validity (Zhang et al. 2021).

Collectively, these AI enabled strategies advance autonomy and efficiency in MACN's bandwidth management, yet recurrent drawbacks such as computational overhead and limited real world validation persist. Addressing these limitations will require hybrid AI and hardware solutions, refined strategies for AI placement and model compression, and extensive field trials to realize the promise of 6 G deployments.

6.2 Energy and battery-aware management

Energy efficiency is a fundamental challenge in MACN because aerial and space nodes such as UAV, HAPS, and satellites are intrinsically resource constrained. Unlike terrestrial base stations that can rely on stable power supplies, these nodes operate on limited batteries or solar based energy harvesting, which imposes strict limits on communication duration, computation, and coverage. Consequently, AI driven strategies have been widely adopted to manage energy consumption intelligently while preserving sustainable operation and acceptable performance. Table 8 highlights representative energy aware contributions, for example SN LSTM navigation, GCN plus DRL hybrid methods, and UAV hovering and power optimization, and records their simulation platforms and notes on robustness to facilitate cross comparison. Energy-aware routing and coordination are critical in long-duration UAV missions, where bio-inspired optimization techniques, such as grey wolf optimization, have been applied to jointly optimize localization accuracy, clustering efficiency, and

network lifetime (Arafat and Moh 2021). Recent bio-inspired algorithms continue to demonstrate strong performance in clustering and routing for flying ad hoc networks, offering a favorable balance between adaptability and computational efficiency under high-mobility conditions (Agrawal and Arafat 2024).

At the radio and MAC layers, a prominent direction is the use of learning to design adaptive transmission policies that balance power efficiency and throughput. Static power control schemes are generally ill suited to highly dynamic SAGIN, where link conditions fluctuate with user mobility, atmospheric effects, and orbital motion. Machine learning models can predict channel states and optimize transmit power accordingly, thereby extending device lifetime without sacrificing reliability. For example, energy efficient coexistence strategies for satellite terrestrial systems dynamically adapt transmit power to avoid interference while conserving energy (Ruan et al. 2022). Similarly, combining advanced multiple access techniques, such as NOMA and rate splitting, with AI driven clustering and beamforming has been shown to improve spectral efficiency while imposing only modest additional energy overhead (Lin et al. 2019; Yin and Clerckx 2022).

At the network and service management level, AI has been applied to resource virtualization frameworks to enable flexible and energy efficient allocation of heterogeneous resources. Traditional terrestrial infrastructures often cannot meet the energy demands of emerging applications such as smart cities, autonomous transportation, and large scale IoT deployments. To address this gap, MACN research has combined service function chaining and network function virtualization with AI based orchestration to reconfigure services on demand while minimizing energy consumption (Zhang et al. 2022; Ozturk et al. 2025). DRL, particularly when integrated with GNN for virtual network embedding, has demonstrated promise: by learning to map virtual network requests onto the physical satellite UAV ground infrastructure, DRL based algorithms such as GD-EA-VNE can minimize total energy consumption while maximizing revenue to cost ratios, thus balancing operational and economic objectives (Zhang et al. 2024).

Task offloading is another crucial area for energy management. Mobile and IoT devices in SAGIN scenarios often lack sufficient battery capacity for intensive local computation. AI enabled self attention mechanisms and related models have been used to decide dynamically whether to process tasks locally or offload them to edge servers hosted on LEO satellites. These models consider task urgency, available bandwidth, and channel quality, and thereby minimize both user side energy consumption and satellite processing cost while also reducing latency (Tianhao and Zhiyong 2024).

The integration of ocean networks into MACN further broadens the scope of energy aware AI solutions. Autonomous underwater gliders operate under extremely tight energy budgets and have traditionally depended on expensive sensors and active propulsion. Lightweight predictive models such as SN LSTM have recently been introduced to support energy efficient navigation by leveraging buoyancy control and trajectory prediction; as a result, these gliders can perform large area environmental monitoring with minimal energy expenditure (Li et al. 2022). This example illustrates how AI can enable sustainable operation across aerial, space, and maritime domains.

Finally, UAV specific constraints motivate tailored energy aware strategies. UAVs are frequently deployed to augment terrestrial coverage, relay traffic, and maintain connectivity, yet they face unique challenges including dynamic topologies, frequent hovering adjustments, and limited onboard batteries. AI based joint optimization frameworks that select

UAV hovering altitude and transmission power simultaneously can extend UAV endurance, preserve communication reliability, and mitigate cross tier interference while also reducing collision risk (Wang et al. 2017, 2018). Collectively, these energy aware AI techniques are essential for enabling long lived, efficient multi domain SAGIN deployments.

6.3 QoS and QoE-aware resource allocation

QoS and QoE are fundamental to user satisfaction in MACN, particularly for latency sensitive and mission critical applications such as intelligent transportation systems, disaster response, and large scale IoT services. These applications impose diverse and stringent requirements, including ultra-low latency, high throughput, robust reliability, and service continuity across heterogeneous tiers. AI based resource allocation has therefore emerged as a key enabler for optimizing network performance. By leveraging ML and optimization techniques, SAGIN infrastructures can dynamically allocate resources, adapt to fluctuating demand patterns, and ensure that application specific requirements are met across heterogeneous domains. Table 8 aggregates representative entries for SFC and NFV, MAPPO, FL based embedding, and auction plus RL schemes; this table enables readers to cross check QoS and QoE claims against simulator settings and reported scalability caveats.

A prominent application is the IoV, where dynamic mobility and safety critical services demand strict delay and reliability guarantees. AI enabled, cost aware service function chaining frameworks exploit SDN and NFV to schedule and map service chains in MACN while balancing provider cost and diverse QoS constraints. These frameworks can, for example, prioritize ultra low latency for vehicular safety messages while allocating high bandwidth for infotainment streams in highly mobile environments (Li et al. 2021).

FL has been applied to SFC embedding in MACN as a distributed approach that supports collaborative learning of resource allocation policies while reducing centralized raw-data exchange. Unlike centralized solutions that require raw data exchange, FL allows space, aerial, and terrestrial segments to train models locally and share only model updates. This approach improves success rates for SFC deployment while reducing communication overhead and helping to ensure that QoS requirements are respected across administrative domains (Zhang et al. 2022).

In vehicular networking scenarios, edge cloud collaborative scheduling is critical for meeting application specific performance targets. AI driven algorithms can optimize task offloading between edge nodes, such as UAVs and roadside units, and cloud resources within SAGIN. By jointly minimizing service delay and energy consumption while maximizing resource utilization, these mechanisms enable diverse vehicular services ranging from real time navigation to high definition video streaming to meet their QoS targets (Cao et al. 2021).

Network slicing provides a systematic mechanism to enforce QoS aware allocation in heterogeneous environments. Multi objective optimization techniques, including centralized and distributed multi agent deep deterministic policy gradient (CDMADDPG) algorithms, have been proposed to orchestrate RAN slices tailored to distinct service profiles. For example, individual slices can be configured to prioritize throughput for urban streaming, to guarantee ultra low latency for vehicular control, or to maximize coverage for rural monitoring. By balancing these often conflicting objectives, AI based orchestration enables simultaneous satisfaction of diverse user demands (Zhou et al. 2023).

Ensuring equitable access to scarce resources is vital in large scale multi tier systems. Auction based mechanisms augmented with RL have been employed to achieve proportionally fair scheduling that prevents resource starvation while satisfying strict QoS constraints. These hybrid economic and learning frameworks improve fairness across competing users and device classes and can adapt to changing demand and network conditions (Sun et al. 2024).

Finally, intent based networking frameworks that combine GNN with RL methods such as DDPG offer higher level automation in QoS management. These systems interpret high level service intents, for instance a request for low latency video calling, and translate them into concrete resource allocation strategies. By dynamically orchestrating resources across the space, air, and ground layers of SAGIN, intent based approaches enable virtual network requests to meet their latency, bandwidth, and reliability requirements even under highly dynamic conditions (Alam and Song 2024).

6.4 Learning-based adaptive resource policies

In the context of dynamic resource policies for AI enabled resource management in MACN, several works have emphasized hybrid FSO and RF links as a means to improve downlink spectral efficiency for emerging 6 G systems (Kaleem et al. 2024; Mao et al. 2023; Qi et al. 2022). These multi layered systems combine LEO satellites and high altitude platform stations to offer direct to cell connectivity that can fill coverage gaps in remote or disaster affected areas. They must also contend with propagation challenges, most notably weather dependent signal degradation on FSO channels, so recent studies examine mixed FSO and RF operation and weather aware link switching to maintain performance under adverse atmospheric conditions (Kodheli et al. 2020; Singh and Swaminathan 2023; Swaminathan et al. 2021). Table 8 collects several architectural proposals, for example edge intelligence, RASAR, MAPPO clusters, and DRL based virtual network embedding, and their implementation notes; the table is useful when evaluating orchestration trade offs such as placement, telemetry overhead, and multi objective performance.

Although much prior analysis has focused on static MACN topologies and uplink or downlink characterization, practical deployments require adaptive mechanisms that respond to distributed and time varying ground traffic. In particular, optimal resource allocation must consider HAPS positioning and adaptable coverage boundaries to trade off direct satellite transmissions against HAPS relayed links as traffic loads and propagation conditions evolve (Kawamoto et al. 2024). Notable contributions propose integrated control methodologies that continuously adjust HAPS placement and satellite or HAPS coverage regions according to measured traffic distributions and channel conditions, thereby maximizing end to end spectral efficiency through a careful balance of transmission capacity and distance (Kaleem et al. 2024; Mao et al. 2023; Qi et al. 2022). (Mashiko et al. 2025) further illustrate the potential of AI driven adaptation, showing how learning agents can enable near real time optimization across changing multi tier aerial topologies.

ML techniques have been applied across several resource management functions in MACN. Edge driven neural networks, for example, have been proposed for user scheduling and can maximize sum rate throughput while satisfying power and backhaul constraints; these schemes can efficiently assign users among geostationary satellites, HAPS with FSO links, and multi antenna ground base stations, yielding reduced computational complex-

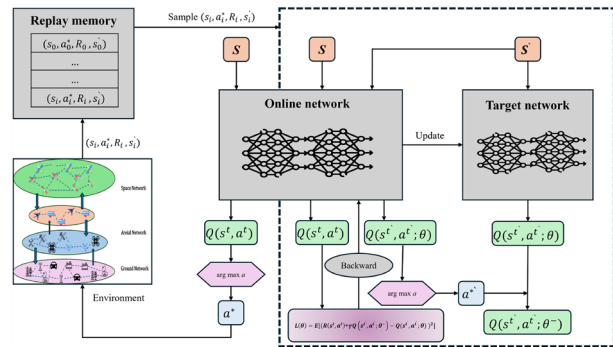
ity and improved performance across regions with heterogeneous user densities (Dahrouj et al. 2023). In mission critical operations such as search, diagnostic, and rescue, hybrid AI frameworks combine system intelligence for orchestration and EI for task partitioning, for example offloading object detection deep neural networks to suitable edge nodes that can adapt to damaged or degraded infrastructure by optimizing latency, throughput, and resource consumption on UAVs that operate as temporary base stations or user equipment (Lins et al. 2021).

RL families have shown particular promise for collaborative and distributed optimization. MAPPO augmented with memory modules such as LSTMs supports collaborative caching and content placement across clustered satellites in large scale integrated systems by adapting to content popularity and network conditions to reduce delivery latency (Peng et al. 2024). Distributed task scheduling formulations that employ MAPPO balance security utility, system cost, and energy consumption while offloading heterogeneous workloads across satellites, UAVs, and ground devices, thereby supporting differentiated task handling in heterogeneous and resource-constrained environments (Cai et al. 2024). Auction style mechanisms coupled with DRL have also been used to enforce proportional fairness in task allocation, dynamically adapting to fluctuating arrival rates to achieve load balancing and to optimize system level profit metrics (Sun et al. 2024).

Beyond individual algorithms, several architectural and orchestration paradigms aim to make AI based resource management practical and scalable in MACN. EI architectures integrate AI capabilities across satellites, UAVs, and ground nodes, often through microservices and knowledge graphs, so that DRL agents can dynamically allocate resources and offload computation to resource constrained users in challenging environments such as remote regions or disaster zones (Jia et al. 2024). The RASAR framework embeds endogenous AI loops for perception, training, and optimization across hierarchical resource, access, and service levels to autonomously manage network slices according to real time demand profiles spanning delay tolerant to delay sensitive services (Ding et al. 2024). For multi domain orchestration, DRL based virtual network embedding enables adaptive placement of virtual network requests onto heterogeneous satellite, aerial, and ground infrastructures, allowing applications such as intelligent transportation systems to maintain service continuity despite topology changes (Zhang et al. 2021). Complementary concepts such as full dimensional programmability and real time telemetry support self driving network functions, for example PPO based load balancing across satellite, aerial, and ground paths, which react to dynamic traffic and link conditions (Wu et al. 2024). Joint modeling of routing, demand, and NFV placement with DRL applied to dynamic service function chaining permits continuous adaptation of function placement and chaining to topology shifts and demand fluctuations, thereby improving the rate of successful SFC deployments across the multi tier ecosystem (Jia et al. 2025). Figure 8 shows the DRL-MSSNL training pipeline, including how states are constructed, rewards are shaped, and training and evaluation phases are separated. Refer to the figure when discussing experimental setup, sensitive hyperparameters, and the algorithm's dependence on reward design.

Taken together, these learning based strategies spanning DRL, GNN, FL, and ensemble methods provide the adaptability needed to manage rapidly changing topologies, variable traffic demands, and heterogeneous resource availability in MACN. At the same time, practical challenges persist, including computational overhead, scalability to continental or global scales, deployment constraints, and the integration of advanced beamforming and multi

Fig. 8 Training workflow of the DRL-MSSNL algorithm: state construction, reward shaping, and evaluation split (Jia et al. 2025)



layer connectivity into unified control loops. Addressing these limitations will be essential to realize real time, robust, and efficient resource policies for 6 G era MACN. Entries in Table 8 provides a comprehensive overview of AI-driven resource management methods in MACNs, revealing consistent patterns across diverse approaches. Deep reinforcement learning methods dominate the landscape, with DRL-based service function chaining (Jia et al. 2025, 2024), self-attention DRL (Tianhao and Zhiyong 2024), and graph convolutional network combined with DRL (Zhang et al. 2024) demonstrating improved deployment efficiency, reduced energy consumption, and enhanced revenue-cost ratios. Multi-agent approaches, including MAPPO with LSTM (Peng et al. 2024) and MAPPO for privacy-aware allocation (Cai et al. 2024), effectively address coordination challenges in distributed settings, achieving improved hit ratios and reduced system costs. Graph neural network methods (Ivanov et al. 2022; Alam and Song 2024) enable topology-aware resource allocation with energy efficiency gains of 3–46 kb/s/J and improved virtual network request acceptance. Federated learning combined with Q-learning (Zhang et al. 2022) addresses privacy concerns while achieving 12.9–33.1% revenue improvement, and PPO-based load balancing (Wu et al. 2024) reduces queue imbalance by 40–50%. Notably, all surveyed methods exhibit medium scalability, with common limitations including coordination complexity, computational overhead, simplified mobility assumptions, and static topology constraints. The consistently high robustness ratings across approaches indicate that current AI methods effectively optimize resource allocation under dynamic conditions, though addressing scalability limitations and bridging the gap between simulation environments and practical deployments remains a critical research priority.

The resource-management studies reviewed in this section show that AI is particularly valuable when allocation decisions must be repeatedly updated under coupled variations in traffic demand, topology, interference, and resource availability across multiple tiers. In such environments, DRL, GNN-based reasoning, and distributed learning methods can offer stronger adaptability than static allocation rules or offline optimization alone. At the same time, many resource-management problems in MACN still retain structure that can be effectively exploited by classical optimization, decomposition, matching, or queue-aware control methods, especially when the system model is sufficiently accurate and operational transparency is important. The key issue is therefore not whether AI should replace classical resource management, but how to choose among classical, AI-based, and hybrid strategies according to the degree of uncertainty, scale of coordination, and resource budget of the deployment. This perspective is important because some reported performance gains from

AI methods may be offset in practice by increased signaling, training cost, and energy consumption if the underlying control problem is not sufficiently dynamic to justify that added complexity.

7 AI-driven optimization techniques

MACN are expected to provide ultra wide coverage and long distance connectivity (Fang et al. 2021), yet standalone satellites remain vulnerable to line of sight disruptions, shadowing, and link instability. Relay based cooperative transmission using UAV has therefore been proposed to strengthen satellite to terrestrial links by increasing the probability of line of sight and providing three dimensional connectivity (Sharma et al. 2019; Lee et al. 2022; Guo and Zhao 2022; Ding et al. 2021; Pan et al. 2020). Under quality of service and resource constraints, transmission mode selection, that is direct satellite to user equipment versus UAV relay, together with joint power and spectrum allocation must be decided adaptively as satellite and UAV mobility and traffic conditions evolve. Solution approaches cluster into two principal families which are classical optimization and RL based methods (Tian et al. 2021; Jia et al. 2021; Shi et al. 2022). Because centralized RL requires global information and scales poorly, multi agent alternatives have received considerable attention (Ding et al. 2021; Oubbati et al. 2023; Messaoudi et al. 2024). Representative algorithms include MAD-DPG and its variants for trajectory planning, power control, and access management (Ding et al. 2021; Oubbati et al. 2023; Messaoudi et al. 2024), and multi agent advantage A2C schemes with action dimensionality reduction for association and trajectory design (Lee et al. 2022).

Sixth generation systems will require MACNs to deliver global coverage and to accommodate growing traffic volumes from applications such as remote sensing, environmental monitoring, industrial automation, and smart cities (Lv et al. 2021; Zhou et al. 2023; Drif et al. 2021; Chen et al. 2021a, b). The rapid growth in satellite deployments driven by large constellations has produced extremely dense networks with numerous interconnections; flat control plane architectures struggle to scale under these conditions because of synchronization inefficiencies. Consequently, hierarchical, domain based control plane designs are necessary to achieve scalable, resilient management.

The integration of AI has fundamentally changed the design and operation of MACN. This section surveys AI driven optimization techniques with emphasis on problem formulation, optimization methods, joint design strategies, and performance evaluation metrics, synthesizing recent advances from the literature. Table 9 summarizes representative optimization and AI driven methods for MACN together with implementation platforms, observations about scalability, and robustness notes; the table serves as a concise reference for the methods discussed in this section.

7.1 Trajectory optimization methods

Trajectory optimization is central to AI driven control of aerial tiers in MACN because the motion of UAV, HAP, and LEO satellites directly shapes channel quality, user coverage, energy consumption, and handover dynamics. Recent work reconceives trajectory planning as a tightly coupled cross layer decision task. Mobility decisions must be co optimized with

Table 9 Summary of methods of optimization techniques in MACN

References	AI model	Simulator	Scalability	Robustness
Jing et al. (2025)	Self-Attention with Meta-Gradient	MATLAB	Medium (Limited mobility and energy simplicity)	High (94% accuracy, 22% latency reduction)
Liu and Yang (2025)	GNN with Meta-Learning	N/A	Medium (Computational overhead and dynamic topology)	High (Improved F1-score)
Cheng et al. (2025)	Hybrid Actor-Critic (H-AC) with QMIX	Python	Medium (Computational complexity or centralized bottleneck)	High (Improved transmitted data)
Liu et al. (2025)	MARL for Trajectory	N/A	Medium (Simplified propagation or no mobility)	High (Improved EE or SE)
Yang et al. (2023)	AI-oriented two-phase authentication (ATMAS)	N/A	Low (High complexity and latency)	High (> 85% accuracy)
Nuo et al. (2025)	Channel-Aware Handover Management (CAHM)	N/A	Medium (Frequent topology changes)	High (Improved delivery ratio)
Li et al. (2022)	Not AI-Specific	N/A	Medium (Uneven distribution or dynamic complexity)	High (Improved coverage ratios)
Yuan et al. (2024)	DRL (DDPG/TD3)	Python	Medium (CSI acquisition and platform instability)	High (Improved anti-jamming)
Zhou et al. (2023)	SCA for NOMA-WPT	MATLAB	Medium (High complexity and perfect CSI assumption)	High (Improved network lifetime)
Zhang et al. (2020)	CNN for traffic balancing	N/A	Medium (Computation overhead and mobility)	High (2× throughput, 50% lower loss)
Bariah et al. (2022)	Not AI-Specific	N/A	Medium (Satellite RIS and cross-layer coordination)	High (Improved SE or EE)
Khoshafa et al. (2025)	Not AI-Specific	N/A	Low (Polarization errors and platform instability)	Medium (Improved SOP and ASR)
Gao et al. (2024)	Semantic Intelligence with LLMs	N/A	Medium (PHY, MAC protocols, semantic routing)	High (Improved energy, task efficiency)
Trinh et al. (2025)	Not AI-Specific	N/A	Medium (Platform instability)	High (Improved SKR, fidelity)
Zeng et al. (2023)	ACO with EAFLM	N/A	Medium (Stable network and gradient overhead)	High (48–53% energy reduction)
Ei et al. (2024)	Gurobi with DDPG	N/A	Medium (Complexity)	High (10–51% service improvement)
Li et al. (2024)	Diffusion Model with Lyapunov Optimization	N/A	Medium (Static satellites and computational complexity)	High (Reduced energy and queue lengths)
Shi et al. (2020)	Hierarchical MADRL (PMADDPG)	N/A	Medium (Training instability)	High (Improved throughput)
Jing et al. (2023)	JULRA (Joint UAV location and resource allocation)	N/A	Medium (Fixed height and computational complexity)	High (48–53% energy reduction)

Table 9 (continued)

References	AI model	Simulator	Scalability	Robustness
Tao et al. (2025)	Diffusion Model with DGHD/MAPPO	Python	Medium (Computational overhead)	High (Reduced jitter, load difference)
Chen et al. (2022)	Genetic Algorithm (GA) with K-Means	MATLAB	Medium (Computational complexity, static load)	High (Reduced delay, and load imbalance)
Chen et al. (2024)	LLM with D3PG/WOA	Python	Medium (Data privacy and LLM reliability)	High (Improved reward and voltage stability)
Wang et al. (2023)	TD3PG for Joint Optimization	N/A	Medium (Simplified assumptions and scalability)	High (Improved EE and carbon reduction)
Mohamed et al. (2023)	Combinatorial Bandit (CB-FBC) with GA	Monte Carlo Simulations	Medium (Simplified mobility and no multi-hop)	High (Improved rate and energy/fairness)
Xu et al. (2025)	MOEA/D-MFAR	N/A	Medium (Parameter sensitivity and static devices)	High (Improved HV and ASDR)
Jia et al. (2025)	Matching Game for SFC Recovery	Python	Medium (Scalability and simplified failures)	High (Reduced time and resource utilization)
Dang and Shin (2024)	Alternating Optimization for FL	MATLAB	Medium (Perfect LoS and synchronization challenges)	High (50% energy reduction)
Wang et al. (2024)	PPO for Node Selection	N/A	Medium (RL overhead and decision lag)	High (Reduced time and energy costs)
Tu et al. (2024)	MADDPG for Load Balancing	Python	Medium (Limited scope and simplified mobility)	High (Improved throughput and delay)
Nguyen et al. (2023)	TD3 for trajectory precoding	Python	Medium (Limited scalability and simplified mobility)	High (8–15% sum-rate gain)
Kakati et al. (2025)	GAI-Enhanced DRL (Gen-DRL)	Python	Medium (Security risks and computational load)	High (Improved SEE or convergence)
Ding et al. (2021)	Hierarchical DRL for trajectory access	N/A	Medium (orthogonal bands or complexity)	High (Improved throughput and POA)

transmit power, access scheduling, beamforming, and higher layer objectives such as FL aggregation or wireless power transfer. Energy aware MARL methods exemplify this integrated perspective by jointly optimizing UAV trajectories together with velocity, acceleration, and propulsion power to trade off spectral efficiency and propulsion cost; shared critic MARL variants reduce training complexity while embedding realistic kinematics and propulsion models. Hierarchical DRL decompositions that separate long horizon global trajectory planning from short term local trajectory and resource allocation have likewise shown strong practical value in highly mobile settings, increasing cumulative throughput and stabilizing learning by reducing per agent decision complexity. Table 9 lists prominent trajectory optimization contributions, for example MARL, twin delayed DDPG, and hierarchical

MARL, and records their reported gains and platform assumptions; consult the MARL and TD3 entries for representative performance and scalability remarks.

Advanced single agent DRL controllers have also matured. Controllers based on twin delayed DDPG that jointly optimize three dimensional flight paths, precoding matrices, and rate splitting parameters for flying base stations demonstrate that explicit altitude control yields measurable sum rate improvements compared with two dimensional schemes, thereby highlighting the value of genuine three dimensional mobility control for radio performance (Nguyen et al. 2023). MARL designs that confront hybrid action spaces, combining continuous controls for trajectory and power with discrete controls for access selection, employ probabilistic mappings such as probabilistic MADDPG to reconcile mixed decisions; these approaches improve long term fair throughput and system level fairness metrics but increase sampling and coordination complexity (Ding et al. 2021). Beyond communications objectives, trajectory variables are increasingly co optimized with application layer tasks. For example, UAV placement and motion can shorten upload distances for federated learning, reduce user device energy, or enable simultaneous data collection and wireless power transfer for energy constrained Internet of Things devices. These joint problems typically require iterative decomposition or unified optimization across the physical, medium access, and application layers (Dang and Shin 2024; Zhou et al. 2023). Diffusion-enabled digital twin synchronization (Li et al. 2024; Zhang et al. 2025) applies generative models for AIGC services in MACNs, optimizing energy consumption and queue management through Lyapunov-constrained diffusion processes.

Most studies ground algorithms in realistic channel and propulsion models, for example rician or rayleigh fading, aerodynamic power consumption, and UAV motion dynamics, and evaluate solutions through simulation toolchains such as MATLAB or Python (Liu et al. 2025; Shi et al. 2020; Nguyen et al. 2023). Common performance metrics include energy efficiency measured in bits per joule or bits per second per hertz, trajectory efficiency capturing trade offs between hovering and transit, convergence and training stability of learning agents, and fairness indices in multiuser settings (Dang and Shin 2024; Ding et al. 2021; Zhou et al. 2023; Kakati et al. 2025). Effective solution strategies blend model based optimizers, for example successive convex approximation and iterative decomposition, with learning based controllers that adapt to stochastic traffic and mobility. Hybrid approaches that incorporate predictive or generative models, for instance GAN augmented DRL, aim to anticipate temporal channel and threat dynamics and to produce more proactive trajectory policies that balance reliability and energy objectives (Kakati et al. 2025).

Despite these advances, significant gaps remain before trajectory optimization techniques can be reliably deployed on operational aerial platforms. Recurring limitations include the heavy computational cost of iterative solvers and MARL training, simplifying assumptions such as perfect channel state information, fixed altitudes, or single UAV scenarios, incomplete modeling of battery and solar dynamics and complex aerodynamics, and a paucity of hardware level validation or field trials to confirm simulated gains (Liu et al. 2025; Zhou et al. 2023; Shi et al. 2020). To bridge the sim to real divide, future work should target full three dimensional, multi UAV and heterogeneous UAV coordination with satellite or HAPS handover; robust, distributionally aware methods that tolerate imperfect channel state information and adversarial actors; energy aware designs that integrate propulsion, battery, and on board compute limits; and hardware efficient MARL implementations capable of on edge inference and real time control (Liu et al. 2025; Zhou et al. 2023; Shi et al. 2020). Experi-

mental testbeds and cross validation with real channel, propulsion, and interference measurements will be essential to validate theoretical gains and to refine trajectory policies for safe, efficient, and scalable aerial mobility control in future multi tier aerial communication networks (Nguyen et al. 2023; Ding et al. 2021; Dang and Shin 2024; Kakati et al. 2025).

7.2 Coverage and connectivity maximization

Maximizing coverage and connectivity in MACNs requires effectively matching multi-tier resources to heterogeneous user needs while maintaining fairness, low latency, and robustness under severe mobility and topology dynamics. Recent studies adopt holistic approaches that jointly optimize user association, aerial placement or trajectories, power or bandwidth allocation, and slice-aware load balancing to expand service areas and enhance per-user performance. For example, joint formulations of user association, aerial unit trajectory, and power allocation solved through mixed-integer optimization for association and DRL (such as DDPG) for trajectory or power control demonstrate significant improvements in aggregate data service compared with naive baselines (Ei et al. 2024). In emergency or post-disaster scenarios, where terrestrial infrastructure is damaged, hybrid online learning and evolutionary schemes, such as combinatorial bandits for fair drone placement combined with genetic algorithms for power or bandwidth tuning enable rapid UAV deployment with improved fairness and rate performance despite uncertain user distributions (Mohamed et al. 2023). Representative studies on coverage optimization, reconfigurable intelligent surfaces (RIS), and learning-based routing, including CNN, and GA-based approaches, are summarized in Table 9, which facilitates comparison of reported throughput, coverage gains, and simulation platforms.

On the orchestration side, MARL has been applied to implement priority-aware load balancing between terrestrial and non-terrestrial layers. These schemes dynamically offload low-priority slices to UAV or LEO layers, preserving terrestrial capacity for latency or throughput-sensitive services. Such approaches improve slice-level throughput, delay, and coverage tradeoffs, but also reveal scalability and interference-management challenges that require further exploration (Tu et al. 2024). Complementary AI-driven routing studies illustrate how traffic can be redistributed across satellite tiers. For instance, CNN-based routing strategies designed to alleviate satellite congestion have been shown to double throughput and reduce packet loss in case studies, highlighting the value of learned policies for cross-tier traffic steering (Zhang et al. 2020). Handover and connection continuity also remain central to effective coverage. Channel-aware handover management that leverages link history, including parameters such as distance, SNR, link duration, and queue states, reduces interruptions and improves delivery ratios in LEO-dominated scenarios, demonstrating the advantages of data-driven handover policies over traditional instantaneous threshold-based methods (Nuo et al. 2025).

At the physical layer, innovations continue to expand coverage possibilities. The integration of RIS across aerial and ground platforms enables programmable propagation environments that can restore line-of-sight links, extend coverage to shadowed regions, and enhance both energy and spectral efficiency, which is particularly beneficial in dense urban or emergency deployments (Bariah et al. 2022). At the frontier of research, optical RIS concepts aim to extend FSO and even quantum links across space-air-ground segments. These approaches offer enormous capacity gains but introduce new challenges in alignment, tur-

bulence mitigation, and hardware manufacturing, all of which require joint solutions combining AI-enabled control with precision mechanics (Trinh et al. 2025). Another pragmatic axis is the use of civil aircraft as high-capacity moving platforms within space-air-ground integrated networks. By leveraging scheduled aircraft flights, these proposals can reduce the number of dedicated satellites required for coverage in densely populated air corridors, though issues such as uneven aircraft traffic patterns and the management of dynamic coverage footprints remain unresolved (Li et al. 2022).

Across these contributions, evaluations are predominantly simulation-driven, typically implemented with MATLAB, Python, or monte carlo-based frameworks (Nuo et al. 2025; Zhang et al. 2020). Reported performance metrics include system throughput, delivery or interruption ratios, per-slice latency, coverage ratios, fairness indices, energy consumption, and bandwidth utilization (Bariah et al. 2022; Trinh et al. 2025). Nevertheless, several limitations persist. Many approaches assume centralized control, simplify interference and mobility models, or incur high computational overhead that limits real-time feasibility. Furthermore, real-world validation remains scarce. Advancing toward operational coverage guarantees requires future research to focus on decentralized and scalable learning algorithms, cross-layer designs that explicitly account for interference and imperfect channel state information, hybrid RF or FSO and RIS-enabled multi-modal links (Ei et al. 2024; Mohamed et al. 2023), slice-aware and multi-operator coordination, and experimental validation through field trials or testbeds. Pursuing these directions holds significant potential to make coverage maximization in real-world MACN deployments (Tu et al. 2024; Bariah et al. 2022).

7.3 Joint communication-computation optimization

UAVs are increasingly deployed as mobile EI platforms, enabling sensing, local model training, and real-time inference. These capabilities position UAVs as critical enablers of distributed learning at the network edge (Liu et al. 2019; Yang et al. 2022; Hou et al. 2023; Dong et al. 2021). Their inherent advantages, including three-dimensional mobility, wide-area coverage, and on-board sensing, are constrained by stringent resource limitations. These include restricted computational capacity, limited energy budgets, intermittent participation, and highly distributed non-independent and identically distributed (non-i.i.d.) datasets, which collectively challenge conventional centralized training approaches (Pham et al. 2022). FL aligns naturally with this environment by facilitating collaborative model training across clients without requiring the exchange of raw data (Hosseinalipour et al. 2021). Its air-ground integrated variant (AGIFL) enables UAVs to upload local updates for global aggregation at base stations (Lim et al. 2020; Cui et al. 2023; Qu et al. 2021). Table 9 provides examples of metaheuristic, multi-objective, and model predictive control (MPC)-style approaches, including genetic algorithms (GA), ACO, multi-objective evolutionary algorithms (MOEA), and diffusion hybrids, along with the associated performance and complexity trade-offs observed in simulation or prototype evaluations. Joint routing and energy replenishment strategies have been explored for logistics and delivery-oriented drone networks, where routing decisions are tightly coupled with charging scheduling and path optimization to extend mission endurance (Arafat and Moh 2022).

For practical UAV-based FL deployment, joint optimization of communication and computation resources is essential. Much of the existing literature assumes static, pre-collected

datasets, which fail to reflect the dynamic conditions of real UAV operations where data arrivals, client participation, and channel states evolve continuously. Consequently, online FL is required to adapt to these changes and sustain model relevance (Jing et al. 2023; Wang et al. 2022). Online learning, however, introduces additional overhead. The continuous incorporation of new samples increases local computation requirements, and some sample selection strategies necessitate pre-training to assess sample utility, further exacerbating on-device burdens (Wu et al. 2024). At the same time, unreliable air-ground links characterized by path loss and small-scale fading increase packet error rates during uplink transmissions, leading to parameter corruption and reduced global model accuracy. These interdependent factors, including computation load, imperfect communication, energy limitations, and variable client participation which necessitate joint communication-computation optimization. Such optimization involves intelligent scheduling and selection of data samples, efficient allocation of radio and computational resources, and error-resilient aggregation methods to sustain learning performance under UAV constraints in AGIFL systems.

EI is pivotal for enabling sixth-generation service requirements through the collection, processing, and analysis of vast amounts of edge-generated data (Liu et al. 2020; Shi et al. 2020; Zhou et al. 2019). FL complements this paradigm by supporting collaborative training without raw data sharing, thereby enhancing privacy compliance (such as adherence to GDPR) while reducing communication traffic and energy costs through distributed on-device training and parameter aggregation (Letaief et al. 2021). Terrestrial FL, however, is limited in remote or emergency contexts where infrastructure is sparse or damaged. In such scenarios, UAVs equipped with edge servers can serve as mobile aggregators and flexible parameter servers, enabling AGIFL systems that benefit from rapid reconfiguration and reliable line-of-sight links (Qu et al. 2021; Liu et al. 2020; Jing et al. 2021).

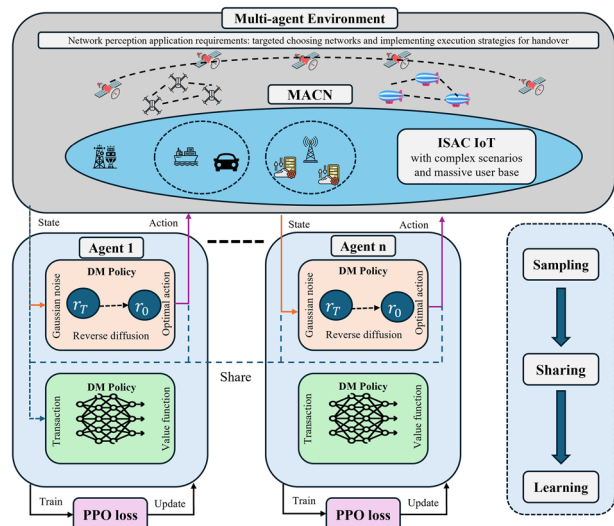
Joint communication-computation optimization addresses the interdependence between wireless resource management and on-device processing in MACN. UAVs and other aerial platforms not only act as data relays but also function as edge servers or FL clients. This dual role requires co-design of communication reliability, client scheduling, and resource allocation alongside local training schedules, model compression, and compute or energy budgets. Such designs aim to optimize both learning and application performance under stringent latency and battery constraints. Recent studies address two critical needs, selective and online processing of streaming data on resource-limited UAVs to avoid unnecessary computation, and robust client scheduling and aggregation mechanisms that accommodate unreliable links and heterogeneous devices. For example, AGIOFL-PE integrates online sample selection with communication-aware client scheduling to maximize model accuracy under packet errors, achieving 94% accuracy at 0% packet error rate (PER) and maintaining 78% accuracy at 40% PER, while outperforming FedAvg in terms of convergence and latency (Jing et al. 2025). Similarly, leader-follower and compression-aware frameworks, such as EAFLM, reduce FL round latency by jointly optimizing transmit power, CPU frequency, and compressed update transmission, resulting in significant communication time savings for latency-sensitive tasks (Zeng et al. 2023). Prototype AGIFL systems that jointly optimize UAV placement and resource allocation have demonstrated substantial energy savings, reducing ground-device energy consumption by approximately 48% to 54% in controlled trials while meeting accuracy requirements (Jing et al. 2023).

From an algorithmic standpoint, existing literature combines model-based optimization and data-driven learning approaches. Centralized and semi-centralized solvers are widely

used to address mixed-integer or nonconvex problems in scheduling and placement, often employing tools such as SCA, or iterative decomposition. In parallel, DRL, MARL, and lightweight RL variants (such as PPO, TD3, and A2C methods) enable online policy adaptation under stochastic traffic and mobility (Ei et al. 2024; Cheng et al. 2025). Asynchronous and decentralized FL approaches, such as DEFEND, mitigate heterogeneity and straggler effects by employing peer-to-peer and meta-learning strategies. These approaches alleviate the need for strict synchronization and centralized timing, while preserving privacy and maintaining robust detection capabilities (Liu and Yang 2025). Generative and predictive AI elements have also been incorporated into control loops. For instance, diffusion or GAN-augmented controllers combined with meta-gradients enable advanced sample selection, PER-aware aggregation, and proactive scheduling for handovers or upload opportunities (Tao et al. 2025). Figure 9 depicts the DMAPPO architecture used for coordinated multi-agent trajectory and power control, where decentralized actors exchange limited summary statistics and a hierarchical or centralized critic stabilizes learning. The figure clarifies the communication pattern and the role of summary statistics in enabling scalable coordination. Multi-objective controllers have further been designed to simultaneously address latency, energy, and carbon emission goals when making decisions about offloading, UAV trajectories, and power allocation policies (Wang et al. 2023).

Evaluations typically consider both learning and communication performance metrics. These include global model accuracy, convergence speed, per-round latency, communication overhead, energy consumption, robustness to PER and stragglers, and fairness across clients. Joint communication-computation designs consistently outperform decoupled baselines. For instance, AGIOFL-PE demonstrates minimal accuracy degradation under high packet error rates (Jing et al. 2025); EAFLM achieves significant latency reductions while maintaining high accuracy (Zeng et al. 2023); and UAV-optimized AGIFL deployments substantially reduce ground-device energy consumption (Jing et al. 2023). Schemes that explicitly optimize for sustainability, such as those accounting for latency, energy, and carbon emissions, highlight the importance of integrating energy harvesting and wireless power transfer models to enable extended missions (Wang et al. 2023).

Fig. 9 DMAPPO architecture for coordinated multi-agent trajectory and resource optimization (Tao et al. 2025)



Despite these promising results, several open challenges limit real-world deployment. Many existing works rely on simplified channel or energy models, assume homogeneous clients, or depend on centralized orchestration that does not scale efficiently. Sample quality estimation methods often introduce additional pre-training burdens, and PER handling typically relies on simplistic exclusion policies rather than advanced error-resilient aggregation strategies (Jing et al. 2025; Liu and Yang 2025). Future research should focus on decentralized and asynchronous FL to manage heterogeneity and intermittent connectivity, lightweight sample-selection and model-compression techniques such as split learning and neural network quantization, PER-aware aggregation and coding schemes, and comprehensive cross-layer energy models that capture propulsion and battery dynamics. Furthermore, field testbeds are essential to bridge the gap between simulation and deployment. Integrating these advances with NFV, SFC resilience, priority-aware slice balancing, and predictive handover or placement controllers will be critical for realizing reliable and efficient joint communication-computation in MACN systems (Jia et al. 2025; Tu et al. 2024; Wang et al. 2024).

7.4 Problem formulation and objectives

AI-driven optimization in MACNs addresses several critical challenges, including coverage, deployment, trajectory planning, and interference mitigation. These objectives are particularly relevant to SAGINs, which combine satellites, UAVs, HAPs, and terrestrial infrastructure.

- **Coverage:** Ensuring seamless connectivity across diverse environments, including urban, rural, and remote regions, remains a central objective. The civil aircraft-assisted SAGIN (CAA-SAGIN) leverages civil aircraft as aerial base stations to extend coverage in areas such as Beijing and Tibet, adapting dynamically to variations in population density (Li et al. 2022). Similarly, UAVs and LEO satellites are deployed in post-disaster environments to provide equitable coverage based on user density (Mohamed et al. 2023).
- **Deployment:** Efficient placement of network nodes, such as UAVs and satellites, is essential to balance resource utilization with coverage. A hierarchical domain-based strategy that integrates k-means clustering with GA has been applied to optimize controller placement in SDN-enabled MACNs, addressing the challenges of high node density and dynamic satellite mobility (Chen et al. 2022). Likewise, the combinatorial bandit algorithm in Mohamed et al. (2023) supports fair UAV deployment across disaster clusters to maximize service equity.
- **Trajectory planning:** Optimizing UAV trajectories is crucial for achieving both energy efficiency and spectral efficiency in highly dynamic environments. MARL frameworks, such as those described in Liu et al. (2025) and Nguyen et al. (2023), optimize UAV flight paths in cell-free massive MIMO and rate-splitting multiple access (RSMA) systems, respectively, to maximize throughput in remote areas. The AG-PMADDPG framework in Ding et al. (2021) further integrates UAV trajectory optimization with user access control to enhance fairness in throughput over a two-square-kilometer deployment region. Figure 10 presents the MADDPG framework applied to joint trajectory, power, and association control, highlighting mixed action spaces that include con-

tinuous mobility commands and discrete association choices.

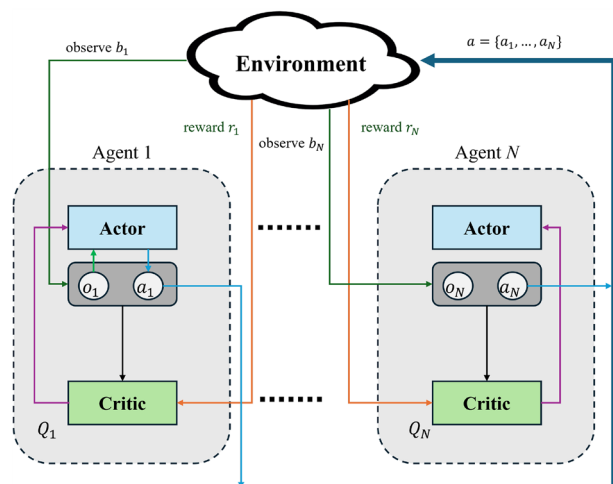
- Interference mitigation:** Interference resulting from heterogeneous devices and dynamic network topologies poses significant obstacles to reliable communication. RIS have been employed to mitigate interference by dynamically manipulating electromagnetic wave propagation, as demonstrated in Bariah et al. (2022); Khoshafa et al. (2025). In addition, NOMA schemes, such as those presented in Zhou et al. (2023), enhance spectral efficiency by enabling multiple devices to share frequency resources, thereby reducing interference during large-scale IoT data collection.

Overall, these optimization objectives are frequently formulated as multi-objective problems that balance competing requirements such as latency, energy consumption, throughput, and robustness (Wang et al. 2023; Tu et al. 2024). This highlights the need for integrated design frameworks that jointly address cross-layer trade-offs to ensure scalable and efficient MACN operation.

7.5 Optimization methods

AI-driven optimization in MACNs leverages a diverse set of approaches, including meta-heuristics, multi-objective solvers, and MPC-style predictors, to address the combinatorial complexity and time-varying nature of multi-tier networks. Metaheuristic methods, such as ACO and GAs, are widely adopted because they consistently deliver high-quality near-optimal solutions for nonconvex and discrete problems in controller placement, resource assignment, and scheduling. For instance, ACO has been integrated into an efficient asynchronous FL mechanism (EAFLM) to jointly optimize communication compression and energy allocation in UAV swarms (Zeng et al. 2023), while GAs have been applied for hierarchical controller placement and LEO resource optimization (Chen et al. 2022; Mohamed et al. 2023). The principal strength of metaheuristics lies in their robustness and generality, although they can be computationally intensive and exhibit slow convergence in very large-scale deployments.

Fig. 10 MADDPG framework: centralized training with decentralized execution for joint mobility and resource control (Ding et al. 2021)



Multi-objective optimization frameworks explicitly capture and manage trade-offs among conflicting goals, including throughput, latency, energy consumption, fairness, and carbon footprint, making them well suited for MACN scenarios with heterogeneous QoS requirements. Algorithms such as the diffusion model DGHD address joint objectives that include handover jitter, load balancing, and robustness in IoT-enabled SAGINs (Tao et al. 2025), while other formulations target intra-category fairness in addition to capacity and bandwidth allocation (Xu et al. 2025). These frameworks reveal Pareto frontiers that assist operators in selecting operating points that align with mission priorities. However, they require careful preference elicitation or scalarization to produce single actionable policies.

Although classical MPC is not always explicitly referenced in the surveyed literature, MPC principles. Namely, predicting near-term network states and optimizing control actions over a receding horizon, underpin several predictive AI methods. GNNs and related forecasting models are increasingly employed to anticipate anomalies or state evolution, thereby enabling proactive orchestration that parallels MPC behavior (Liu and Yang 2025). In practice, these predictive components are often integrated with RL and DL. RL provides sequential decision making under uncertainty, while DL, including learned surrogates, offers efficient state estimation and feature extraction. Such hybrid approaches combine the online adaptability of RL with the predictive foresight of MPC and the search efficiency of metaheuristics.

The associated trade-offs are evident. Metaheuristics deliver breadth and reliability but often incur significant computational cost. Multi-objective solvers enable principled management of competing objectives but complicate policy selection. MPC-style predictors enhance responsiveness but introduce prediction overhead and the risk of model mismatch. A promising direction is therefore the design of hybrid and hardware-aware frameworks, including metaheuristic guided RL, learned MPC surrogates, and model compression techniques, combined with rigorous multi-metric benchmarking under realistic mobility, energy, and channel models to ensure practical deployability on resource-constrained aerial platforms.

7.6 AI-based joint optimization strategies

Joint optimization strategies based on AI integrate multiple objectives and network layers to achieve holistic performance improvements in MACN environments. DRL is widely employed for coupled problems such as three-dimensional trajectory planning, resource allocation, and access control. For instance, the TD3-RFBS framework applies Twin-Delayed DDPG (TD3) to jointly optimize UAV trajectories, precoding matrices, and rate allocation in RSMA-enhanced downlink links (Nguyen et al. 2023), while other DRL formulations adjust RIS parameters to strengthen air-to-ground IoT links against jamming and eavesdropping (Yuan et al. 2024). The end-to-end and model-free nature of DRL makes it particularly effective for complex, continuous control tasks. However, it also introduces challenges related to sample efficiency and the computational cost of on-board inference.

MARL extends joint optimization into cooperative and distributed scenarios where UAVs, satellites, and ground stations must coordinate their actions. Architectures such as the multi-agent cooperation transmission strategy (MCTS) employ hybrid A2C schemes with centralized critics in the style of QMIX to optimize transmission and resource scheduling across agents (Cheng et al. 2025). Similarly, AG-PMADDPG demonstrates how coor-

minated trajectory planning can balance throughput and fairness across users (Ding et al. 2021). While MARL effectively captures inter-agent coupling and enables decentralized execution, it continues to face challenges related to credit assignment, scalability, and communication overhead.

Generative AI techniques are increasingly incorporated to enhance robustness and sample efficiency in decision making policies. Diffusion-based generative models, for example, have been used to augment MAPPO by generating diverse and realistic network-state trajectories for pretraining. This improves convergence and reduces jitter in vertical handover tasks, as demonstrated by the DGHD framework (Tao et al. 2025). Similarly, GAN-augmented DRL can anticipate channel states or adversarial conditions, thereby optimizing secrecy and energy efficiency by enriching training distributions for policies operating under non-stationary channel dynamics (Kakati et al. 2025). These hybrid methods reduce dependence on limited real-world traces but add model complexity and increase data-generation costs.

LLMs are emerging as semantic reasoning and task-planning engines within networking stacks. Architectures such as MAIN employ LLMs for high-level task planning, semantic-aware routing, and multimodal data fusion, which are particularly useful in domains such as intelligent transportation, disaster response, and semantic routing (Gao et al. 2024). Other works integrate LLMs with conventional control algorithms, such as D3PG combined with Whale Optimization, to interpret human-driven preferences, including the intentions of EV drivers, and translate them into optimization objectives for power dispatch or service orchestration (Chen et al. 2024). LLMs provide strong generalization for symbolic and semantic tasks, but incorporating them into latency-sensitive control loops requires careful modularization, formal verification, and lightweight distillation.

In practice, the most effective strategies hybridize these techniques. DRL provides continuous control, MARL facilitates coordination, generative models improve training efficiency, and LLMs enable semantic orchestration, collectively supporting cross-layer optimization of routing, spectrum, mobility, and service objectives (Zhang et al. 2020). The key trade-offs involve balancing computational and data requirements, ensuring interpretability and safety of learned policies, and managing the complexity of evaluating multi-objective performance under realistic mobility and channel conditions. Future research should focus on scalable and hardware-aware hybrid methods, sample-efficient pretraining techniques such as generative augmentation or model-based RL, and rigorous sim-to-real validation to ensure the practical deployment of AI-driven optimization in resource-constrained MACN environments.

7.7 Performance evaluation metrics

Evaluating the performance of AI-driven optimization techniques in MACNs requires a comprehensive set of metrics that capture the diverse objectives and constraints of multi-tier networks. The key metrics include the following.

- **Latency:** Reducing latency is essential for time-sensitive applications such as real-time monitoring and autonomous vehicles. For example, Zeng et al. (2023) examines latency reduction in UAV swarms using EAFLM, while Chen et al. (2022) measures network delay in SDN-enabled MACNs. Latency metrics often consider end-to-end delay and

handover jitter (Tao et al. 2025).

- **Energy efficiency:** Energy consumption remains a central concern, particularly for battery-limited devices such as UAVs and IoT sensors. In Dang and Shin (2024), UAV trajectories and UE transmit power are optimized to improve energy efficiency in FL, while Wang et al. (2023) incorporates renewable energy sharing and wireless power transfer to mitigate carbon emissions.
- **Throughput:** Ensuring high throughput is vital for maintaining data rates required by end users. The AG-PMADDPG framework in Ding et al. (2021) evaluates long-term fair throughput, whereas Tu et al. (2024) assesses throughput across network slices to support high-throughput services such as video streaming.
- **Coverage and fairness:** Coverage metrics evaluate the capability of networks to serve diverse regions and heterogeneous user groups. For instance, Li et al. (2022) investigates coverage across the Chinese mainland, while Mohamed et al. (2023) employs fairness measures to ensure equitable drone deployment in disaster-affected areas. Intra-category fairness is further emphasized in Xu et al. (2025) for IoT devices.
- **Security:** Security related metrics, including secrecy energy efficiency, are critical for safeguarding communications. In Khoshafa et al. (2025), RIS is evaluated for its capability to degrade eavesdropper channels, and Yang et al. (2023) examines the effectiveness of AI-based continuous authentication in MACNs.
- **Resource utilization:** The efficient use of bandwidth, power, and computational resources is evaluated in Ei et al. (2024) for data service maximization and in Shi et al. (2020) for drone-cell resource allocation. The metrics include spectrum efficiency and resource allocation fairness. Efficient use of bandwidth, power, and computational resources is another key performance dimension. In Ei et al. (2024), data service maximization is analyzed, while Shi et al. (2020) evaluates drone-cell resource allocation. Metrics in this category include spectrum efficiency and fairness in resource distribution.

These performance metrics, including latency, energy efficiency, throughput, and security, are commonly evaluated through a combination of computer-based simulations and practical field experiments to validate theoretical models under realistic conditions. For instance, in the study by Jing et al. (2023), a UAV-based FL system was empirically tested on a football pitch, providing insight into real-world deployment challenges such as signal interference and mobility constraints in outdoor environments. Similarly, Jia et al. (2025) employed simulations over a two-square-kilometer area to evaluate service recovery mechanisms in MACNs, underscoring the importance of rapid fail-over strategies in maintaining network resilience during disruptions, including satellite outages or aerial node failures.

In the context of AI-driven optimization for aerial networks, there is a growing trend toward hybrid methodologies that integrate complementary techniques to address the multifaceted challenges of dynamic, resource-constrained environments. Examples include the combination of DRL with metaheuristic algorithms, as explored in Mohamed et al. (2023) for LEO satellite systems, where DRL manages adaptive decision making while metaheuristics enhance global search efficiency for optimal resource allocation. Another approach merges FL with energy control strategies, as demonstrated in Dang and Shin (2024), enabling distributed learning across aerial nodes while minimizing power consumption through intelligent scheduling and power-aware model updates. These hybrid strategies

leverage the strengths of individual methods to provide more robust solutions for trajectory planning, spectrum management, and load balancing in heterogeneous aerial ecosystems.

Generative AI is increasingly recognized as a pivotal tool for predictive optimization in highly volatile settings, where traditional reactive methods are insufficient. By generating synthetic data or scenarios, generative AI facilitates proactive adjustments to network parameters, such as anticipating traffic surges or environmental changes in real time. This is exemplified in Wang et al. (2023), which applies generative AI for joint optimization of communication and computation in aerial networks, and in Kakati et al. (2025), which envisions its role in enabling autonomous, self-optimizing systems that adapt to emerging threats and evolving operational demands.

Future research must prioritize scalability in ultra-dense MACNs, where large networks of interconnected nodes, including satellites, UAVs, and ground stations, risk overwhelming algorithms and creating processing bottlenecks. A critical gap remains in real-world validation, as simulations often neglect factors such as weather, regulatory constraints, and hardware imperfections. Addressing this gap requires standardized benchmarks and large-scale testbeds. Synergistic AI integration—using DRL for single-agent learning, MARL for cooperative node coordination, generative AI for predictive optimization, and LLMs for high-level orchestration—can deliver measurable gains in latency, energy efficiency, throughput, and security, as evidenced in the cited studies. Collectively, these advances support the development of resilient, efficient, and secure MACN that are essential for 6 G and beyond. The entries in Table 9 serve as a practical guide for selecting appropriate optimization techniques, pairing algorithmic families with deployment considerations and reported robustness, thereby assisting in the identification of methods suitable for specific MACN scenarios.

Overall, the surveyed optimization literature suggests that the distinction between classical and AI-driven optimization in MACN should be viewed as complementary rather than adversarial. Classical optimization remains highly effective when the problem can be modeled with sufficient accuracy, the dimensionality is manageable, and performance guarantees or interpretability are required. By contrast, AI-driven optimization becomes particularly attractive when trajectory planning, association, communication, and computing decisions interact over time in ways that are difficult to capture through static formulations alone. In these cases, learning-based methods can provide adaptive policies that respond to nonstationary environments and partial observability, although often at the cost of higher training complexity, weaker interpretability, and greater dependence on simulation assumptions. This comparison reinforces a broader conclusion of the survey: the most practical direction for MACN optimization is likely to involve hybrid frameworks in which model-based optimization provides structure and reliability, while learning-based components supply adaptability in those parts of the problem where uncertainty and dynamics are most pronounced.

8 Comparison, open issues, and future research directions

This section synthesizes the comparative strengths, limitations, and trade-offs across key research categories, including routing, computing, handover, resource management, and optimization. It further provides an integrated discussion of open challenges and presents a prioritized research agenda. The section also consolidates information on datasets, simula-

tors, and benchmarks, and concludes with practical methodological recommendations for future work.

8.1 Comparative analysis of AI focusing in routing, computing, handover, resource management, and optimization techniques

Table 10 presents a concise cross-category comparison that summarizes the principal strengths, core limitations, and recurring trade-offs, such as centralized versus distributed and online versus offline approaches. The table is intended to provide a clear reference for understanding how different methodologies perform under varying constraints and to highlight the contexts in which each approach is most suitable.

Many of the limitations summarized in Table 10 arise from similar underlying causes. For example, routing and optimization methods frequently exhibit high computational and energy demands and often rely on idealized channel or traffic assumptions, which constrain their applicability in real-world scenarios (Chen et al. 2025; Hu et al. 2023; Jing et al. 2025). Computing and resource management approaches demonstrate measurable energy and latency improvements in controlled environments (Gu et al. 2021; Wu et al. 2021); however, scalability and heterogeneity, including edge constraints and simplified task models, remain significant barriers to deployment (Zhu et al. 2025; Wu et al. 2025; Jia et al. 2024). Handover solutions can experimentally reduce interruption rates (Niu et al. 2024), yet many rely on overly simplistic mobility traces, which obscure the latency and signaling overheads encountered in realistic UAV or vehicular settings (Lv et al. 2022; Guo et al. 2022).

The trade-offs column captures recurrent design tensions that merit further attention. Centralized frameworks, such as spatio-temporal controllers, typically enable stronger

Table 10 Cross-category summary: strengths, limitations and key trade-offs

Category	Strengths	Limitations	Key trade-offs
Routing	Improved robustness and QoS using AI-based routing. Guo et al. (2024)	High computational/resource demand; many works assume ideal conditions. Chen et al. (2025); Hu et al. (2023)	Centralized: better coordination but potential bottleneck. Distributed: privacy/resilience benefits but possible instability
Computing	Energy/latency gains from coded/distributed and hybrid methods. Gu et al. (2021); Zhang et al. (2024)	Scalability and energy limits on edge platforms; simplified task models. Zhu et al. (2025); Wu et al. (2025)	Centralized: high optimality, single point of failure. Distributed: better privacy, higher communication overhead
Handover	Reduced interruptions with AI and quantum-inspired methods. Niu et al. (2024); Kim et al. (2025)	Oversimplified mobility models; latency and decision complexity concerns. Lv et al. (2022); Guo et al. (2022)	Centralized: consistent decisions, poor scale. Distributed: responsive, may increase signalling
Resource Management	Fairer, more efficient allocation via ML and auction schemes. Wu et al. (2021); Jiang et al. (2023)	Heterogeneity of multi-tier hardware complicates deployment. Jia et al. (2024); Li and Shang (2025)	Centralized: near-optimal but fragile. Distributed/DRL: scalable but convergence-sensitive
Optimization	Hybrid AI yields strong convergence and performance gains. Cheng et al. (2025); Kakati et al. (2025)	High computational cost; many approaches struggle with dynamic topologies. Jing et al. (2025); Trinh et al. (2025)	Centralized solvers: global optima, latency. Distributed/metaheuristic: scalable, often heuristic

global coordination and, in some cases, achieve superior objective values; however, they introduce single points of failure and scalability limitations (Jiang et al. 2023). In contrast, distributed approaches, including FL or local learning and decision agents, enhance privacy, resilience, and scalability but incur additional communication overhead, potential convergence instability, and more complex robustness requirements (Yuan et al. 2022; Zeng et al. 2023). Similarly, online methods excel at responding to dynamic conditions, such as mobility or sudden load fluctuations, while imposing run-time computation and signaling costs. Offline methods, in contrast, reduce run-time overhead but require large, representative datasets and often generalize poorly to rapidly evolving topologies. Collectively, these constraints motivate hybrid architectures that combine hierarchical control, split or federated learning, and model-compression with edge inference to achieve a balanced operational point between performance, cost, and robustness.

8.2 Open issues & future research directions

Based on the comparative analysis, several technical and practical challenges remain in MACN design and deployment; however, not all of them require AI-based solutions. In a number of cases, classical optimization, heuristic, or model-based methods remain effective under structured and well-characterized conditions, whereas AI becomes more useful when mobility, intermittency, cross-tier coupling, or partial observability make static or manually tuned solutions less effective. The discussion below therefore focuses on challenges that remain open specifically from the perspective of method selection, deployment feasibility, and operation under realistic MACN conditions. Below, we organize the principal open issues and future research directions according to the five core functional areas covered in this survey.

- **Routing:** GNN-DRL and GAN-DRL methods achieve strong adaptability in dynamic topologies but impose substantial computational and memory demands that limit deployment on resource-constrained aerial platforms without offloading or acceleration (Chen et al. 2025; Hu et al. 2023). Lightweight approaches such as Extended ELM offer edge-suitable inference but remain sensitive to noisy or scarce data (Yuan et al. 2022). Most routing protocols assume ideal conditions and lack supplementary security mechanisms (Hu et al. 2023; Li et al. 2022). Cross-layer routing that integrates access-layer dynamics into forwarding logic remains underexplored (Srinath et al. 2022; Pan et al. 2022). Future work should target model compression and distillation for on-device routing inference, hybrid frameworks combining digital twins with online RL for safe adaptation, integration of blockchain-based trust and network slicing into routing decisions. Validation under realistic mobility, interference, and environmental models using hardware testbeds. At the same time, in comparatively stable or resource-constrained routing scenarios, lightweight topology-based and heuristic methods may remain more practical than data-intensive learning-based solutions.
- **Computing and Task Offloading:** RL-based offloading methods report 20–53% improvements in cost and energy but incur high training overhead that constrains edge deployment (Zhu et al. 2025; Li et al. 2025). Many schemes assume predictable mobility and simplified task models (Alam et al. 2024; Xie et al. 2025), and integrated approaches that jointly address load distribution, mobility management, and energy ef-

efficiency within a unified framework remain scarce (Li and Chen 2023). Scalability for large UAV swarms and fairness in heterogeneous offloading are often overlooked (Xia et al. 2022), as are security considerations in distributed task scheduling (Lan et al. 2024; Tang et al. 2022a). Future directions include MARL frameworks that jointly optimize latency, energy, and fairness across tiers, closer integration of predictive analytics with real-time offloading decisions (Alam et al. 2024), hierarchical or federated learning architectures for swarm scalability (Peng et al. 2025), and testbed deployment with standardized benchmarks that capture realistic device and mobility constraints. For smaller or more predictable systems, optimization-based scheduling and heuristic offloading strategies may already provide adequate performance with lower implementation complexity.

- Handover Management:** DRL approaches such as A2C and MAPPO effectively model handover as multi-agent decision processes but require substantial training latency and compute that limit on-board deployment (Tong et al. 2025; Tao et al. 2025). Many solutions rely on oversimplified mobility traces, and vertical handover failure rates can reach 40% due to mismatched thresholds or inadequate trajectory prediction (Zhang et al. 2024; Mohamed et al. 2024). Authentication mechanisms can introduce up to 300% latency increase during polar handovers (Yao et al. 2021), and hardware validation remains rare, with roughly half of surveyed papers omitting simulation platform details (Kim et al. 2025). Future work should combine trajectory predictors with low-latency RL controllers for anticipatory handovers, develop hybrid SDN controllers that integrate predictive channel reservation (Guo et al. 2022; Lv et al. 2022), extend HAP-assisted scheduling to joint RF and optical multiplexing (Niu et al. 2024), and adopt shared benchmark scenarios such as ADS-B snapshots and TLE traces alongside mandatory computational cost reporting. Similarly, conventional threshold-based, hysteresis-based, and predictive handover mechanisms remain competitive when mobility patterns are sufficiently regular and the decision space is limited.
- Resource Management:** All surveyed methods exhibit medium scalability, with coordination complexity, static topology assumptions, and heterogeneous multi-tier hardware posing persistent deployment barriers (Jia et al. 2024; Li and Shang 2025). Strategies that jointly consider HAPS positioning, coverage control, and AI-driven allocation across diverse scenarios remain largely unexplored (Mashiko et al. 2025), and security-aware scheduling that accounts for path vulnerabilities and encryption strength is nascent (Zhi et al. 2024; Cai et al. 2024). Future directions include explainable allocation policies with attention-aware heads and uncertainty estimation (Wu et al. 2024), transfer learning across constellations to reduce retraining cost (Ivanov et al. 2022), joint optimization of HAPS positioning with spectrum and relay selection (Mashiko et al. 2025), and hierarchical SDN architectures combining local fast-loop controllers with global orchestrators informed by FL or offline RL. In many structured allocation settings, classical decomposition, matching, or queue-aware control methods continue to offer strong performance with clearer interpretability and lower runtime overhead.
- Optimization Techniques:** Trajectory optimization faces heavy computational cost from iterative solvers and MARL training, compounded by assumptions of perfect channel state information and single-UAV scenarios (Liu et al. 2025; Nguyen et al. 2023). Joint communication-computation optimization for UAV-based FL often relies on static datasets that fail to capture dynamic operational conditions (Zeng et al. 2023; Jing et al.

Table 11 Common tools, datasets and benchmarks used in MACN research

Tool type	Common examples	Frequency	Recommendation
Simulators	Python (ML scripts), MATLAB, NS-3, OMNeT++, Mininet, STK, ROS/Gazebo	High (Python: ~40–50%)	Combine discrete-event and emulation stacks (e.g., NS-3 + Mininet) and publish configurations to enable reproducibility
Datasets	ADS-B, Didi mobility, MNIST/EuroSAT for FL, synthetic channel datasets	Medium	Encourage use of domain-relevant traces (ADS-B, vehicular/IOT traces) and standardized synthetic scenario generators
Benchmarks	FedAvg/DQN/DPG/MAPPO baselines; metrics: throughput/latency/EE/SE	High	Propose a shared benchmark suite (fixed mobility profiles, channel models, and baseline implementations) to measure scalability and robustness

2025), and LLM integration into latency-sensitive control loops introduces unresolved challenges in verification and distillation (Gao et al. 2024; Chen et al. 2024). Future work should pursue full 3D multi-UAV coordination with satellite handover under imperfect CSI, energy-aware designs integrating propulsion and battery dynamics with hardware-efficient MARL for on-edge inference, decentralized and asynchronous FL with lightweight model compression (Liu and Yang 2025), and synergistic AI integration combining DRL, MARL, generative AI, and LLMs, validated through field testbeds to bridge the simulation-to-reality gap. More generally, classical optimization remains an effective baseline whenever the problem structure is sufficiently known and real-time adaptation demands do not justify the added complexity of learning-based control.

Across all five areas, recurring cross-cutting challenges include the need for lightweight distributed intelligence, interpretable and certifiable AI policies, standardized cross-tier interoperability, and security-by-design for distributed learning. Progress will require community-driven benchmarks, real-world trace collection, and interdisciplinary efforts integrating wireless systems, ML robustness, and secure distributed protocols.

8.3 Datasets, simulators, and benchmarking: state and recommendations

Simulations remain the predominant methodology for evaluating AI-driven MACNs due to the inherent complexity and scale of MACNs, whereas real-world testbeds are comparatively rare. Table 11 provides a summary of commonly used tools and their frequency of application. The following discussion offers recommendations to enhance reproducibility and comparability across studies, emphasizing the adoption of standardized datasets, consistent traffic and mobility models, and shared evaluation protocols to facilitate meaningful cross-study benchmarking.

To enhance reproducibility and comparability in MACN research, it is recommended that authors publish complete scenario scripts, random seeds, and full configuration files for simulators to enable exact replication of results. Wherever feasible, simulation outcomes should be validated on small-scale hardware prototypes, such as Raspberry Pi, SDR platforms, or UAV testbeds, to bridge the sim-to-real gap (He et al. 2022). Additionally, establishing a standardized minimal benchmark set, including representative mobility traces, channel and blockage scenarios, and baseline algorithms would allow consistent and meaningful assessment of performance improvements across different studies.

8.4 Prioritized research agenda and actionable directions

Addressing open challenges in AI-driven MACNs requires a coordinated research agenda that integrates algorithmic innovation, system engineering, and rigorous evaluation. A primary priority is the development of lightweight, distributed intelligence. Practical deployments demand neural and decision models that conform to the constrained compute, memory, and energy budgets of UAVs, edge gateways, and satellite payloads. Research should therefore combine model-compression tool chains, including structured pruning, post-training and quantization-aware techniques, and knowledge distillation, with runtime optimizations such as operator fusion, condensed architectures, and efficient inference execution. These methods should be complemented by architectural strategies, including split learning and FL schemes that transmit only essential gradients or compact representations to central servers, or by hierarchical orchestration where intensive training is performed off-network while compact policies execute at the edge. Experimental evaluations must quantify not only accuracy or reward but also inference latency, model size, energy per inference, and end-to-end signaling overhead to expose practical trade-offs (Zeng et al. 2023).

Equally important is explainable and certifiable decision making for safety-critical functions, including handover, resource orchestration, and emergency response. Research should move beyond post-hoc saliency analysis to integrate interpretable modules and uncertainty estimates directly into policies. Examples include attention-aware policy heads, SHAP or LIME style attribution on state features, epistemic and aleatoric uncertainty in value estimates, and policy certificates that provide verifiable bounds on decision consequences. Complementary investigations should focus on human-in-the-loop interfaces and lightweight verification mechanisms that allow operators to inspect, constrain, or override automated control under conditions of high ambiguity or risk. Evaluations should include user studies, where feasible, and stress tests that assess how interpretability and uncertainty signals mitigate catastrophic actions (Wu et al. 2024; Mohamed et al. 2023).

Practical operation also hinges on interoperability-focused control planes and protocol standardization. MACN face challenges when each domain, including LEO satellites, UAVs, maritime platforms, and terrestrial infrastructure, exposes distinct state abstractions and handover semantics. Research should therefore define minimal cross-tier primitives for state transfer, capability advertisement, and graceful handover, alongside O-RAN style control abstractions that decouple policy logic from vendor hardware. This work is both conceptual, involving API and information model definition, and experimental, implementing adapters and measuring state transfer latency, synchronization error, and recovery under link disruptions. Standards-oriented prototypes that publish interface definitions and sam-

ple reference implementations will facilitate broader adoption (Jia et al. 2024; Zhang et al. 2024).

Security- and privacy-aware communication is an important consideration in MACNs, especially for distributed learning and cross-tier data exchange. Relevant mechanisms include robust aggregation, Byzantine-resilient federated updates, anomaly detection under sparse observations, and privacy-aware designs that account for utility trade-offs under differential privacy or secure multi-party computation. Lightweight ledger-based support for provenance and auditability may also be useful, provided that its computational and communication overheads are compatible with constrained UAV and satellite platforms. Robustness should be evaluated under representative channel conditions, including poisoning, model inversion, and spoofed telemetry scenarios, to assess practical resilience (Zhi et al. 2024; Tang et al. 2022a).

Mobility represents one of the most challenging dimensions, making predictive, mobility-aware control a high-impact area. Combining sequence and trajectory predictors, such as RNNs, Transformers, and Kalman or particle filters, with low-latency RL controllers enables anticipatory handovers, pre-positioned resources, and smooth multi-agent coordination. Emphasis should be placed on lightweight predictors capable of on-device execution, feature engineering that captures topology and channel dynamics, and integration of prediction uncertainty into decision policies to support risk-aware actions. Benchmarking should incorporate realistic mobility traces, including urban UAV corridors, maritime routes, and vehicular flows, while evaluating metrics such as prediction horizon benefits, false-positive reservation costs, and handover reductions under varying traffic conditions (Tao et al. 2025; Nguyen et al. 2023).

Finally, exploration of RIS and emerging primitives, including quantum computing and ledger technologies, should be pursued pragmatically. Research on joint beamforming and orchestration should co-optimize RIS phase profiles, satellite link scheduling, and terrestrial resource allocation under latency and energy constraints. Semantic communications may enable compact control channels for constrained links (Bariah et al. 2022; Meng et al. 2024; Gao et al. 2024). Quantum-enhanced optimization, such as QMARL prototypes, and ledger-assisted trust schemes present promising directions, but initial studies should employ hybrid simulations and small-scale prototypes to assess resource costs, error-correction and synchronization requirements, and transaction overhead in energy-limited nodes. Each experimental campaign should include a thorough cost-benefit analysis, quantifying performance gains relative to hardware, energy, and complexity overheads, to guide the community on the practical value of these emerging primitives (Kim et al. 2025; Tang et al. 2022a; Conti et al. 2024).

8.5 Evaluation metrics and recommended baselines

To ensure fair and comprehensive evaluation of future proposals, we recommend reporting standardized QoS metrics, including latency, throughput, packet loss, and handover failure rate, alongside resource metrics such as energy per bit, computational overhead in FLOPs, memory footprint, and signaling load. Learning performance should be quantified in terms of convergence time, sample efficiency, and robustness under non-i.i.d. data distributions and adversarial nodes. Reproducibility artifacts, including random seeds, dataset links or generator code, simulator versions, and baseline implementations, should also be

provided. Baselines should encompass simple heuristic methods, such as greedy or random approaches, classical optimization techniques, including MILP or GA where applicable, and widely used RL and federated learning baselines, such as DQN, DDPG, TD3, FedAvg, or MAPPO. Bridging the gap from promising algorithms to deployed, trustworthy MACNs requires a coordinated research agenda that simultaneously addresses lightweight distributed intelligence, interpretable decision-making, standardized cross-tier interoperability, and security-by-design. Progress will be accelerated by community-driven benchmarks, the collection of real-world traces, testbed evaluations, and interdisciplinary efforts that integrate expertise in wireless systems, ML robustness, and secure distributed protocols. The directions outlined here prioritize deployability and resilience while maintaining the performance gains demonstrated by recent AI-driven approaches.

8.6 Practical deployment, testing, and evaluation

Bridging the gap from simulation to operational MACN requires a compact, reproducible evaluation pipeline that explicitly accounts for real-world impairments, staged validation, and deployment safety; practical experiments should therefore combine representative simulation (using the tools and traces summarized in Table 11) with hardware-in-the-loop emulation and progressively larger field trials, and should report both networking metrics and system-level costs as in Table 10. A critical yet underexplored dimension of deployment readiness concerns the placement of training and inference workloads across space, air, and ground tiers; heavyweight model training typically must reside at ground stations or cloud infrastructure due to computational and thermal constraints, while inference on aerial platforms demands compressed models, quantized weights, and hardware accelerators that fit within the power envelopes of UAVs and small satellites, which range from tens to hundreds of watts depending on platform class (Xu et al. 2023; Zeng et al. 2023).

Model update frequency presents additional challenges under intermittent connectivity, as LEO satellites may experience contact windows of only minutes per orbit and UAV swarms operating beyond line-of-sight rely on sporadic relay opportunities, necessitating asynchronous update protocols, staleness-tolerant aggregation, and local adaptation mechanisms that can function effectively between synchronization events (Jing et al. 2025; Han et al. 2024; Liu and Yang 2025). Communication overhead in FL and MARL further constrains deployment, because gradient exchange, policy synchronization, and coordination signaling compete with mission data for limited uplink and crosslink capacity; techniques such as gradient compression, sparsification, and hierarchical aggregation reduce this burden but introduce accuracy and convergence trade-offs that must be quantified under realistic link budgets (Tang et al. 2022a, b; Zeng et al. 2023). Energy and compute budgets for on-board AI inference impose hard constraints that are frequently overlooked in simulation studies, yet operational UAVs must balance inference workloads against propulsion, sensing, and communication demands, while satellite payloads face strict power and thermal dissipation limits that preclude continuous operation of large neural networks without duty cycling or adaptive model switching (Li et al. 2025; Gong et al. 2022; Li et al. 2024).

Although hardware validation remains scarce, several surveyed works provide preliminary real-world evidence. For example, a reliable transport system was validated using the Qilu-I satellite prototype demonstrating substantial delay reductions compared to simulation estimates (He et al. 2022), a UAV-based federated learning framework was empirically

tested in outdoor field trials on a football pitch revealing practical challenges such as signal interference and mobility constraints (Jing et al. 2023), and AI-driven UAV communication systems were evaluated using open-source 5 G platforms including OAI and free5GC (Lins et al. 2021). These studies highlight the simulation-to-reality gap and underscore the need for expanded testbed development. Experiments must inject realistic faults and stressors beyond idealized channels, for example long propagation delays and intermittent outages on space links, burst and correlated packet loss on aerial links, GNSS drift and positioning errors for mobile platforms, telemetry noise and timestamp jitter, node overload under CPU or memory pressure, and a fraction of adversarial or malfunctioning nodes to evaluate robustness and security; reliance on simplified simulation setups has been noted as a recurrent limitation in the literature. Reproducibility artifacts should be published with every study and include simulator versions and configuration files, random seeds, mobility traces and channel parameters, baseline implementations and hyperparameters, and any hardware recipes for emulation, because standardized scenario definitions enable meaningful cross-paper comparison and benchmark development.

Validation should follow a staged rollout from parameter sweeps and stress tests in simulation, to hardware-in-the-loop experiments that measure inference latency, energy per inference, and thermal behavior on representative processors, to controlled field trials and finally canary or shadow production deployments with continuous monitoring, rollback criteria, and human-in-the-loop overrides; such staged practice exposes gaps in model compression, observability, and failover mechanisms that are often under-addressed. Security and privacy evaluations must be integral rather than add-on, encompassing poisoning and inversion attacks, robust aggregation and differential privacy trade-offs, and lightweight provenance mechanisms whose overheads are measured under realistic resource constraints, because distributed ML in multi-tier settings introduces novel threat surfaces. Finally, reported results should include not only throughput and latency but also handover failure rate, energy and FLOP footprints, signaling overhead, convergence and sample efficiency, and robustness to non-i.i.d. data so that practitioners can perform practical cost-benefit analyses before adoption; this operational emphasis complements the comparative and system-readiness gaps identified earlier in this survey (see Sect. 8.1 and Tables 10 and 11) and directly addresses the proper guidance on deployment, testing, and evaluation.

8.7 Emerging AI paradigms in MACN

While the preceding analysis has concentrated on classical supervised learning, deep reinforcement learning, and multi-agent frameworks, the broader AI research landscape is undergoing a methodological shift toward Transformer-based architectures, generative and diffusion models, and large language models that function as planners or solution synthesizers rather than purely reactive decision policies. Within the surveyed MACN literature, early applications of these paradigms have begun to appear. Self-attention mechanisms have been integrated into resource management frameworks for dynamic allocation in satellite-terrestrial networks (Tianhao and Zhiyong 2024), and multi-attention architectures have been employed for latency-aware cross-tier switching decisions (Ozturk et al. 2025). Diffusion-based generative models have been applied to vertical handover optimization, where the DGHD framework (Tao et al. 2025) synthesizes diverse network-state trajectories

for pretraining MAPPO agents, accelerating convergence and improving robustness under dual-mobility conditions.

GAN-augmented DRL (Guo et al. 2024) addresses data scarcity in routing by generating synthetic network states, while generative AI-enhanced DRL (Kakati et al. 2025) combines generative models with reinforcement learning for proactive secrecy optimization. At the semantic reasoning level, LLM-based architectures have been proposed for high-level task planning and intent interpretation in space-air-ground integrated networks (Gao et al. 2024), and for translating human-driven preferences into optimization objectives in vehicular scenarios (Chen et al. 2024). Graph neural networks, discussed throughout this survey, increasingly serve as relational encoders within these emerging pipelines, providing topology-aware representations that can be combined with Transformer decoders or diffusion-based generators (Zhu et al. 2025; Zhang et al. 2024; Ivanov et al. 2022), and Alam and Song (2024). Despite these advances, significant limitations constrain practical deployment: the quadratic complexity of self-attention and the iterative sampling requirements of diffusion models conflict with the energy and latency constraints of aerial platforms; LLM inference latency is incompatible with real-time control loops; training data requirements exceed what is currently available in standardized MACN benchmarks; and the interpretability and verifiability of generative decisions remain inadequate for safety-critical applications. Consequently, current applications primarily position these emerging paradigms in offline planning, training data augmentation, or advisory roles rather than closed-loop control.

Future research should prioritize efficient Transformer variants with linear attention mechanisms, constraint-aware diffusion sampling for direct solution synthesis, hierarchical architectures that combine LLM-based reasoning with lightweight local controllers, and hybrid GNN-Transformer encoders that leverage complementary inductive biases. Addressing these directions will be essential to transition MACN optimization beyond the RL-centric methodological perspective that currently dominates the field and to capitalize on the representational and generative capabilities that foundation model architectures increasingly offer for complex, high-dimensional network problems.

9 Conclusion

This survey reviewed and organized the rapidly expanding literature on AI applications in MACNs, with a focus on routing, computing, handover, resource management, and optimization. The surveyed AI methods range from lightweight predictors such as ELM, which are suitable for edge platforms, to large-scale approaches including GNN driven DRL and GAN augmented DRL for mega constellations; these methods deliver measurable improvements in adaptability, throughput, and latency under dynamic topologies. RL and MARL techniques dominate adaptive decision problems such as handover and trajectory planning, while FL and hybrid schemes are emerging to reconcile performance with privacy and scalability. Our comparative analysis exposes persistent barriers to real-world deployment, notably the computational and energy demands that constrain on-node implementation, the reliance on idealized simulation assumptions, the scarcity of real-world datasets and testbeds, and the practical challenges of deploying distributed learning pipelines in resource-constrained environments. Addressing these challenges will require advances in model compression and hierarchical or distributed control, incorporation of XAI and adversarial robustness, and the

establishment of community benchmarks alongside reproducible evaluation practices. We therefore propose that research in MACN can be prioritized by using (1) lightweight, communication efficient distributed learning such as FL with compression and transfer learning across tiers, (2) interpretable and certifiable AI policies for safety critical handover and resource control, (3) realistic mobility and propagation modeling and large scale testbeds to bridge the simulation to reality gap, and (4) standardized metrics and open datasets to enable fair comparison and reproducibility. Progress on these fronts will be essential for transitioning AI driven MACNs from promising prototypes to resilient, secure, and deployable components of 6 G and beyond.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10462-026-11654-y>.

Acknowledgments This publication has emanated from research conducted with the financial support of Taighde Éireann – Research Ireland under Grant number 13/RC/2077_P2 at CONNECT: the Research Ireland Centre for Future Networks. The work of M. Noor-A-Rahim was supported in part by Taighde Éireann – Research Ireland under Grant No. 24/FFP-P/12832 and was also supported through collaboration with Xu Zhu as part of the 111 Project. The work of Z. Liu was supported in part by the UK Engineering and Physical Sciences Research Council under Grants EP/Y037243/1 ('TITAN/REVOL6G' and 'TITAN/LEGEND6G'), EP/X040569/1 ('HASC/RETHIN6G'), EP/X035352/1 ('DRIVE'), EP/Y000986/1 ('SORT'), and by the Royal Society under Grants IEC\NSFC\233292 and IES\R1\241212.

Author contributions Conceptualization, S.K.S.; M.Y.A., M.N.A.R Methodology, S.K.S.; M.Y.A., M.N.A.R Validation, M.Y.A., M.M.A., X.Z., P.Y., Z.L., K.G., M.N.A.R Investigation, M.Y.A., M.M.A., X.Z., P.Y., Z.L., K.G., M.N.A.R Resources, S.K.S., M.Y.A. Writing-original draft preparation, S.K.S.; Writing-review and editing, M.Y.A., M.M.A., X.Z., P.Y., Z.L., K.G., M.N.A.R Project administration, K.G., M.N.A.R; Funding acquisition, K.G., M.N.A.R. All authors have read and agreed to the published version of the manuscript.

Funding Open Access funding provided by the IReL Consortium. This publication has emanated from research conducted with the financial support of Taighde Éireann – Research Ireland under Grant number 13/RC/2077_P2 at CONNECT: the Research Ireland Centre for Future Networks. The work of M. Noor-A-Rahim was supported in part by Taighde Éireann – Research Ireland under Grant No. 24/FFP-P/12832 and was also supported through collaboration with Xu Zhu as part of the 111 Project. The work of Z. Liu was supported in part by the UK Engineering and Physical Sciences Research Council under Grants EP/Y037243/1 ('TITAN/REVOL6G' and 'TITAN/LEGEND6G'), EP/X040569/1 ('HASC/RETHIN6G'), EP/X035352/1 ('DRIVE'), EP/Y000986/1 ('SORT'), and by the Royal Society under Grants IEC\NSFC\233292 and IES\R1\241212.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Aalamifar F, Lampe L, Bavarian S, Crozier E (20214) Wimax technology in smart distribution networks: architecture, modeling, and applications. In: IEEE PES T&D conference and exposition. IEEE 2014:1–5
- Agrawal J, Arafat MY (2024) Bio-inspired algorithms for efficient clustering and routing in flying ad hoc networks. *Sensors* 25(1):72
- Alam S, Song WC (2024) Intent-based network resource orchestration in space-air-ground integrated networks: a graph neural networks and deep reinforcement learning approach. *IEEE Access*
- Alam MM, Trina SA, Hossain T, Mahmood S, Ahmed MS, Arafat MY (2025) Variations in multi-agent actor-critic frameworks for joint optimizations in uav swarm networks: recent evolution, challenges, and directions. *Drones* 9(2):153
- Altubbaishi ES, Alhamawi K (2019) Capacity analysis of hybrid af multi-hop fso/rf system under pointing errors and weather effects. *IEEE Photonics Technol Lett* 31(15):1304–1307
- Arafat MY, Moh S (2018) A survey on cluster-based routing protocols for unmanned aerial vehicle networks. *IEEE Access* 7:498–516
- Arafat MY, Moh S (2019) Localization and clustering based on swarm intelligence in uav networks for emergency communications. *IEEE Internet Things J* 6(5):8958–8976
- Arafat MY, Moh S (2021a) Bio-inspired approaches for energy-efficient localization and clustering in uav networks for monitoring wildfires in remote areas. *IEEE Access* 9:18649–18669
- Arafat MY, Moh S (2021b) A q-learning-based topology-aware routing protocol for flying ad hoc networks. *IEEE Internet Things J* 9(3):1985–2000
- Arafat MY, Moh S (2022) Jrcs: Joint routing and charging strategy for logistics drones. *IEEE Internet Things J* 9(21):21751–21764
- Bai J, Song H, Yi Y, Liu L (2021) Multiagent reinforcement learning meets random access in massive cellular internet of things. *IEEE Internet Things J* 8(24):17417–17428
- Bakambekova A, Kouzayha N, Al-Naffouri T (2024) On the interplay of artificial intelligence and space-air-ground integrated networks: a survey. *IEEE Open J Commun Soc*
- Bao L, Wu C, Bu X, Ren N, Shen M (2019) Performance modeling and workflow scheduling of microservice-based applications in clouds. *IEEE Trans Parallel Distrib Syst* 30(9):2114–2129
- Bariah L, Mohjazi L, Abumarshoud H, Selim B, Muhaidat S, Tatipamula M, Imran MA, Haas H (2022) Risk-assisted space-air-ground integrated networks: New horizons for flexible access and connectivity. *IEEE Network* 37(3):118–125
- Cai Y, Yao H, Gong Y, Wang F, Zhang N, Guizani M (2024) Privacy-driven security-aware task scheduling mechanism for space-air-ground integrated networks. *IEEE Trans Netw Sci Eng* 11(5):4704–4718
- Cao B, Zhang J, Liu X, Sun Z, Cao W, Nowak RM, Lv Z (2021) Edge-cloud resource scheduling in space-air-ground-integrated networks for internet of vehicles. *IEEE Internet Things J* 9(8):5765–5772
- Chandrasekharan S, Gomez K, Al-Hourani A, Kandeepan S, Rasheed T, Goratti L, Reynaud L, Grace D, Bucaille I, Wirth T et al (2016) Designing and implementing future aerial communication networks. *IEEE Commun Mag* 54(5):26–34
- Chen N, Qiu T, Zhao L, Zhou X, Ning H (2021a) Edge intelligent networking optimization for internet of things in smart city. *IEEE Wirel Commun* 28(2):26–31
- Chen C, Hui Q, Xie W, Wan S, Zhou Y, Pei Q (2021b) Convolutional neural networks for forecasting flood process in internet-of-things enabled smart city. *Comput Netw* 186:107744
- Chen H, Xiao M, Pang Z (2022a) Satellite-based computing networks with federated learning. *IEEE Wirel Commun* 29(1):78–84
- Chen C, Liao Z, Ju Y, He C, Yu K, Wan S (2022b) Hierarchical domain-based multicontroller deployment strategy in sdn-enabled space-air-ground integrated network. *IEEE Trans Aerosp Electron Syst* 58(6):4864–4879
- Chen Q, Guo Z, Meng W, Han S, Li C, Quek TQ (2024a) A survey on resource management in joint communication and computing-embedded sagn. *IEEE Commun Surv Tutor*
- Chen X, Lu X, Li Q, Li D, Zhu F (2024b) Integration of llm and human-ai coordination for power dispatching with connected electric vehicles under sagvns. *IEEE Trans Veh Technol*
- Chen Y, Cao H, Wang L, Chen D, Liu Z, Zhou Y, Shi J (2025) Deep reinforcement learning-based routing method for low earth orbit mega-constellation satellite networks with service function constraints. *Sensors* 25(4):1232
- Cheng N, Quan W, Shi W, Wu H, Ye Q, Zhou H, Zhuang W, Shen X, Bai B (2020) A comprehensive simulation platform for space-air-ground integrated network. *IEEE Wirel Commun* 27(1):178–185
- Cheng L, Li X, Feng G, Peng Y, Qin S, Quek TQ (2025) Cooperative transmission for space-air-ground integrated networks: a multi-agent cooperation method. *IEEE Trans Veh Technol*

- Choi J, Ding J (2021) Co-existing preamble and data transmissions in random access for mtc with massive mimo. *IEEE Trans Commun* 69(11):7576–7586
- Conti M, Giordano S (2014) Mobile ad hoc networking: milestones, challenges, and new research directions. *IEEE Commun Mag* 52(1):85–96
- Conti A, Malaney R, Win MZ (2024) Satellite-terrestrial quantum networks and the global quantum internet. *IEEE Commun Mag* 62(10):34–39
- Cui L, Yu FR, Yan Q (2016) When big data meets software-defined networking: Sdn for big data and big data for sdn. *IEEE Network* 30(1):58–65
- Cui Y, Liu F, Jing X, Mu J (2021) Integrating sensing and communications for ubiquitous iot: Applications, trends, and challenges. *IEEE Network* 35(5):158–167
- Cui H, Zhang J, Geng Y, Xiao Z, Sun T, Zhang N, Liu J, Wu Q, Cao X (2022) Space-air-ground integrated network (sagin) for 6g: Requirements, architecture and challenges. *China Commun* 19(2):90–108
- Cui Z, Yang T, Wu X, Feng H, Hu B (2023) The data value based asynchronous federated learning for uav swarm under unstable communication scenarios. *IEEE Trans Mob Comput* 23(6):7165–7179
- Dahrouj H, Liu S, Alouini M-S (2023) Machine learning-based user scheduling in integrated satellite-haps-ground networks. *IEEE Network* 37(2):102–109
- Dai CQ, Yang Q, Wu J, Chen Q (2021) Intelligent gateway placement in satellite-terrestrial integrated network. In: *IEEE INFOCOM 2021-IEEE conference on computer communications workshops (INFOCOM WKSHPs)*. IEEE, pp. 1–6
- Dai C-Q, Luo J, Fu S, Wu J, Chen Q (2020) Dynamic user association for resilient backhauling in satellite-terrestrial integrated networks. *IEEE Syst J* 14(4):5025–5036
- Dang X-T, Shin O-S (2024) Optimization of energy efficiency for federated learning over unmanned aerial vehicle communication networks. *Electronics* 13(10):1827
- Demestichas P, Georgakopoulos A, Karvounas D, Tsagkaris K, Stavroulaki V, Lu J, Xiong C, Yao J (2013) 5g on the horizon: key challenges for the radio-access network. *IEEE Veh Technol Mag* 8(3):47–53
- Di B, Song L, Li Y, Poor HV (2019) Ultra-dense leo: Integration of satellite access networks into 5g and beyond. *IEEE Wirel Commun* 26(2):62–69
- Ding R, Xu Y, Gao F, Shen X (2021) Trajectory design and access control for air-ground coordinated communications system with multiagent deep reinforcement learning. *IEEE Internet Things J* 9(8):5785–5798
- Ding F, Bao C, Zhou D, Sheng M, Shi Y, Li J (2024) Toward autonomous resource management architecture for 6g satellite-terrestrial integrated networks. *IEEE Network* 38(2):113–121
- Dong C, Shen Y, Qu Y, Wang K, Zheng J, Wu Q, Wu F (2021) Uavs as an intelligent service: Boosting edge intelligence for air-ground integrated networks. *IEEE Network* 35(4):167–175
- Drif Y, Chaput E, Lavinal E, Berthou P, Tiomela Jou B, Gremillet O, Arnal F (2021) An extensible network slicing framework for satellite integration into 5g. *Int J Satell Commun Network* 39(4):339–357
- Du J, Jiang C, Wang J, Ren Y, Yu S, Han Z (2017) Resource allocation in space multiaccess systems. *IEEE Trans Aerosp Electron Syst* 53(2):598–618
- Du J, Jiang C, Zhang H, Ren Y, Guizani M (2018a) Auction design and analysis for sdn-based traffic offloading in hybrid satellite-terrestrial networks. *IEEE J Sel Areas Commun* 36(10):2202–2217
- Siam SK et al (2026) Federated Deep Reinforcement Learning for Joint Coverage and Connectivity in Cooperative UAV Networks for Emergency Communications, in *IEEE Internet of Things Journal*
- Du J, Kong Z, Sun A, Kang J, Niyato D, Chu X, Yu FR (2023) Mddpg-based joint service placement and task offloading in mec empowered air-ground integrated networks. *IEEE Internet Things J* 11(6):10600–10615
- Ei NN, Kim K, Tun YK, Han Z, Hong CS (2024) Data service maximization in space-air-ground integrated 6g networks. *IEEE Commun Lett*
- E. U. T. R. A. Network (2011) 3rd generation partnership project; technical specification group services and system aspects; general packet radio service (gprs) enhancements for evolved universal terrestrial radio access network (e-utran) access. *EUTRA Network*
- Fang X, Feng W, Wei T, Chen Y, Ge N, Wang C-X (2021) 5g embraces satellites for 6g ubiquitous iot: Basic models for integrated satellite terrestrial networks. *IEEE Internet Things J* 8(18):14399–14417
- Fang Q, Zhai Z, Yu S, Wu Q, Gong X, Chen X (2022) Olive branch learning: A topology-aware federated learning framework for space-air-ground integrated network. *IEEE Trans Wirel Commun* 22(7):4534–4551
- Ferreira PVR, Paffenroth R, Wyglinski AM, Hackett TM, Bilen SG, Reinhart RC, Mortensen DJ (2019) Reinforcement learning for satellite communications: From leo to deep space operations. *IEEE Commun Mag* 57(5):70–75
- Ferrús R, Koumaras H, Sallent O, Agapiou G, Rasheed T, Kourtis M-A, Boustie C, Gélard P, Ahmed T (2016) Sdn/nfv-enabled satellite communications networks: Opportunities, scenarios and challenges. *Physical Communication* 18:95–112

- Fontanesi G, Ortiz F, Lagunas E, Garcés-Socarrás LM, Baeza VM, Á. Vázquez M, Vázquez-Peralvo JA, Minardi M, Vu HN, Honnaiah PJ, et al. (2025) Artificial intelligence for satellite communication: a survey. *IEEE Commun Surv Tutor*
- Gao H, Cao R, Xu W, Yuan C, Chen HH (2024) Space-air-ground integrated networks with task-driven connected intelligence. *IEEE Wirel Commun*
- Gardikis G, Koumaras H, Sakkas C, Koumaras V (2017) Towards sdn/nfv-enabled satellite networks. *Telecommun Syst* 66(4):615–628
- Gong Y, Yao H, Wu D, Yuan W, Dong T, Yu FR (2022) Computation offloading for rechargeable users in space-air-ground networks. *IEEE Trans Veh Technol* 72(3):3805–3818
- Gong Y, Yao H, Nallanathan A (2024) Intelligent sensing, communication, computation and caching for satellite-ground integrated networks. *IEEE Netw*
- Gu S, Zhang Q, Xiang W (2021) Coded storage-and-computation: a new paradigm to enhancing intelligent services in space-air-ground integrated networks. *IEEE Wirel Commun* 27(6):44–51
- Guo S, Zhao X (2022) Multi-agent deep reinforcement learning based transmission latency minimization for delay-sensitive cognitive satellite-uav networks. *IEEE Trans Commun* 71(1):131–144
- Guo H, Li J, Liu J, Tian N, Kato N (2021) A survey on space-air-ground-sea integrated network security in 6g. *IEEE Commun Surv Tutor* 24(1):53–87
- Guo C, Gong C, Xu H, Zhang L, Han Z (2022) A dynamic handover software-defined transmission control scheme in space-air-ground integrated networks. *IEEE Trans Wirel Commun* 21(8):6110–6124
- Guo Q, Tang F, Kato N (2024) Routing for space-air-ground integrated network with gan-powered deep reinforcement learning. *IEEE Trans Cognit Commun Netw*
- Han DJ, Fang W, Hosseinalipour S, Chiang M, Brinton CG (2024) Orchestrating federated learning in space-air-ground integrated networks: adaptive data offloading and seamless handover. *IEEE J Select Areas Commun*
- Hassan NU, Huang C, Yuen C, Ahmad A, Zhang Y (2020) Dense small satellite networks for modern terrestrial communication systems: Benefits, infrastructure, and technologies. *IEEE Wirel Commun* 27(5):96–103
- Hassan SS, Tun YK, Tran NH, Saad W, Hong CS et al (2022) Seamless and energy-efficient maritime coverage in coordinated 6g space-air-sea non-terrestrial networks. *IEEE Internet Things J* 10(6):4749–4769
- He H, Hou Y, Yang J, Jiang X, Chen S, Hanzo L (2022) Towards reliable space-ground integrated networks: From system-level design to implementation. *IEEE Network* 37(5):154–161
- Hosseinalipour S, Brinton CG, Aggarwal V, Dai H, Chiang M (2021) From federated to fog learning: Distributed machine learning over heterogeneous wireless networks. *IEEE Commun Mag* 58(12):41–47
- Hou X, Wang J, Jiang C, Zhang X, Ren Y, Debbah M (2023) Uav-enabled covert federated learning. *IEEE Trans Wireless Commun* 22(10):6793–6809
- Hu Z, Zeng F, Xiao Z, Fu B, Jiang H, Xiong H, Zhu Y, Alazab M (2023) Joint resources allocation and 3d trajectory optimization for uav-enabled space-air-ground integrated networks. *IEEE Trans Veh Technol* 72(11):14214–14229
- Huang R, Wong VW, Schober R (2020) Throughput optimization for grant-free multiple access with multiagent deep reinforcement learning. *IEEE Trans Wireless Commun* 20(1):228–242
- Ivanov A, Tonchev K, Poulkov V, Manolova A, Neshov NN (2022) Graph-based resource allocation for integrated space and terrestrial communications. *Sensors* 22(15):5778
- Jang HS, Lee H, Quek TQ, Shin H (2021) Deep learning-based cellular random access framework. *IEEE Trans Wireless Commun* 20(11):7503–7518
- Jia Z, Sheng M, Li J, Han Z (2021) Toward data collection and transmission in 6g space-air-ground integrated networks: Cooperative hap and leo satellite schemes. *IEEE Internet Things J* 9(13):10516–10528
- Jia M, Wu J, Guo Q, Yang Y (2024) Service-oriented sagin with pervasive intelligence for resource-constrained users. *IEEE Network* 38(2):79–86
- Jia Z, Cao Y, He L, Li G, Zhou F, Wu Q, Han Z (2025a) Nfv-enabled service recovery in space-air-ground integrated networks: a matching game based approach. *IEEE Trans Netw Sci Eng*
- Jia Z, Cao Y, He L, Wu Q, Zhu Q, Niyato D, Han Z (2025b) Service function chain dynamic scheduling in space-air-ground integrated networks. *IEEE Trans Veh Technol*
- Jiang W, Han B, Habibi MA, Schotten HD (2021) The road towards 6g: a comprehensive survey. *IEEE Open J Commun Soc* 2:334–366
- Jiang W, Zhan Y, Xiao X (2023a) Multi-domain network slicing in satellite-terrestrial integrated networks: a multi-sided ascending-price auction approach. *Aerospace* 10(10):830
- Jiang X, Huang Y, Li J, He H, Chen S, Yang F, Yang J (2023b) Spatio-temporal routing, redundant coding and multipath scheduling for deterministic satellite network transmission. *IEEE Trans Commun* 71(5):2860–2875

- Jing Y, Qu Y, Dong C, Shen Y, Wei Z, Wang S (2021) Joint uav location and resource allocation for air-ground integrated federated learning, IEEE Global Communications Conference (GLOBECOM). IEEE 2021:1–6
- Jing Y, Qu Y, Dong C, Ren W, Shen Y, Wu Q, Guo S (2023) Exploiting uav for air-ground integrated federated learning: A joint uav location and resource optimization approach. IEEE Trans Green Commun Netw 7(3):1420–1433
- Jing Y, Qu Y, Wu T, Dong C, Guo S, Wu Q (2025) Air-ground integrated online federated learning under unreliable communication. IEEE Trans Cognit Commun Netw
- Kak A, Guven E, Ergin UE, Akyildiz IF (2018) Performance evaluation of sdn-based internet of space things, IEEE Globecom Workshops (GC Wkshps). IEEE 2018:1–6
- Kakati A, Li G, Diallo EM, Kawala LC, Hussain N, Adam AB (2025) Towards proactive, secure and efficient space-air-ground communications: generative ai-based drl framework. IEEE Open J Commun Soc
- Kaleem Z, Orakzai FA, Ishaq W, Latif K, Zhao J, Jamalipour A (2024) Emerging trends in uavs: From placement, semantic communications to generative ai for mission-critical networks. IEEE Trans Consum Electron
- Kato N, Fadlullah ZM, Tang F, Mao B, Tani S, Okamura A, Liu J (2019) Optimizing space-air-ground integrated networks by artificial intelligence. IEEE Wirel Commun 26(4):140–147
- Kawamoto Y, Okawara Y, Verma S, Kato N, Kaneko K, Sata A, Ochiai M (2024) Interference suppression in haps-based space-air-ground integrated networks using a codebook-based approach. IEEE Trans Veh Technol
- Khairy S, Balaprakash P, Cai LX, Poor HV (2021) Data-driven random access optimization in multi-cell iot networks using noma. IEEE Trans Wirel Commun 21(7):4938–4953
- Khoshafa MH, Bueno F, Ngatched TMN, Di Renzo M (2025) Ris-empowered secured space-air-ground integrated networks: Opportunities and challenges. IEEE Commun Mag 63(6):130–136
- Kim GS, Cho Y, Park S, Jung S, Kim J (2025) Quantum multi-agent reinforcement learning for joint cube-satellites and high-altitude long-endurance aerial vehicles in sagin. IEEE Trans Aerosp Electron Syst
- Kodheli O, Lagunas E, Maturo N, Sharma SK, Shankar B, Montoya JFM, Duncan JCM, Spano D, Chatzinotas S, Kisseleff S et al (2020) Satellite communications in the new space era: a survey and future challenges. IEEE Commun Surv Tutor 23(1):70–109
- Lan W, Chen K, Cao J, Li Y, Li N, Chen Q, Sahni Y (2024) Security-sensitive task offloading in integrated satellite-terrestrial networks. IEEE Trans Mob Comput
- Lee J-H, Park J, Bennis M, Ko Y-C (2022a) Integrating leo satellites and multi-uav reinforcement learning for hybrid fso/rf non-terrestrial networks. IEEE Trans Veh Technol 72(3):3647–3662
- Lee D, Zhao Y, Seo J-B, Lee J (2022b) Multi-agent reinforcement learning for a random access game. IEEE Trans Veh Technol 71(8):9119–9124
- Letaief KB, Shi Y, Lu J, Lu J (2021) Edge artificial intelligence for 6g: Vision, enabling technologies, and applications. IEEE J Sel Areas Commun 40(1):5–36
- Li Z, Chen P (2023) Risk-aware distributionally robust optimization for mobile edge computation task offloading in the space-air-ground integrated network. Sensors 23(12):5729
- Li X, Shang B (2025) Advancing multi-connectivity in satellite-terrestrial integrated networks: architectures, challenges, and applications. IEEE Netw
- Li T, Zhou H, Luo H, Yu S (2017) Service: A software defined framework for integrated space-terrestrial satellite communication. IEEE Trans Mob Comput 17(3):703–716
- Li X, Feng W, Chen Y, Wang C-X, Ge N (2020a) Maritime coverage enhancement using uavs coordinated with hybrid satellite-terrestrial networks. IEEE Trans Commun 68(4):2355–2369
- Li J, Xue K, Wei DS, Liu J, Zhang Y (2020b) Energy efficiency and traffic offloading optimization in integrated satellite/terrestrial radio access networks. IEEE Trans Wireless Commun 19(4):2367–2381
- Li J, Shi W, Wu H, Zhang S, Shen X (2021) Cost-aware dynamic sfc mapping and scheduling in sdn/nfv-enabled space-air-ground-integrated networks for internet of vehicles. IEEE Internet Things J 9(8):5824–5838
- Li Z, Wen J, Yang J, He J, Ni T, Li Y (2022a) Energy-efficient space-air-ground-ocean-integrated network based on intelligent autonomous underwater glider. IEEE Internet Things J 10(11):9329–9341
- Li Z, Hu Y, Zhu D, Wu J, Gu Y (2022b) Esmd-flow: An intelligent flow forwarding scheme with endogenous security based on mimic defense in space-air-ground integrated network. China Communications 19(1):40–51
- Li H, Ota K, Dong M (2022c) Ai in sagin: Building deep learning service-oriented space-air-ground integrated networks. IEEE Network 37(2):154–159
- Li S, Chen Q, Li Z, Meng W, Li C (2022d) Civil aircraft assisted space-air-ground integrated networks: Architecture design and coverage analysis. China Communications 19(1):29–39
- Li Z, Wang S, Han S, Meng W, Li C (2023) Joint design of beam hopping and multiple access based on cognitive radio for integrated satellite-terrestrial network. IEEE Network 37(1):36–43

- Li Y, Jin K, Tang J, Zhang Y, Feng Y (2024a) Diffusion-enabled digital twin synchronization for aigc services in space-air-ground integrated networks. *IEEE Internet Things J*
- Li D, Sun Y, Peng J, Cheng S, Yin Z, Cheng N, Liu J, Li Z, Xu C (2024b) Dual network computation offloading based on drl for satellite-terrestrial integrated networks. *IEEE Trans Mob Comput*
- Li L, Zhu L, Li W (2025a) Privacy-preserving federated learning for space-air-ground integrated networks: A bi-level reinforcement learning and adaptive transfer learning optimization framework. *Sensors* 25(9):2828
- Li M, Li M, Wang K, Yu FR, Wang Z, Si P (2025b) Task offloading and resource management for iiot with satellite-terrestrial integrated computing power network based on d3qn. *IEEE Internet Things J*
- Lim WYB, Luong NC, Hoang DT, Jiao Y, Liang Y-C, Yang Q, Niyato D, Miao C (2020) Federated learning in mobile edge networks: A comprehensive survey. *IEEE communications surveys & tutorials* 22(3):2031–2063
- Lin Z, Lin M, Wang J-B, De Cola T, Wang J (2019) Joint beamforming and power allocation for satellite-terrestrial integrated networks with non-orthogonal multiple access. *IEEE J Select Top Signal Process* 13(3):657–670
- Lin Y, Feng W, Zhou T, Wang Y, Chen Y, Ge N, Wang C-X (2023) Integrating satellites and mobile edge computing for 6g wide-area edge intelligence: minimal structures and systematic thinking. *IEEE Network* 37(2):14–21
- Lin Z, Yang J, Chen Y, Xu C, Zhang X (2024) Maritime distributed computation offloading in space-air-ground-sea integrated networks. *IEEE Commun Lett*
- Lins S, Cardoso KV, Both CB, Mendes L, De Rezende JF, Silveira A, Linder N, Klautau A (2021) Artificial intelligence for enhanced mobility and 5g connectivity in uav-based critical missions. *IEEE Access* 9:111792–111801
- Liu M (2021) Research on handover strategies in low earth orbit mobile satellite networks. Chongqing University of Posts and Telecommunications
- Liu J, Shi Y, Fadlullah ZM, Kato N (2018) Space-air-ground integrated network: A survey. *IEEE Communications Surveys & Tutorials* 20(4):2714–2741
- Liu J, Han Z, Li W (2019a) Performance analysis of tcp new reno over satellite dvb-rcs2 random access links. *IEEE Trans Wireless Commun* 19(1):435–446
- Liu M, Yang J, Gui G (2019b) Dsf-noma: Uav-assisted emergency communication technology in a heterogeneous internet of things. *IEEE Internet Things J* 6(3):5508–5519
- Liu Y, James J, Kang J, Niyato D, Zhang S (2020a) Privacy-preserving traffic flow prediction: A federated learning approach. *IEEE Internet Things J* 7(8):7751–7763
- Liu Y, Yuan X, Xiong Z, Kang J, Wang X, Niyato D (2020b) Federated learning for 6g communications: Challenges, methods, and future directions. *China Communications* 17(9):105–118
- Liu W, Cui Y, Yang F, Ding L, Sun J (2022a) Joint optimization of preamble selection and access barring for random access in mtc with general device activities. *IEEE Trans Commun* 70(6):3930–3946
- Liu D, Zhang J, Cui J, Ng S-X, Maunder RG, Hanzo L (2022b) Deep learning aided routing for space-air-ground integrated networks relying on real satellite, flight, and shipping data. *IEEE Wirel Commun* 29(2):177–184
- Liu Y, Yang K (2025) Asynchronous decentralized federated anomaly detection for 6g networks. *IEEE Trans Cognit Commun Netw*
- Liu Z, Zhang J, Zeng Y, Ai B (2025) Energy-efficient multi-agent reinforcement learning for uav trajectory optimization in cell-free massive mimo networks. *IEEE Trans Wirel Commun*
- Lv N, Ma H, Chen C, Pei Q, Zhou Y, Xiao F, Li J (2021) Remote sensing data augmentation through adversarial training. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14:9318–9333
- Lv X, Wu S, Li A, Jiao J, Zhang N, Zhang Q (2022) A weighted graph-based handover strategy for aeronautical traffic in leo satcom networks. *IEEE Networking Letters* 4(3):132–136
- Mahboob S, Liu L (2024) Revolutionizing future connectivity: A contemporary survey on ai-empowered satellite-based non-terrestrial networks in 6g. *IEEE Communications Surveys & Tutorials* 26(2):1279–1321
- Mao S, He S, Wu J (2020) Joint uav position optimization and resource scheduling in space-air-ground integrated networks with mixed cloud-edge computing. *IEEE Syst J* 15(3):3992–4002
- Mao B, Zhou X, Liu J, Kato N (2023) Digital twin satellite networks toward 6g: Motivations, challenges, and future perspectives. *IEEE Network* 38(1):54–60
- Mashiko K, Kawamoto Y, Kato N, Yoshida K, Ariyoshi M (2025) Combined control of coverage area and haps deployment in hybrid fso/rf sagsin. *IEEE Trans Veh Technol*
- Meng S, Wu S, Wu H, Li A, Zhang Q (2024a) Effectiveness-oriented sagsin: unveiling a unified metric and a comprehensive framework. *IEEE Network* 38(6):39–47
- Meng S, Wu S, Zhang J, Cheng J, Zhou H, Zhang Q (2024b) Semantics-empowered space-air-ground-sea integrated network: new paradigm, frameworks, and challenges. *IEEE Commun Surv Tutor*

- Messaoudi K, Baz A, Oubbati OS, Rachedi A, Bendouma T, Atiquzzaman M (2024) Ugv charging stations for uav-assisted aoi-aware data collection. *IEEE Trans Cognit Commun Netw* 10(6):2325–2343
- Mohamed EM, Hashima S, Hatano K, Khallaf HS (2023) Leo-assisted aerial deployment in post-disaster scenarios using a combinatorial bandit and genetic algorithmic approach. *Electronics* 12(24):4964
- Mohamed EM, Alnakhli MA, Fouda MM (2024) Joint uav trajectory planning and leo-sat selection in sagin. *IEEE Open Journal of the Communications Society* 5:1624–1638
- Morshed Alam M and Moh S (2024) Joint Optimization of Trajectory Control, Task Offloading, and Resource Allocation in Air-Ground Integrated Networks. *IEEE Internet Things J* 11(13):24273–24288
- Morshed Alam M, Kabir MA, Omei MFA, Ahmed S, Bin Faruq K, Ahmed T, Arafat MY (2026) Integrated trajectory, association, and fair resource allocation for aoi and energy-aware data collection in air-ground collaborative networks. *IEEE Open Journal of the Communications Society* 7:685–700
- Motlagh NH, Taleb T, Arouk O (2016) Low-altitude unmanned aerial vehicles-based internet of things services: Comprehensive survey and future perspectives. *IEEE Internet Things J* 3(6):899–922
- Mozaffari M, Saad W, Bennis M, Nam Y-H, Debbah M (2019) A tutorial on uavs for wireless networks: Applications, challenges, and open problems. *IEEE communications surveys & tutorials* 21(3):2334–2360
- Nguyen T-H, Nguyen LV, Dang LM, Hoang VT, Park L (2023) Td3-based optimization framework for rsma-enhanced uav-aided downlink communications in remote areas. *Remote Sensing* 15(22):5284
- Niu Z, Yang H, Yao Q, Yu A, Yin S, Shen S, Wei B, Zhang J, Vasilakos AV (2024) Hap networking enables highly reliable space-air-ground optical interconnect: an integrated network perspective. *IEEE Netw*
- Nuo C, Zhili S, Yujie S, Yue C, Xu X, Sali AB (2025) Channel-aware handover management for space-air-ground integrated networks. *China Communications* 22(2):62–76
- Oubbati OS, Badis H, Rachedi A, Lakas A, Lorenz P (2023) Multi-uav assisted network coverage optimization for rescue operations using reinforcement learning. In: *IEEE 20th consumer communications & networking conference (CCNC)*. *IEEE* 2023:1003–1008
- Ozturk M, Salamattmoghadasi M, Yanikomeroğlu H (2025) Integrating terrestrial and non-terrestrial networks for sustainable 6g operations: a latency-aware multi-tier cell-switching approach. *IEEE Netw*
- Pan G, Ye J, Zhang Y, Alouini M-S (2020) Performance analysis and optimization of cooperative satellite-aerial-terrestrial systems. *IEEE Trans Wireless Commun* 19(10):6693–6707
- Pan H, Chan T-T, Li J, Leung VC (2022) Age of information with collision-resolution random access. *IEEE Trans Veh Technol* 71(10):11295–11300
- Park J, Youn J, Oh J, Im J, Ahn S, Kim S, Cho S (2023) Random access protocol for massive internet of things connectivity in space-air-ground-integrated networks. *IEEE Internet Things J* 10(23):20442–20457
- Pei X, Qian H, Wang H, Kang K (2021) An improved random access scheme using directional beams for 5g massive machine-type communications. *IEEE Internet Things J* 9(11):8913–8924
- Peng R, Chen S, Xue C (2024) Collaborative content caching algorithm for large-scale istns based on mappo. *IEEE Wirel Commun Lett*
- Peng G, Wang S, Li G, Huang T, Huang Y, Liu Y (2025) Space-terrestrial integrated time-sensitive networks: architecture, challenges, and open issues. *IEEE Netw*
- Pham Q-V, Le M, Huynh-The T, Han Z, Hwang W-J (2022) Energy-efficient federated learning over uav-enabled wireless powered communications. *IEEE Trans Veh Technol* 71(5):4977–4990
- Pietrabissa A, Celsi LR, Cimorelli F, Suraci V, Priscoli FD, Di Giorgio A, Giuseppe A, Monaco S (2018) Lyapunov-based design of a distributed wardrop load-balancing algorithm with application to software-defined networking. *IEEE Trans Control Syst Technol* 27(5):1924–1936
- Qi W, Song Q, Guo L, Jamalipour A (2022) Energy-efficient resource allocation for uav-assisted vehicular networks with spectrum sharing. *IEEE Trans Veh Technol* 71(7):7691–7702
- Qiu Y, Niu J, Zhu X, Zhu K, Yao Y, Ren B, Ren T (2022) Mobile edge computing in space-air-ground integrated networks: Architectures, key technologies and challenges. *J Sens Actuator Netw* 11(4):57
- Qu Y, Dong C, Zheng J, Dai H, Wu F, Guo S, Anpalagan A (2021) Empowering edge intelligence by air-ground integrated federated learning. *IEEE Network* 35(5):34–41
- Ruan Y, Li Y, Zhang R, Jiang L (2022) Energy efficient power control for cognitive multibeam-satellite terrestrial networks with poisson distributed users. *IEEE Transactions on Cognitive Communications and Networking* 8(2):964–974
- Shang B, Yi Y, Liu L (2021) Computing over space-air-ground integrated networks: Challenges and opportunities. *IEEE Network* 35(4):302–309
- Sharif S, Zeadally S, Ejaz W (2023) Space-aerial-ground-sea integrated networks: Resource optimization and challenges in 6g. *J Netw Comput Appl* 215:103647
- Sharma SK, Chatzinotas S, Arapoglou P-D (2018) *Satellite communications in the 5G era*. Institution of Engineering and Technology
- Sharma PK, Deepthi D, Kim DI (2019) Outage probability of 3-d mobile uav relaying for hybrid satellite-terrestrial networks. *IEEE Commun Lett* 24(2):418–422

- Sheng M, Wang Y, Li J, Liu R, Zhou D, He L (2017) Toward a flexible and reconfigurable broadband satellite network: Resource management architecture and strategies. *IEEE Wirel Commun* 24(4):127–133
- Sheng J, Cai X, Li Q, Wu C, Ai B, Wang Y, Kadoch M, Yu P (2021) Space-air-ground integrated network development and applications in high-speed railways: A survey. *IEEE Trans Intell Transp Syst* 23(8):10066–10085
- Shi Y, Liu J, Fadlullah ZM, Kato N (2018) Cross-layer data delivery in satellite-aerial-terrestrial communication. *IEEE Wirel Commun* 25(3):138–143
- Shi Y, Cao Y, Liu J, Kato N (2019) A cross-domain sdn architecture for multi-layered space-terrestrial integrated networks. *IEEE Network* 33(1):29–35
- Shi W, Li J, Wu H, Zhou C, Cheng N, Shen X (2020a) Drone-cell trajectory planning and resource allocation for highly mobile networks: A hierarchical drl approach. *IEEE Internet Things J* 8(12):9800–9813
- Shi Y, Yang K, Jiang T, Zhang J, Letaief KB (2020b) Communication-efficient edge ai: algorithms and systems. *IEEE Commun Surv Tutor* 22(4):2167–2191
- Shi Y, Wu J, Liu L, Lan D, Taherkordi A (2022) Energy-aware relay optimization and power allocation in multiple unmanned aerial vehicles aided satellite-aerial-terrestrial networks. *IEEE Syst J* 16(4):5293–5304
- Singh D, Swaminathan R (2023) Comprehensive performance analysis of hybrid fso/rf space-air-ground integrated network. *Opt Commun* 527:128964
- Song Z, Hao Y, Liu Y, Sun X (2021) Energy-efficient multiaccess edge computing for terrestrial-satellite internet of things. *IEEE Internet Things J* 8(18):14202–14218
- SpaceX (2020) Home business enterprise software SpaceX: we've launched 32,000 Linux computers into space for Starlink Internet. <https://www.zdnet.com/article/>, accessed: Jun. 27, 2025
- Srinath HG, Rana M, Balasubramanya NM (2022) Grant-free access for mmhc: a performance analysis based on number of preambles, repetitions, and retransmissions. *IEEE Internet Things J* 9(16):15169–15183
- Sun R, Wang Y, Su R, Cheng N, Shen XS (2018) A destination-aided wireless energy transfer scheme in multi-antenna relay sensor networks. *IEEE Wirel Commun Lett* 8(3):689–692
- Sun G, Wang Y, Yu H, Guizani M (2024) Proportional fairness-aware task scheduling in space-air-ground integrated networks. *IEEE Trans Serv Comput*
- Swaminathan R, Sharma S, Vishwakarma N, Madhukumar A (2021) Haps-based relaying for integrated space-air-ground networks with hybrid fso/rf communication: a performance analysis. *IEEE Trans Aerosp Electron Syst* 57(3):1581–1599
- Tang F, Wen C, Zhao M, Kato N (2022a) Machine learning for space-air-ground integrated network assisted vehicular network: a novel network architecture for vehicles. *IEEE Veh Technol Mag* 17(3):34–44
- Tang F, Wen C, Luo L, Zhao M, Kato N (2022b) Blockchain-based trusted traffic offloading in space-air-ground integrated networks (sagin): a federated reinforcement learning approach. *IEEE J Sel Areas Commun* 40(12):3501–3516
- Tao S, Yuan M, Wu Q, Wang R, Hao J (2025) Generative ai-aided vertical handover decision in sagin for iot with integrated sensing and communication. *IEEE Internet Things J*
- Tian Y, Pan G, Kishk MA, Alouini M-S (2021) Stochastic analysis of cooperative satellite-uav communications. *IEEE Trans Wireless Commun* 21(6):3570–3586
- Tianhao L, Zhiyong L (2024) A self-attention based dynamic resource management for satellite-terrestrial networks. *China Communications* 21(4):136–150
- Tong C, Chen C, Cong L, Mu T, Pei Q, Wan S (2025) Leo satellite handover using advantage actor-critic algorithm in giant constellation network. *IEEE Trans Aerosp Electron Syst*
- Trinh PV, Sugiura S, Xu C, Hanzo L (2025) Towards quantum sagins harnessing optical riss: applications, advances, and the road ahead. *IEEE Netw*
- Tu H, Bellavista P, Zhao L, Zheng G, Liang K, Wong K-K (2024) Priority-based load balancing with multi-agent deep reinforcement learning for space-air-ground integrated network slicing. *IEEE Internet Things J* 11(19):30690–30703
- Wang K, Wang Y, Zeng D, Guo S (2017a) An sdn-based architecture for next-generation wireless networks. *IEEE Wirel Commun* 24(1):25–31
- Wang H, Wang J, Ding G, Wang L, Tsiftsis TA, Sharma PK (2017b) Resource allocation for energy harvesting-powered d2d communication underlying uav-assisted networks. *IEEE Transactions on Green Communications and Networking* 2(1):14–24
- Wang J, Jiang C, Wei Z, Pan C, Zhang H, Ren Y (2018) Joint uav hovering altitude and power control for space-air-ground iot networks. *IEEE Internet Things J* 6(2):1741–1753
- Wang J, Tan Y, Liu J, Zhang Y (2020) Topology poisoning attack in sdn-enabled vehicular edge network. *IEEE Internet Things J* 7(10):9563–9574
- Wang C, Liu L, Jiang C, Wang S, Zhang P, Shen S (2021a) Incorporating distributed drl into storage resource optimization of space-air-ground integrated wireless communication network. *IEEE Journal of Selected Topics in Signal Processing* 16(3):434–446

- Wang T, Wang Y, Wang C, Yang Z, Cheng J (2021b) Group-based random access and data transmission scheme for massive mtc networks. *IEEE Trans Commun* 69(12):8287–8303
- Wang Z, Zhou Z, Zhang H, Zhang G, Ding H, Farouk A (2022a) Ai-based cloud-edge-device collaboration in 6g space-air-ground integrated power iot. *IEEE Wirel Commun* 29(1):16–23
- Wang S, Hosseinalipour S, Gorlatova M, Brinton CG, Chiang M (2022b) Uav-assisted online machine learning over multi-tiered networks: a hierarchical nested personalized federated learning approach. *IEEE Trans Netw Serv Manage* 20(2):1847–1865
- Wang Y, Li B, He J, Dai J, Liu Y, Yang Y (2023) Joint latency-oriented, energy consumption, and carbon emission for a space-air-ground integrated network with newly designed power technology. *Electronics* 12(17):3537
- Wang W, Li P, Li S, Zhang J, Zhou Z, Wu DO, Kim DK, Zhang G, Gong P (2024a) Optimizing proximity strategy for federated learning node selection in the space-air-ground information network for smart cities. *IEEE Internet Things J* 12(6):6418–6430
- Wang Y, Yang C, Li T, Mi X, Li L, Han Z (2024b) A survey on mean-field game for dynamic management and control in space-air-ground network. *IEEE Commun Surv Tutor*
- Wu D-F, Huang C, Yin Y, Huang S, Ashraf MWA, Guo Q, Zhang L (2021a) Lb-ddqn for handover decision in satellite-terrestrial integrated networks. *Wirel Commun Mob Comput* 2021(1):5871114
- Wu H, Chen J, Zhou C, Shi W, Cheng N, Xu W, Zhuang W, Shen XS (2021b) Resource management in space-air-ground integrated vehicular networks: Sdn control and ai algorithm design. *IEEE Wirel Commun* 27(6):52–60
- Wu F, Qu Y, Wu T, Dong C, Guo K, Wu Q, Guo S (2024a) Participant and sample selection for efficient online federated learning in uav swarms. *IEEE Internet Things J* 11(12):21202–21214
- Wu T, Yao H, Mai T, Wang Z, Wang F, Guizani M (2024b) Using full-dimensional programmability to power self-driving 6g networks. *IEEE Netw*
- Wu W, Feng W, Fang Y, Lin Z, Lu X (2025) Multi-hap-assisted computation offloading in space-air-ground-sea integrated network. *IEEE Internet Things J*
- Xia Z, Du J, Ren Y, Han Z (2022) Distributed artificial intelligence enabled aerial-ground networks: Architecture, technologies and challenges. *IEEE Access* 10:105447–105457
- Xiao Y, Ye Z, Wu M, Li H, Xiao M, Alouini MS, Al-Hourani A, Cioni S (2024) Space-air-ground integrated wireless networks for 6g: basics, key technologies and future trends. *IEEE J Select Areas Commun*
- Xie R, Tang Q, Qiao S, Zhu H, Yu FR, Huang T (2021) When serverless computing meets edge computing: Architecture, challenges, and open issues. *IEEE Wirel Commun* 28(5):126–133
- Xie W, Chen C, Ju Y, Shen J, Pei Q, Song H (2025) Deep reinforcement learning-based computation computational offloading for space-air-ground integrated vehicle networks. *IEEE Trans Intell Transp Syst*
- Xu H, Gao H, Zhou C, Duan R, Zhou X (2019) Resource allocation in cognitive radio wireless sensor networks with energy harvesting. *Sensors* 19(23):5115
- Xu Z, Zhang P, Li C, Zhu H, Xu G, Sun C (2023a) A collaborative inference algorithm in low-earth-orbit satellite network for unmanned aerial vehicle. *Drones* 7(9):575
- Xu X, Wang Q, Hou Y, Wang S (2023b) Ai-space: A cloud-edge aggregated artificial intelligent architecture for tiansuan constellation-assisted space-terrestrial integrated networks. *IEEE Network* 37(2):22–28
- Xu Y, Tang X, Huang L, Ullah H, Ning Q (2025) Multi-objective optimization for resource allocation in space-air-ground network with diverse iot devices. *Sensors* 25(1):274
- Yang Y, Ma M, Wu H, Yu Q, You X, Wu J, Peng C, Yum T-SP, Aghvami AH, Li GY et al (2022a) 6g network ai architecture for everyone-centric customized services. *IEEE Network* 37(5):71–80
- Yang B, Shi H, Xia X (2022b) Federated imitation learning for uav swarm coordination in urban traffic monitoring. *IEEE Trans Industr Inf* 19(4):6037–6046
- Yang B, Liu S, Xu T, Li C, Zhu Y, Li Z, Zhao Z (2023) Ai-oriented two-phase multifactor authentication in sagins: Prospects and challenges. *IEEE Consumer Electronics Magazine* 13(1):79–90
- Yao S, Guan J, Wu Y, Xu K, Xu M (2021) Toward secure and lightweight access authentication in sagins. *IEEE Wirel Commun* 27(6):75–81
- Yasir AM, Moh S (2019) Routing protocols for unmanned aerial vehicle networks: A survey. *IEEE Access* 7:99694–99720
- Yin L, Clerckx B (2022) Rate-splitting multiple access for satellite-terrestrial integrated networks: Benefits of coordination and cooperation. *IEEE Trans Wireless Commun* 22(1):317–332
- Yoo S, Lee W (2021) Federated reinforcement learning based aans with leo satellites and uavs. *Sensors* 21(23):8111
- Yu S, Gong X, Shi Q, Wang X, Chen X (2021) Ec-sagins: Edge-computing-enhanced space-air-ground-integrated networks for internet of vehicles. *IEEE Internet Things J* 9(8):5742–5754
- Yuan X, Liu J, Du H, Zhang Y, Li F, Kadoch M (2022) Machine learning-based satellite routing for sagin iot networks. *Electronics* 11(6):862

- Yuan X, Hu S, Ni W, Wang X, Jamalipour A (2024) Empowering reconfigurable intelligent surfaces with artificial intelligence to secure air-to-ground internet-of-things. *IEEE Internet of Things Magazine* 7(2):14–21
- Yuan S, Peng M, Sun Y (2025) Satellite-terrestrial integrated fog networks: architecture, technologies, and challenges. *IEEE Wirel Commun*
- Yuhui Z (2020) System architecture and networking technology of railway 5g private network. *China Railway* 11:10–15
- Zeng Y, Wu Q, Zhang R (2019) Accessing from the sky: A tutorial on uav communications for 5g and beyond. *Proc IEEE* 107(12):2327–2375
- Zeng B, Zhang Z, Ding X, Bu X, An J (2022a) Predictive decision and reliable accessing for uav communication in space-air-ground integrated networks. *China Commun* 19(1):166–185
- Zeng L, Wang W, Zuo W (2023) A federated learning latency minimization method for uav swarms aided by communication compression and energy allocation. *Sensors* 23(13):5787
- Zhan W, Sun X, Wang X, Fu Y, Li Y (2021) Performance optimization for massive random access of mmte in cellular networks with preamble retransmission limit. *IEEE Trans Veh Technol* 70(9):8854–8867
- Zhang J (2020) Study on railway communication methods based on lte-r and ad hoc integrated networking. *Railway Signalling Commun Eng* 2020(3):68–71
- Zhang W, Hranilovic S, Shi C (2009) Soft-switching hybrid fso/rf links using short-length raptor codes: Design and implementation. *IEEE J Sel Areas Commun* 27(9):1698–1708
- Zhang N, Zhang S, Yang P, Alhussein O, Zhuang W, Shen XS (2017) Software defined space-air-ground integrated vehicular networks: Challenges and solutions. *IEEE Commun Mag* 55(7):101–109
- Zhang S, Zhu D, Wang Y (2020a) A survey on space-aerial-terrestrial integrated 5g networks. *Comput Netw* 174:107212
- Zhang W, Li L, Zhang N, Han T, Wang S (2020b) Air-ground integrated mobile edge networks: a survey. *IEEE Access* 8:125998–126018
- Zhang J, Xie D, Wang X (2020c) Tara: An efficient random access mechanism for nb-iot by exploiting ta value difference in collided preambles. *IEEE Trans Mob Comput* 21(3):1110–1123
- Zhang P, Wang C, Kumar N, Liu L (2021) Space-air-ground integrated multi-domain network resource orchestration based on virtual network architecture: A drl method. *IEEE Trans Intell Transp Syst* 23(3):2798–2808
- Zhang P, Zhang Y, Kumar N, Guizani M (2022a) Dynamic sfc embedding algorithm assisted by federated learning in space-air-ground-integrated network resource allocation scenario. *IEEE Internet Things J* 10(11):9308–9318
- Zhang P, Su Y, Wang J, Jiang C, Hsu C-H, Shen S (2022b) Reinforcement learning assisted bandwidth aware virtual network resource allocation. *IEEE Trans Netw Serv Manage* 19(4):4111–4123
- Zhang L, Zhang H, Guo C, Xu H, Song L, Han Z (2020c) Satellite-aerial integrated computing in disasters: User association and offloading decision. In: ICC 2020-2020 IEEE international conference on communications (ICC). IEEE, pp. 554–559
- Zhang Y, Li Q, Wang J, Wang J, Chen J, Han Z (2023) Toward throughput maximization of integrated sensing and communications enabled predictive beamforming for 6g. *IEEE Network* 38(4):292–300
- Zhang W, Yang D, Zhang C, Ye Q, Zhang H, Shen X (2024a) (com) 2 net: A novel communication and computation integrated network architecture. *IEEE Network* 38(2):35–44
- Zhang Y, Wang J, Li Q, Chen J, Feng H, He S (2024b) Joint communication, sensing, and computing in space-air-ground integrated networks: System architecture and handover procedure. *IEEE Veh Technol Mag* 19(2):70–78
- Zhang P, Li Z, Guizani M, Kumar N, Yu K, Wang J (2024c) Energy aware space-air-ground integrated network resource orchestration algorithm. *IEEE Trans Veh Technol*
- Zhang Y, Wang J, Li Q, Chen J, Feng H, He S (2024d) Joint communication, sensing, and computing in space-air-ground integrated networks: system architecture and handover procedure. *IEEE Veh Technol Mag*
- Zhang Z, Wang J, Chen J, Fu H, Tong Z, Jiang C (2025a) Diffusion-based reinforcement learning for cooperative offloading and resource allocation in multi-uav assisted edge-enabled metaverse *IEEE Trans Veh Technol*
- Zhang Y, Wang X, Gang Y, Wang J, Wu S, Zhang P, Shi Y (2025b) 6g sagin information transmission model. *IEEE Commun Mag*
- Zhi L, Hehao N, Yuanzhi H, Kang A, Xudong Z, Zheng C, Pei X (2024) Self-powered absorptive reconfigurable intelligent surfaces for securing satellite-terrestrial integrated networks. *China Communications* 21(9):276–291
- Zhou D, Sheng M, Wang X, Xu C, Liu R, Li J (2017) Mission aware contact plan design in resource-limited small satellite networks. *IEEE Trans Commun* 65(6):2451–2466

- Zhou Z, Chen X, Li E, Zeng L, Luo K, Zhang J (2019) Edge intelligence: Paving the last mile of artificial intelligence with edge computing. *Proc IEEE* 107(8):1738–1762
- Zhou G, Zhao L, Zheng G, Song S, Zhang J, Hanzo L (2023a) Multiobjective optimization of space-air-ground-integrated network slicing relying on a pair of central and distributed learning algorithms. *IEEE Internet Things J* 11(5):8327–8344
- Zhou C, Shi S, Wu C, Xu Z (2023b) Noma empowered energy efficient data collection and wireless power transfer in space-air-ground integrated networks. *China Commun* 20(8):17–31
- Zhu W, Deng X, Gui J, Zhang H, Min G (2025) Cost-effective task offloading and resource scheduling for mobile edge computing in 6g space-air-ground integrated network. *IEEE Internet Things J*
- Zhuang W, Ye Q, Lyu F, Cheng N, Ren J (2019) Sdn/nfv-empowered future iov with enhanced communication, computing, and caching. *Proc IEEE* 108(2):274–291
- Zhu L, Zhang J, Xiao Z, Cao X, Wu DO, Xia X-G (2019) Millimeter-wave noma with user grouping, power allocation and hybrid beamforming. *IEEE Trans Wirel Commun* 18(11):5065–5079

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Authors and Affiliations

Shafkat Khan Siam¹  · Muhammad Yeasir Arafat¹  · Muhammad Morshed Alam²  · Xu Zhu³  · Ping Yang⁴  · Zilong Liu⁵  · Krishnendu Guha¹  · Md. Noor-A-Rahim¹ 

✉ Md. Noor-A-Rahim
md.noorarahim@ucc.ie

Shafkat Khan Siam
125115970@umail.ucc.ie

Muhammad Yeasir Arafat
MArafat@ucc.ie

Muhammad Morshed Alam
dr.malam@aiub.edu

Xu Zhu
xuzhu@ieee.org

Ping Yang
yang.ping@uestc.edu.cn

Zilong Liu
zilong.liu@essex.ac.uk

¹ School of Computer Science and IT, University College Cork, Cork T12 K8AF, Ireland

² Department of Electrical and Electronic Engineering, American International University-Bangladesh, Dhaka 1229, Bangladesh

³ School of Electronic and Information Engineering, Harbin Institute of Technology, Shenzhen, China

⁴ National Key Laboratory of Wireless Communications, University of Electronic Science and Technology of China, Sichuan, China

⁵ School of Computer Science and Electronic Engineering, University of Essex, Colchester Campus, UK