ELSP Adv. Inf. Commun.

Review | Received 1 April 2026; Revised 6 May 2026; Accepted 10 June 2026; Published 28 July 2026
https://doi.org/10.55092/aic20260012

Resource management in 6G SAGINs: from optimization-based methods to LLM-enabled agentic decision making

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Highlights:

- A structured taxonomy of resource management paradigms in 6G SAGINs is presented, clarifying the evolution from optimization-based and learning-based methods to reasoning-centric, LLM-enabled agentic intelligence.
- The key functional components of LEAs for SAGIN management are articulated, including perception, memory, thought, execution, and tool-grounded decision making, along with a discussion of representative multi-agent frameworks for distributed orchestration.
- The capability of LEAs to support four representative SAGIN resource management tasks is demonstrated: proactive spectrum control, autonomous cross-tier routing, multi-service scheduling, and dynamic network slicing. The main barriers to practical deployment include low-latency reasoning, data quality and availability, and trustworthy agent operation in highly dynamic SAGIN environments.

Abstract: Resource management in sixth-generation (6G) space-air–ground integrated network (SAGINs) is becoming increasingly challenging due to cross-tier heterogeneity, multi-timescale dynamics, and distributed decision making under partial and delayed information. These characteristics expose the limitations of conventional optimization-based and learning-based approaches, whose effectiveness often depends on accurate modeling, large amounts of task-specific data, or opaque policy adaptation. This article revisits the evolution of SAGIN resource management from optimization and learning to reasoning-centric, large language model (LLM)-enabled agentic intelligence. A unified taxonomy of existing paradigms is first presented, clarifying their respective strengths and limitations. The operational foundations of LLM-enabled agents (LEAs) are then introduced, including perception, memory, thought, execution, and tool-grounded decision making, followed by a discussion of emerging multi-agent frameworks for distributed orchestration. Building on this foundation, LEAs are shown to support proactive spectrum control, autonomous cross-tier routing, multi-service scheduling, and dynamic network

slicing. Finally, key open challenges are identified, and future directions toward practical, trustworthy, and scalable agentic resource management in 6G SAGINs are outlined.

Keywords: 6G networks; space–air–ground integrated networks (SAGINs); resource management; LLM-enabled agents (LEAs); multi-agent system

1. Introduction

Sixth-generation (6G) space-air–ground integrated network (SAGINs) are envisioned to provide seamless, ubiquitous, and intelligent connectivity by synergizing underground, terrestrial, aerial, and space network tiers into a unified architecture [1–4], as shown in Figure 1. Unlike conventional terrestrial-dominant networks, SAGINs must support heterogeneous services with diverse latency, reliability, and intelligence requirements across tiers [5–7]. However, the fundamental challenge extends beyond mere network expansion; it manifests as a structural mismatch between traditional resource management paradigms and the network's intrinsic nature. Consequently, traditional centralized, static asset management frameworks are constrained by heterogeneity across layers and misaligned time scales, leading to a significant decline in resource management efficiency, severe inefficiency, and difficulty in maintaining strict service level agreements (SLAs).

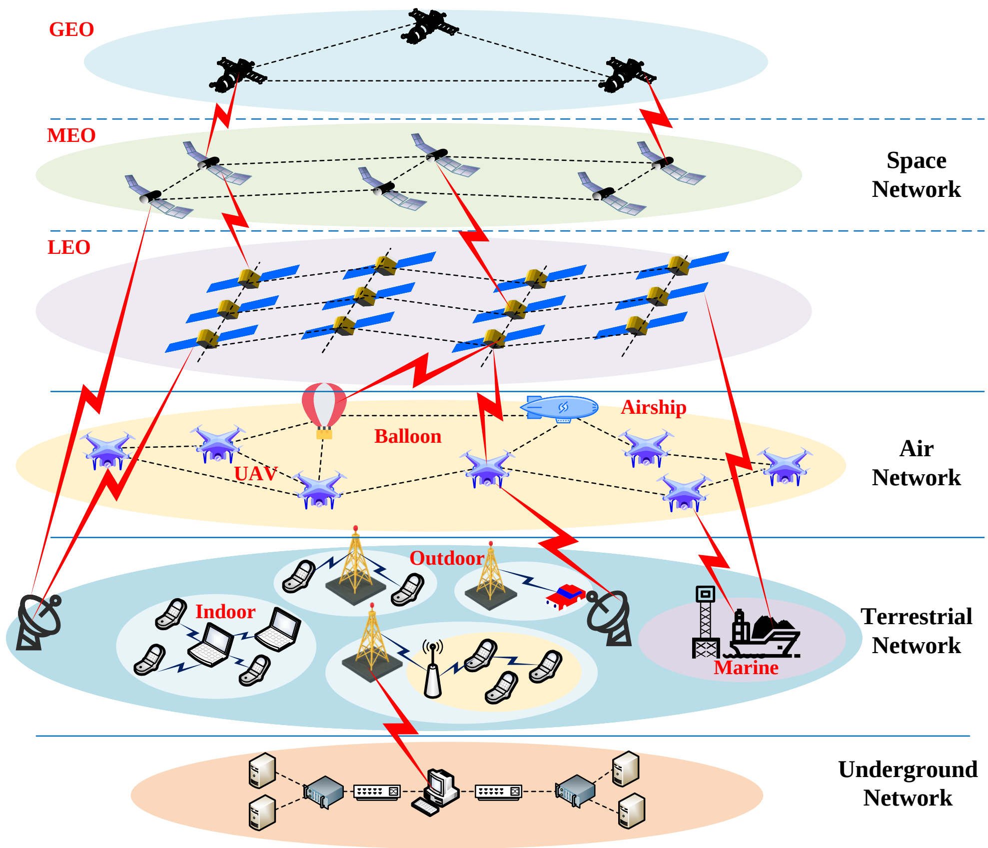

Figure 1. Architecture of SAGINs.

To solve this problem, resource management in SAGIN shifts from traditional optimization-based methods towards learning-based methods. Optimization-based methods [8], through rigorous mathematical modeling, are able to provide effective theoretical performance benchmarks; however, these methods have difficulty adapting to dynamic network resource management and increasing computational complexity when scaling up networks. Moreover, because of cross-layer propagation delays, optimization-based methods also tend to have difficulties obtaining precise global state information (GSI) leading to inaccurate resource management. Learning-based methods [9], especially deep reinforcement learning (DRL), can quickly identify environmental changes via trial-and-error interactions with an environment, demonstrating better adaptability in dynamic environments. Nevertheless, in highly heterogeneous SAGIN environments, there exists a significant generalization gap that limits its effectiveness. In scenarios where specific mobility patterns or SLA requirements exist, we need to re-train our model on specific raw data, thus making it hard to transfer knowledge from pre-trained models. Additionally, DRL is a black-box model lacking explanations, posing challenges in guaranteeing reliability and trustworthiness of critical 6G applications.

The rapid advancement of large language models (LLMs) in recent years brings new insight for SAGIN network resource management. Instead of relying on numerical mapping, SAGIN networks with LLMs are able to communicate with its environment using natural language which allows intelligent dynamic resource management [10–13]. Furthermore, emerging LLM-enabled agents (LEAs), show great promise as the cognitive core of network nodes [14]. First, LEAs can provide semantic abstraction by unified heterogeneous protocols and SLA into one representation [15]. Secondly, they can decompose complex tasks into locally executable subtasks at various tiers. Thirdly, LEAs offer decentralized reasoning capability. The deployment of LEAs over different tiers allows effective local resource management and agents interacting via negotiation mechanism. Besides, currently mainstream LLMs allow agents to call up external solvers or learning module, converting high-level decision into actionable physical layer control command.

As discussed above, one LEA cannot cope with the inherent distributed and heterogeneous characteristics of SAGIN; thus we urgently call for proposing and studying a multi-agent system (MAS), consisting of multiple specialized LEAs. The MAS allows us to acquire comprehensive system information via local interaction, encourage collaboration/competition between agents, and realize complex cooperation which transcends those of each component—“emergent” capabilities. Such emergent intelligence helps the network adaptively manage resources. In particular, by coordinating interactions across multiple agents in an LEA-based MAS architecture, enhanced reasoning/planning/problem solving capabilities could emerge that are hard for a single agent alone [16,17]. Decoupled local resource allocation from global strategic coordination at the system level and leveraging emergent behavior enable such collaborative intelligence, enhancing the system’s generalization capabilities in complex, dynamic SAGIN scenarios so as to better adapt to unknown environments and diverse task requirements. It provides a smarter way towards realizing autonomous, adaptive, and intent-driven network management in future 6G SAGIN systems.

A summary of SAGIN survey papers is provided in Table 1. Foundational research by [2] established the framework for satellite-aerial-terrestrial integration under heterogeneous and time varying conditions. This architectural vision was further expanded by [1] to incorporate communication sensing computation integration for the 6G era. In the context of network security and trustworthiness, reference [4] analyzed threats under multi-layer cooperation, while reference [18] introduced blockchain solutions to ensure data reliability in multi hop IoT scenarios. The interplay between AI and network optimization was reviewed by [19], emphasizing how distributed data and edge computing support can advance learning models. Targeted resource management strategies have also been a focus of recent literature. Reference [20] evaluated the spatiotemporal complexity of coupled resources in joint communication and computing (JCC) SAGINs. Similarly, reference [21] explored rapid emergency deployment and backhaul reliability specifically for disaster management missions. To address the prohibitive computational complexity of multi-layer networks, reference [22] surveyed quantum machine learning applications. Furthermore, reference [23] explored the role of generative paradigms, such as variational autoencoders and LLMs, in mitigating multi-layer security threats.

Table 1. Comparison of the related surveys in resource allocation of SAGINs.

Reference	Year	Network	MAS	LLM	Main Contribution
[2]	2018	SAGIN	×	×	Foundational survey of the integration of space, air, and ground network segments
[18]	2022	SAGIN(IoT)	×	×	Comprehensive survey on securing space air ground IoT applications via decentralized and auditable blockchain frameworks
[4]	2022	SAGIN(Security)	×	×	Comprehensive survey on security threats, attack methodologies, and defense countermeasures for full coverage 6G networks
[1]	2024	SAGIN	×	×	Comprehensive survey of technological advances in 6G communication and computing within integrated architectures
[19]	2024	SAGIN	×	×	Investigation of the reciprocal interplay between AI and integrated networks, emphasizing edge intelligence development
[20]	2025	JCC-SAGIN	×	×	First exhaustive review detailing the evolution of network integration and computing hardware in SAGIN
[21]	2025	SAGIN(Disaster)	×	×	Systematic review of emergency communication architectures and backhaul reliability for rescue operations
[22]	2026	SAGIN	×	×	Systematic evaluation of quantum enhanced technologies and classification for hybrid network architectures
[23]	2026	SAGIN(Security)	×	✓	Analysis of generative method for authenticity, confidentiality, integrity, and availability across the protocol stack
Ours	2026	SAGIN	✓	✓	Hierarchical LEA based resource management with four distinct applications and adaptability analysis to frontier MAS

Although some reviews have covered topics ranging from traditional optimization to learning-based algorithms, areas such as MAS architectures and reasoning-based coordination have not yet been sufficiently studied. Most existing research focuses on data-driven approaches rather than logical decision-making in highly dynamic environments. Unlike previous reviews, our study focuses on the principles and applications of LEA in MAS collaborative resource management, aiming to provide a cognitive framework that integrates perception, memory, and logical reasoning to enable autonomous, distributed resource coordination.

2. Resource management challenges in SAGINs

The resource management for 6G SAGIN will be complicated due to its huge scale together with the different physical states, control loops, service goals of different tiers. Underground segment, terrestrial segment, maritime segment, low altitude and space segment each have their own bottlenecks, and cross-layer control needs to coordinate communication, computing, storage and other network resources across different types of large spaces. Therefore resource management for SAGIN is an inherent distributed, multiscale and partially observable problem.

2.1. Underground network

For underground networks, resource management is necessarily constrained by harsh and random physical environments. Underground space is limited, and shadowing and waveguide effects in underground space can result in a huge signal attenuation. Meanwhile, underground sensors are often subject to tight and time-varying energy constraints [24]. In such contexts, the core problem is the coupling between limited energy budget and various, time-varying sensing, communication and computing demands. Furthermore, the conditions in underground environments are often highly dynamic and it is challenging to conduct optimizations based on an accurate model. From a cross-tier point of view, the backhaul capacity of links connecting underground nodes to underground ground gateways or satellite gateways is limited, and the uplink and downlink data rates are also different. Under such a situation, obtaining GSI or maintaining GSI is rather difficult; it forms isolated "information silos" that further enhances the difficulty of managing resources across tiers. As a result, resource management in underground networks has to rely more heavily on locality, autonomy and closed-loop control style.

2.2. Terrestrial network

Terrestrial networks are mainly affected by the huge number of connections in the heterogeneous environment. The mixed type of user equipments and networks, as well as the dynamism of the wireless transmission environment, make complex and realtime multipath interference [25]. Alongside the diverse service requirements terrestrial networks need to cater to, terrestrial networks suffer from high-dimensional, highly dynamic resource optimization problems [26,27]. With the increase in network scale and network heterogeneity, balancing competing requirements such as throughput, fairness and reliability become more difficult. From the cross-layer view, ground networks are the doorway to traffic traffic access and service, it needs to do real-time intent translation, translate global SLAs to resource setting policies for which ground networks can do locally. This nature of functions brings even more complexity, local decisions need to satisfy global goals within tight latency and scalability constraints.

2.3. Maritime network

While resource management in maritime networks is hard to achieve because of sparse infrastructure and changing weather in the sea. Maritime communications face the physical-layer challenges such as long sea-surface reflections and mainly depend on long-range satellite links or sporadic backhaul links. Maritime networks are inherently unstable and long delays make it hard to provide continuous high-quality communication [28], and enormous propagation delay makes channel state information (CSI) severely out-dated, which can result in a huge mismatch between observed environment and executed actions and even deteriorate the quality of decision-making. So, learning-based approaches might converge to locally suboptimal solutions, or fail to converge in those situations. From a cross-layer view, service continuity needs task offloading and coordinated decision-making procedures that are aware of the dependence and capable of reasoning under uncertainty, able to adapt to fragile and sporadic links and achieve efficient resource management.

2.4. *Low-altitude network*

For low-altitude networks, the impact of resource management mainly comes from high dynamic mobility of UAVs, limited energy budget and time-varying characteristic of LOS link. They are inter-coupled, resulting in change of network topology with high frequency and channel quality changing extremely greatly [29]. In optimization, the key bottlenecks lie in the high degree of coupling among the trajectories planning, propulsion power consumption, computation offloading decisions [30] and strong resource management decision issues must meet tight real-time requirements to ensure reliability of the coordination for communication and computation tasks, particularly for delay sensitive communication tasks such as emergency rescue task, the demand for extremely low decision latency is even stronger. From the perspective of cross-layer operations, the frequent topology changes make stable cross-layer resource management difficult. Consequently, UAVs must move from the role of passive relay node in the central structure to intelligent nodes that have the ability for autonomous decision, so as to adjust their maneuvering trajectory and resource allocation adaptively according to their local perception state and cross-layer services request.

2.5. *Space network*

Resource management for space networks involves massive satellite constellations that span low, medium, and high earth orbits. One key feature of a space network is its frequently evolving topology with significant signal propagation delays. The combination of high dynamics and strict delay constraints makes it very difficult to coordinate the network in real time [31,32]. High uncertainty leads to severe decision lags when applying large-scale frequency reuse and beam hopping. Because of the real-time dynamic changes in network states, the relationship between state perception and control decisions can be invalidated prior to execution. Traditional static resource slicing and reactive control strategies are unable to ensure system performance under this scenario. From a cross-layer perspective, the spatial layer is a global backbone network for wide area coverage; however due to inherently high latency it cannot be used in frequent centralized real time scheduling. Effective cross-layer coordination should therefore move towards predictive reasoning and intent-driven autonomous decision making so that satellite nodes can proactively perform resource scheduling aligned with global objectives despite information lag or incompleteness.

2.6. *Structural mismatch in cross-tier resource orchestration*

Combining these tiers introduces structural mismatches that invalidate conventional resource management. The remainder of this section will discuss the three dimensions of these key bottlenecks.

2.6.1. Objective heterogeneity *vs.* unified optimization

Traditional optimization models rely on a unified objective function to find a global optimum. However, SAGIN tiers pursue inherently conflicting goals (e.g., the energy-saving focus of UAVs *vs.* the coverage-maximization of satellites). A single mathematical model can rarely accommodate such cross-tier semantic conflicts without suffering from extreme computational complexity and loss of physical intuition.

2.6.2. Spatiotemporal scale misalignment *vs.* static policy learning

While DRL offers a path to handle dynamics, a single policy learner assumes a consistent environment distribution. In SAGIN, however, dynamics occur across vastly different timescales, ranging from millisecond-level terrestrial fading to minute-level orbital shifts. This time-scale misalignment leads to a distribution drift, where learning-based agents struggle to generalize across tiers and cannot coordinate effectively across temporal horizons. As a result, a higher-level reasoning core is necessary to decompose tasks and align decision-making across these heterogeneous timescales.

2.6.3. Partial observability *vs.* centralized control

The centralized control suffers from a high round-trip delay for maritime and space links when the GSI is delayed or inaccurate; the traditional perception-decision loop cannot sustain anymore. With Agentic AI using tool invocation and decentralized negotiation, we eliminate the dependence on global snapshots which provides an effective way in distributed autonomous coordination.

3. A taxonomy of resource management in 6G SAGINs

Complexity of 6G SAGINs have catalysed an evolution in paradigm for resource management. Resource management is moving beyond static algorithmic rules toward a fundamental shift in decision dependencies. This trajectory spans explicit mathematical models, data-driven statistical mappings, and ultimately logic-driven cognitive orchestration.

Table 2. Comparison of resource allocation paradigms in 6G SAGINs.

Feature	Optimization-Based	Learning-Based	Reasoning-Based
Modeling	Mathematical models (e.g., MINLP)	Data-driven/MDP models, interacting with the environment	LLM-based cognitive architecture with knowledge-driven planning
Decision	Closed-form or iterative solvers	Reactive state-to-action mapping	Agent loop integrating perception, memory, thought, and execution
Application	Static or semi-static planning for network resource allocation	Dynamic cross-layer resource allocation for time-varying networks	Complex on-demand resource management for autonomous networks
Strengths	Provable optimality Strong interpretability	High adaptability Superior scalability	High generalization Logical reasoning
Limitations	Model-dependency Poor scalability	Black-box nature Sample inefficiency	Inference latency Deployment immaturity
Reference	[33–35]	[36–41]	[42,43]

This section establishes a taxonomy categorized by core decision logic as summarized in Table 2. Optimization-based methods emphasize model-driven feasibility by mathematical formulation for performance guarantees but suffer from scalability issues with large-scale SAGINs. The learning-based methods mainly rely on neural networks, deep learning, and DRL to build data-driven policy mapping that allows adapting to dynamic environment without having perfect model knowledge. On the other hand, the reasoning-based method changes the paradigm into using LLM-driven agents that use LLM to conduct logical reasoning and task orchestration to facilitate high-level cognitive planning and self-reflection. In the next part of this section we will review these paradigms, emphasizing their underlying principles, representative advances, and inherent limitations in SAGIN resource management.

3.1. Optimization-based methods: model-driven feasibility

The model-driven nature of optimization-based methods guarantees resource feasibility with explicit analytical structures. The underlying philosophy lies in the analytical decomposition of objective functions and constraints using popular tools like sequential convex approximation (SCA), or dynamic programming to deal with non-convex coupling and integer constraints. Examples can be found in low earth orbit (LEO) beam-hopping [33] and network functions virtualization profit maximization [34] which allow tractable reformulation of otherwise intractable problems. For SAGIN, however, optimization-based methods remain essential in establishing theoretical performance upper bounds and serving as offline benchmarks particularly for tasks such as user association and power allocation [35], but face a dependency on accurate GSI. The high dimensional non-convexity along with large propagation delays render their computations prohibitively complex and decision making outdated (optimized solutions may be obsolete before executing). Optimization-based methods thus move away from standalone solvers toward specialized components providing precise physical layer decisions within more adaptive and hierarchical resource management frameworks.

3.2. Learning-based methods: data-driven policy mapping

Learning-based methods especially DRL move away from explicit modeling to data-driven state-to-action mapping. Forming resource allocation as a MDP allows edge nodes to learn mapping from local network attributes into optimal actions via reward-guided training [36], evolves towards multi-agent DRL (MADRL) to achieve decentralized load balancing [37], followed by graph neural networks-based meta-learning capturing topological dependencies under rapid network shifts [38]. In addition to traditional action selection, recent works use learning-based techniques to handle complex/hybrid dependencies; e.g., decision-assisted DRL addresses hybrid action space consisting of discrete offloading decisions among satellites and UAVs and continuous power control, and interdependent tasks modeled as directed acyclic graphs ensure their feasibility in constrained environments [39]. The integration of generative AI pushes this paradigm one step forward: Intelligence-Native architectures optimizes semantic communication between bandwidth efficiency and reconstruction fidelity [40]; diffusion models synthesizing intricate resource configurations for artificial intelligence-generated content-driven digital twins [41]. Despite all these advancements, learning-based approaches are reflexive with inherent generalization gap on unseen heterogeneous tiers. Their black-box nature hinders interpretability making justification/adjustment of resource allocations difficult due to mission-critical constraints. Efficient at agile/reactive decision-making but fails to offer deliberative/cross-tier reasoning required for robust 6G SAGIN orchestration.

3.3. Reasoning-based methods: logic-driven orchestration

Reasoning-based methods use LLMs as a logic-driven layer of SAGIN orchestration, prioritizing semantic understanding and tool-grounded execution. It is based upon structured reasoning and pre-trained knowledge that bridges human intent an As summarized in Table 3, the field has moved from hierarchical LLM-augmented architectures to native agentic AI.

Table 3. Evolution of reasoning-based paradigms.

Evolution Dimension	Hierarchical LLM-Augmented	Native Agentic AI (LEA)
Evolutionary Stage	Plug-in Augmentation	Agentic-Native
Role of LLM	High-level Planner	Orchestrator
Decision Logic	Task Decomposition	Agent Loop
Tool Interaction	Predefined Hierarchy (LLM + RL)	Autonomous Invocation
Generalization	Limited by the Underlying Executor	Logic-driven Zero-shot Adaptation
Closed-loop Mechanism	One-shot Feedback	Self-Reflection & Re-planning
Explainability	Planning level only	Traceable Reasoning Chains

3.3.1. Hierarchical LLM-augmented architectures

The first wave of reasoning-based methods focuses on synergizing the high-level planning of LLMs with the low-level execution of RL.

- Semantic planning: Reference [42] proposed a two-layer structure with a mixture of experts (MoE) model where an LLM is used as a logical reasoning engine for handling high-level orchestration complexities whereas specialized RL agents perform fine-grained numerical tasks.
- Intent-driven decomposition: Following that, reference [43] presented a hierarchical task network powered by LLMs. Complex user intents such as minimizing latency in video streaming over air-ground links were decomposed into structured sub-tasks, executed by MADRL modules. The hybrid structure connects human-language level to machine-resource control.

3.3.2. Native agentic AI

From hierarchical modules towards native agentic AI management is our frontier. Now LEAs do not only assist RL, they become an autonomous cognitive core orchestrating the entire network lifecycle:

- Tool-grounded reasoning: Instead of relying on a black-box policy, agents think about the SAGIN constraints, formulate a problem, and autonomously call in the right tool, e.g., a convex optimization (CVX) solver or DRL agent.
- Closed-loop self-correction: LEAs can reason and reflect upon their actions across turns. e.g., if an allocation strategy fails due to satellite link occlusion, we may have the agent analyze the feedback, revise its logical plan and re-allocate resources without extensive re-training.
- Cross-agent coordination via semantic exchange: In MAS, LEAs replace rigid signaling protocols by semantic negotiation. Heterogeneous nodes (e.g., a maritime gateway and a LEO satellite), can negotiate for resolving resource conflicts through high-level logic aligned globally with service intents.

Ultimately, this paradigm shift aims to ensure that SAGIN management is no longer limited by mathematical tractability or data availability, but is instead envisioned to be driven by cognitive intelligence potentially capable of zero shot generalization across the vast and heterogeneous 6G landscape.

4. The foundations of LEAs for SAGINs resource management

To bridge the gap between high-level service intent and low-level physical resource constraints, LEAs in SAGIN need not only to be general-purpose assistants but also act as autonomous network orchestrators that can operate at various time scales and over heterogeneous layers. In this section we introduce the main modules of LEAs with their implementation principles; discuss three mainstream multi-LEA collaboration frameworks, and finally explain how to deploy LEAs in complex networks.

4.1. SAGIN-specific core components

The SAGIN-specific core components are structured around the continuous interaction of four integrated modules: perception,memory, thought, and execution, as shown in Figure 2.

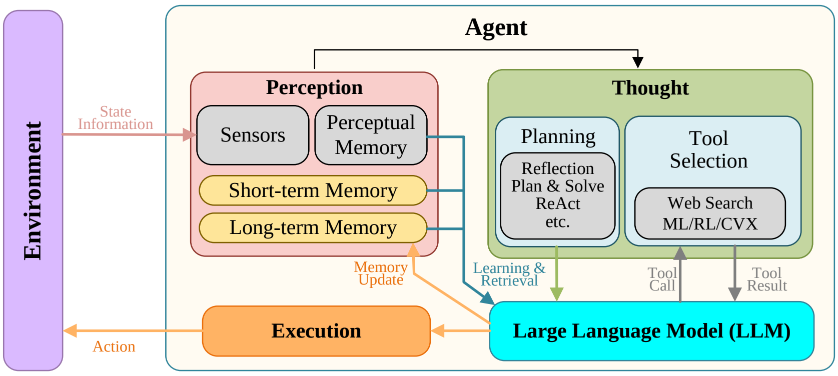

Figure 2. Reasoning-centric closed-loop.

4.1.1. Semantic perception

Sensors module provides first layer of raw data collection from both physical sensing (e.g., UAV positioning and battery monitoring), and virtual network sensing (e.g., CSI estimation and ephemeris tracking). On top of it, the perception module translates telemetry into semantics. This in SAGIN means multi-modal alignment between numerical CSI, satellite ephemeris, and UAV battery levels collected through sensors, mapped into a common semantic space. A Low-SNR state is not just a number anymore but has context like LEO link occlusion or Maritime multipath fading which enables the LLM to reason about its roots cause.

4.1.2. Knowledge-driven memory

The knowledge-driven memory forms a basis of information that enables LEAs to assist with real-time decision making as well as long term adaptation within SAGIN environments. This is generally composed by two complementary parts, working on different time-scales:

- Short-term working memory: Tracks the immediate state for the multi-timescale control loop, tracks the current sub-task status in both space and air tiers.
- Long-term strategic memory: Archives historical network fingerprints such as seasonal traffic patterns in remote areas or recurring interference profiles. By leveraging retrieval-augmented

generation (RAG), the LEA recalls that a certain optimization tool failed on high mobility UAVs and opts for a more robust learning-based tool for the current task.

4.1.3. Thought

The cognitive engine is a hierarchical planner. To maximize maritime coverage with minimum UAV energy for such a complex objective, our LEA uses chain-of-thought (CoT) or self-reflection to: (1) Identify the tier-wise dependencies; (2) Decide what sub-tasks need numerical solvers and what needs logical coordination; (3) Generate an overall execution plan aligned with 6G SLAs.

4.1.4. Execution

The execution module parses the LEA's logical conclusion into machine-executable commands (e.g., API calls for RAN slicing or SD-WAN configuration). Crucially, the outcome is fed back as Semantic Feedback, allowing the agent to understand why a certain trajectory adjustment failed and subsequently refine its long-term memory.

4.2. The dual-loop operational framework

Unlike the generic agent loop, a SAGIN-oriented LEA operates through a Dual-Loop structure to resolve the conflict between LLM inference latency and 6G real-time requirements.

- The strategic reasoning loop (slow loop): Driven by the LLM cognitive engine, this loop handles high-level logical deduction. It processes non-stationary information such as user intent shifts, mission-critical priority changes, and cross-tier topology evolution. Since LLM reasoning typically occurs on a second-level timescale, it is reserved for non-real-time orchestration and policy refinement.
- The tactical execution loop (fast loop): To achieve millisecond-level resource control, the LEA adopts a tool-grounded approach. Rather than reason about an exact beamforming vector, we invoke fast loop tools (e.g., pre-trained DRL modules on power control and CVX-based solvers for trajectory optimization). This ensures that the high-level thought is grounded into physical-layer precision without being bottlenecked by LLM token generation speed.

4.3. Multi-agent frameworks for network coordination

SAGIN's decentralized nature requires MAS as an indispensable component. We will introduce in this section three emerging LEA multi-agent frameworks mapping existing frameworks to particular network management challenges.

- AutoGen (negotiation-centric): Best suited for inter-tier resource auctions in which satellite agents and terrestrial agents need to "negotiate" frequency reuse via dialogue.
- LangGraph (topology-aware): Ideal for cross-tier routing and task offloading, where the graph-based abstraction naturally reflects the SAGIN physical topology with stateful, cyclical reasoning across hops.
- AgentScope (scalability-centric): Appropriate for massive UAV swarms or Large-scale Satellite Constellations where robust message-passing, lifecycle management of thousands of agents is required.

4.4. *Deployment stance: hierarchical reasoning architecture*

A critical prerequisite for LEAs in 6G SAGIN is the hierarchical deployment of cognitive intelligence, as running a full-scale LLM at every terminal is energy-prohibitive. We propose a three-tier deployment stance:

- Cloud-level reasoning (ground/core): Large-scale LLMs (e.g., 70 B parameters) are deployed at terrestrial core clouds to handle global strategic reasoning, such as long-term cross-tier slice planning and inter-operator negotiation.
- Edge-level coordination (satellite/HAP gateways): Medium-scale or distilled LLMs (e.g., 7 B–14 B parameters) reside at satellite gateways or high altitude platforms (HAPs). They perform regional task decomposition, translating global strategies into executable sub-tasks for local clusters.
- Terminal-level execution (UAV/BS/UE): Lightweight, task-specific agents (SLMs or quantized models) manage real-time local adjustments and tool-triggering, ensuring millisecond-level responsiveness.

5. SAGINs resources management applications of LLM-enabled agents

Resource management problems in 6G SAGINs are heterogeneous, dynamic, partial observation that might challenge traditional optimization or learning-based methods. The LEA's inherent abilities in semantic reasoning, multi-agent collaboration, and tool invocation provide a fit for such challenges. In this section we explore four representative applications, illustrated in Figure 3, where the unique properties of LEAs match best against the intrinsic demands of SAGINs, thus unveiling new degrees of flexibility and performance.

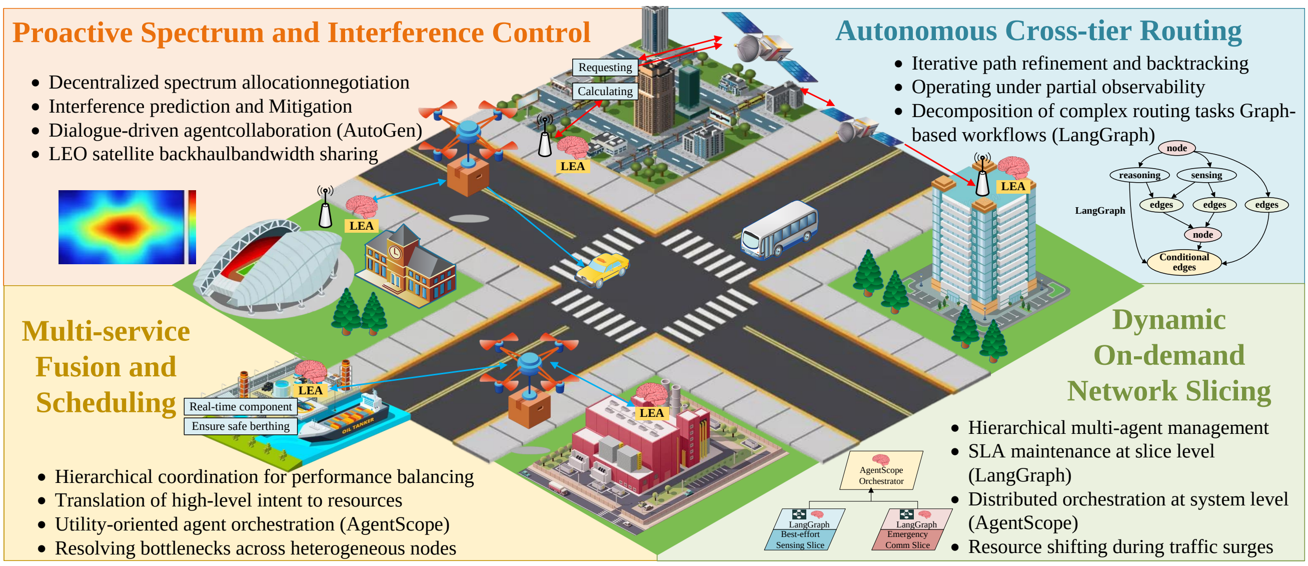

Figure 3. Future applications of LEAs in 6G SAGINS.

5.1. *Proactive spectrum and interference control*

Spectrum sharing in SAGINs across heterogeneous space-air-ground nodes is challenged by dynamic interference and nonlinear constraints. LEAs address this by transforming spectrum allocation into a decentralized negotiation process. In a typical end-to-end workflow, the agent first aggregates multi-modal telemetry, including GSI, real-time orbital trajectories from satellite ephemeris, and terrestrial buffer occupancy levels. Given this input, the LEA conducts hierarchical reasoning that breaks down complex spectrum conflicts by prioritizing mission-critical traffic in terms of negotiation tasks. In order to substantiate its logical deductions, it calls external tools like PyTorch-based interference predictors or SINR simulators to analyze possible frequency shifting strategies. The resulting orchestrated logic leads to a conflict-free spectrum consensus, greatly improving spectral efficiency while reducing packet drop rates despite intense spectral contention.

AutoGen's dialogue-based multi-agent collaboration is well-suited for such scenarios: several different role agents (e.g., LEO satellite agent, ground station agent, UAV agent), which are instantiated in a conversation group exchanging structured messages to jointly improve on allocations. e.g., if multiple LEO satellites simultaneously backhaul high-definition video to a ground station, their agents negotiate bandwidth sharing based on orbital trajectories and downlink priorities; AutoGen's automatic turn-taking and built-in feedback mechanism guarantee convergence of negotiations towards an optimal policy ensuring service continuity while requiring no constant human intervention.

5.2. Autonomous cross-tier routing

Traditional cross-tier routing algorithms require global network state knowledge that are usually not feasible for vast and dynamically reconfiguring SAGIN topologies. The LEAs overcome this challenge by being effective with partial observability via a systematic workflow: First, they ingest localized telemetry (neighbor node link quality, current battery levels of aerial platforms, high-priority traffic demands). Based upon them, the LEA conducts hierarchical reasoning to synthesize a local view of the global context, breaking down complex routing problems into sub-tasks including selecting paths at the satellite tier and scheduling aerial relays. With the ability to call external tools (graph-theoretic solvers (e.g., NetworkX), routing simulators) to validate the chosen routes' stability and latency feasibility, the agent orchestrates autonomously forming resilient data paths, thus optimizes end-to-end latency and packet delivery success rates even in volatile environments.

LangGraph is aligned with our application via their graph-based workflows: Routing decisions within this framework are organized as a directed graph that contains nodes representing LLM reasoning/tool-mediated environmental sensing; conditional edges control the logic flow by routing the shared state according to real-time evaluations. Furthermore, LangGraph supports cycles which enable iterative path refinement and backtracking—both critical in unpredictable SAGIN scenarios. For example, agents utilize such cyclic flows during disaster recovery to negotiate emergency routes under energy constraints. The feedback-driven approach guarantees reliable data delivery even without a global network map, turning routing from a static calculation into an adaptive, intent-aware process.

5.3. Multi-service fusion and scheduling

Diverse applications for communication, sensing, and computing tasks in 6G require sharing a common resource pool that requires sophisticated multi-service scheduling. The LEA orchestrates such competitions via an end-to-end workflow accepting high-level service intents along with multi-modal telemetry (ship proximity sensing data), computational task deadlines and available spectral bandwidths, performing hierarchical reasoning prioritizing safety critical sensing streams over elastic background computation, thereby decomposing its broad intent into actionable resource partitions; using external tools like CVX-based optimization solvers or specialized heuristics schedulers to fine tune these actions, which eventually optimizes the system's utility increasing sensing accuracy, task completion time, and overall throughput in dynamic and volatile port environments.

AgentScope facilitates this process through its distributed architecture and utility-oriented orchestration, enabling agents to utilize specialized tools for real-time resource estimation across heterogeneous SAGIN nodes. In maritime ports, AgentScope coordinates sub-agents, such as sensing, computing, and communication agents, to resolve resource bottlenecks through structured message exchange. This approach ensures reliable data delivery and operational efficiency, fulfilling the stringent demands of modern marine networks under volatile conditions.

5.4. Dynamic on-demand network slicing

Network slicing partitions SAGIN infrastructure into custom virtual networks according to Service Level Agreements, enabling dynamic resource sharing across heterogeneous domains. Traditional schemes use a static or centralized optimization which cannot adapt to the extreme mobility and unpredictable traffic surges of SAGINs leading to resource under-utilization and poor performance when facing rapidly changing topology or peak demands.

In order to overcome these challenges, we propose a hierarchy of multi agent architecture for network slicing in SAGINs that reconciles local service demands against global utility. We start by gathering input information such as: (1) real time traffic load telemetry; (2) specific SLA requirements; and (3) dynamic link availability on the SAGIN substrate. Slice level agents leverage it for stateful reasoning to detect possible SLA violation and converting local resource deficit into an intent driven request. To evaluate the feasibility of various slicing configurations, they call upon external tools like graph neural network based traffic predictors. Lastly, our slice level entities are orchestrated through system level agents via AgentScope for facilitating large scale coordination. The resources can be moved from best effort sensing slices to emergency communication during a sudden traffic surge. By integrating stateful reasoning with scalability allows us to have agile local response while optimizing resource utilization efficiency and SLA satisfaction rates overall.

6. Open challenges and research directions for LEAs in SAGINs

6.1. Reasoning under resource and latency constraints

The LEAs in 6G SAGINs environments suffer from strict resource and latency requirements. The limited computation, memory, and energy capacity at edge, aerial, maritime, and underground nodes limit the use of large-scale models for real-time decisions. For example, UAVs serving as temporary base stations need local processing on high-rate management and sensing data; similarly, maritime platforms and remote industrial infrastructures also have such limitations for network slicing and edge-assisted services. Lightweight model design methods like model compression, knowledge distillation, and quantization can be used to minimize computational overhead without much performance degradation. Hierarchical model partitioning and adaptive inference strategies allow a latency-aware deployment that distributes reasoning tasks over edge, aerial, and cloud resources.

6.2. Data availability and quality

LEA performance heavily depends on data availability and quality. For 6G heterogeneous networks, training data should cover very different environments including terrestrial and aerial, maritime and space to guarantee model generalization and robustness. Collecting such large-scale, high-fidelity datasets are expensive and complicated. Most network data belongs to operators and infrastructure providers with little access available for large-scale model training and evaluation. Pre-training then fine-tuning is widely used so that large foundation models can adapt with small datasets. Transfer learning and meta-learning allow reusing knowledge between related domains when facing data scarcity. Synthetic data generation via digital twins like channel-aware generative models (e.g., ChannelGPT) offers an exciting way to augment datasets and improve robustness under rare/hard-to-observed network conditions.

6.3. Reliability and security

Reliability and security issues are bottlenecks for deployment of LEA in 6G heterogeneous networks. The model hallucination leads to wrong reasoning and unsafe management action; lack of adversarial robustness make agent vulnerable against input and network state perturbation. These failures would be especially critical when managing closed loop resource management and management scenario. For improving reliability, we explore grounding and reasoning enhancement techniques. RAG provides factual grounding with integration of external knowledge source and structured reasoning like chain-of-thought prompting improves decision consistency and interpretability. Robust training strategy contribute towards stability under uncertain/noisy network condition. Regarding security, pretrained LLMs present new attack surfaces: adversarial manipulation, data poisoning, backdoor triggers, and prompt-based attacks. Biases from large-scale training corpora might be propagated into agent's decisions resulting in unfair/unsafe outcome. Despite ongoing advancements in alignment, robustness, and debiasing techniques, it is still an open research challenge to achieve trustworthy LEAs satisfying strict reliability and security requirement of 6G systems.

7. Conclusion

This article provides a systematic roadmap for resource management in 6G SAGINs, moving beyond optimization and learning-based techniques. The comparison between traditional algorithms and the operational principles of LEAs showcase that multi-agent management frameworks can be used as a robust basis for reasoning-based management. The analysis suggests that LEA-based MAS are uniquely suited for the complexities of cross-tier resource management, potentially offering enhanced superior generalization and adaptation in heterogeneous environments. Nevertheless, to bridge the gap toward practical deployment, research priorities should focus on achieving low-latency reasoning, ensuring data availability and quality, and bolstering the reliability and security of LEAs method. Ultimately, the convergence of LEAs with cross-tier network architectures is expected to open up new frontiers for autonomous SAGINs within next-generation wireless systems.

Data availability statement

No supplementary or additional data were generated in this study.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used generative AI tools only to improve language and readability. Specifically, the authors used Grammarly and ChatGPT for language polishing only. The authors take full responsibility for the content of the manuscript.

Acknowledgements

The authors highly appreciate the anonymous reviewers for their valuable comments and suggestions that helped improve this paper.

Authors' contribution

Zishan Huang: conceptualization, methodology, visualization, writing, original draft preparation; Yongjun Xu: conceptualization, supervision, project administration, review and editing; Bowen Gu: methodology, formal analysis, review and editing; Haibo Zhang: formal analysis, review and editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

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