Resource Allocation for Space-Air-Ground Integrated Networks: A Comprehensive Review

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***Abstract*—The space-air-ground integrated networks (SAGIN) has emerged as a critical paradigm to address the growing demands for global connectivity and enhanced communication services. This paper gives a thorough review of the strategies and methodologies for resource allocation within SAGIN, focusing on the challenges and solutions within its complex structure. With the advent of technologies such as 6G, the dynamics of resource optimization have become increasingly complex, necessitating innovative approaches for efficient management. We examine the application of mathematical optimization, game theory, artificial intelligence (AI), and dynamic optimization techniques in SAGIN, offering insights into their effectiveness in ensuring optimal resource distribution, minimizing delays, and maximizing network throughput and stability. The survey highlights the significant advances in AI-based methods, particularly deep learning and reinforcement learning, in tackling the inherent challenges of SAGIN resource allocation. Through a critical review of existing literature, this paper categorizes various resource allocation strategies, identifies current research gaps, and discusses potential future directions. Our findings highlight the crucial role of integrated and intelligent resource allocation mechanisms in realizing the full potential of SAGIN for next-generation communication networks.**

***Keywords*—space-air-ground integrated networks, resource allocation, 6G, optimization theory, game theory, artificial intelligence**

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I. Introduction

The explosive growth in user demand and the growing diversity of services have challenged the capabilities of conventional terrestrial wireless communication systems. To meet the increased traffic needs for a variety of applications, especially in geographically challenging environments like oceans and mountain terrains, there is an urgent requirement for future networks to manage a more complex and extensive set of resources. The space-air-ground integrated networks (SAGIN)[1], an innovative architecture that combines the capabilities of satellite, aerial, and terrestrial networks, is drawing significant attention from both academia and industry. This attention is driven by SAGIN's potential to provide complete coverage, high data transfer rates, and improved stability. SAGIN not only offers significant advantages to various practical services and applications but also faces new challenges due to its unique diversity, self-organization, and changes over time. Compared to traditional terrestrial or satellite networks, SAGIN is affected by the limited and uneven network resources from all three network dimensions, making it difficult to achieve optimal traffic transmission performance[2]. Consequently, system integration, protocol optimization, and resource management and allocation in SAGIN are extremely important. With the continued advancements in mobile communication technology, 6G is expected to further enhance the concept of SAGIN and broaden the scope of resource optimization[3]. 6G is expected to provide a key technological boost for SAGIN while also setting higher standards for resource management, protocol optimization, performance analysis, and optimization. Therefore, choosing the most suitable resource allocation method to match the characteristics of different wireless communication systems is an immediate requirement for both academia and industry. The resource allocation architecture of SAGIN is depicted in Fig. 1.

Up to now, there is a lot of literature regarding the SAGIN system architecture. As the construction of SAGIN to

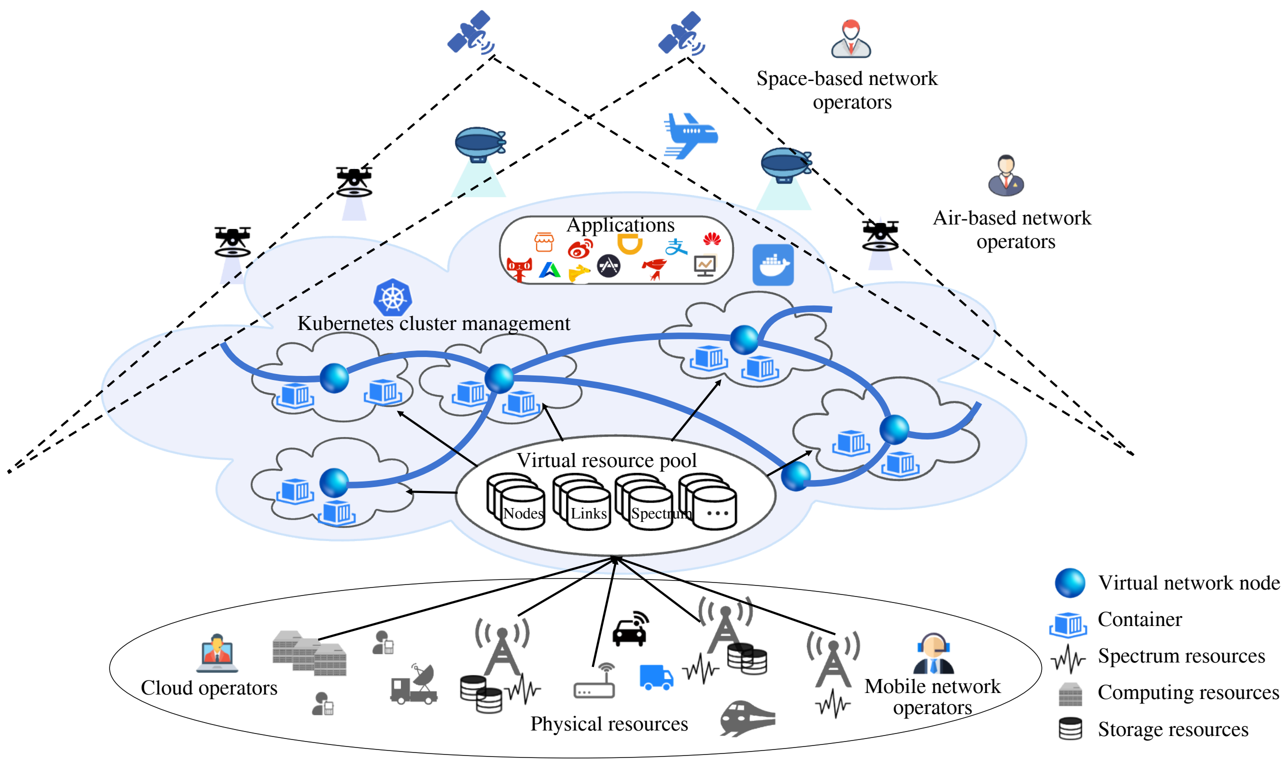

Fig. 1 Resource allocation architecture of SAGIN

support the future 6G progresses, resource allocation strategy has emerged as a key research direction. SAGIN aims to achieve complete coverage and broadband access capabilities to meet the demands of various services and applications such as the Internet of things (IoT)[31], communication in remote areas, and emergency communications. SAGIN encompasses not just simple connections among satellites, aerial platforms, and terrestrial networks, but also deep integration at the system, technological, and application levels. Studies by Cui et al.[32] show that as network architectures evolve, resource allocation strategies must adjust to working together among different components and solve problems such as high latency and restricted flexibility. Current research trends suggest that using machine learning and edge computing technologies introduces new ways for resource allocation within SAGIN, while artificial intelligence is used in the satellite communication area to improve the efficiency and smartness of resource allocation[33]. Furthermore, game theory has shown its usefulness and practical value in studies of resource allocation for satellite communication networks[34], with the main approaches outlined in research being used to explain and model complex actions among players in satellite communication networks. Game theory includes both team and individual competitions and uses a variety of different game models. Shang et al.[35] propose that inter-domain software defined network (SDN) designs can support resource management and easy switching in multi-layer SAGINs. These studies not only highlight the significance of resource allocation strategies, but also provide a theoretical and technological foundation for the efficient operation of SAGIN.

In this rapidly evolving landscape, the literature illuminates the unique scenarios that span-space-air-ground networks, pointing out their key roles in achieving the objectives of future space-air-ground integrated networks. Tab. 1 provides a comprehensive overview of these typical application scenarios, detailing their resource allocation objectives and the methods employed to address these goals. For the Internet of remote things and power Internet of things show the importance of reducing delay and increasing data transfer speed and energy use efficiency, all while keeping up with the high expectations for reliability and safety. These situations also look into the complex issues of managing resources, highlighting the use of sophisticated methods to solve these problems, from mixed integer nonconvex optimization to deep reinforcement learning. These methods are designed to serve the changing and varied nature of network settings, ensuring strength, fast communication, and instant data analysis. Importantly, bringing these networks together within SAGIN introduces special challenges and possibilities for improving data handling, coverage, and instant monitoring abilities, essential for supporting a wide range of services including emergency communications and edge computing networks. The emphasized research shows a growing interest in examining and improving resource management strategies to meet the complex needs

Tab. 1 Resource allocation in typical space-air-ground integrated networks scenarios

Typical scenarios	Ref.	Main objectives	Solution approaches	Features
Internet of remote things	[3-10]	Minimize delay Maxmize throughput Maximize revenue Minimize the energy consumption Maximizing bandwidth efficiency	Mixed integer nonconvex optimization Convex optimization Matching theory Successive convex approximation Constrained MDP	High reliability and availability Low latency Enhanced data processing
Power Internet of things	[11-15]	Minimize the energy consumption Maximizing energy efficiency Load balancing	Lyapunov optimization Lagrange dual decomposition Dynamic optimization Bargaining game	Comprehensive coverage Real-time monitoring Advanced data analytics Resilience and security
SAG vehicular networks	[16-18]	Minimize delay Maxmize throughput Reliability Network stability Minimizing packet drop rate	Reinforcement learning Deep reinforcement learning Geometric programming Genetic algorithms Differential game	High mobility support Robustness and reliability Low latency communication Enhanced data exchange
Edge computing networks	[12,19-25]	Minimize delay Quality of service (QoS) requirements Minimize service blockage probability	Integer nonlinear programming Auction theory K-means algorithm Markov decision process	Distributed data processing Scalability Real-time analytics High security and privacy
Emergency networks	[26-30]	Minimize delay Minimize packet drop rate Load balancing Maximizing bandwidth efficiency Reliability	Adaptive particle swarm optimization Heuristic algorithm Lagrange dual decomposition Deep reinforcement learning Integer nonlinear programming	Real-time information sharing Interoperable communications High bandwidth capacity Dynamic network reconfiguration

of SAGIN, marking an important step towards optimizing the interaction among satellite, aerial, and ground network resources for uninterrupted and effective communication.

However, the existing studies in this research area haven't fully developed in their review and categorization of SAGIN resource allocation methods, facing problems like offering basic explanations of the overall architecture, not enough focus on specific network situations, and a missing detailed analysis of the use of new technologies. Even though there has been progress in the use of different areas like mobile edge computing, artificial intelligence, mathematical optimization, and game theory in SAGIN resource allocation, a thorough analysis and categorization of these methods, along with their specific uses within SAGIN, are still missing. This work organizes these methods as shown in Fig. 2 intending to give network designers a clear guide, helping them more effectively choose the most appropriate resource allocation strategies for particular application situations and technology needs.

The remainder of this paper is organized as follows. Section II explores mathematical optimization methods, assessing their efficiency and adaptability for SAGIN. Section III dynamic optimization methods such as Lyapunov optimization etc., focusing on maintaining the stability and efficiency of SAGIN. Section IV delves into game theory, and examines their strategic implications in multi-decision maker environments. Section V explores AI-based methods such as machine learning and deep reinforcement learning in resource allocation. Finally, the paper is concluded in section VI with a summary of findings, implications for network designers, and suggestions for future research directions.

II. Mathematical Optimization

In the study of how to best distribute resources in networks that include space, air, and ground communications, traditional ways of solving problems, like constrained Markov decision processes (CMDP) and using a method called Lagrange dual decomposition, are very important. They help keep the network stable and reduce delays. SAGIN is complex, but we can solve tough problems known as mixed integer nonlinear programming (MINLP) by breaking them down with something called Lyapunov optimization. This is a good way to decide how to allocate resources. Also, simple but effective algorithms and more complex strategies, such as greedy algorithms, genetic algorithms, tabu search, simulated annealing, and adaptive particle swarm optimization, provide powerful ways to handle the ever-changing and complex task of managing resources in SAGIN.

A. *Classical Optimization Methods*

1) In resource allocation for the SAGIN, traditional optimization methods are still the main solutions for managing

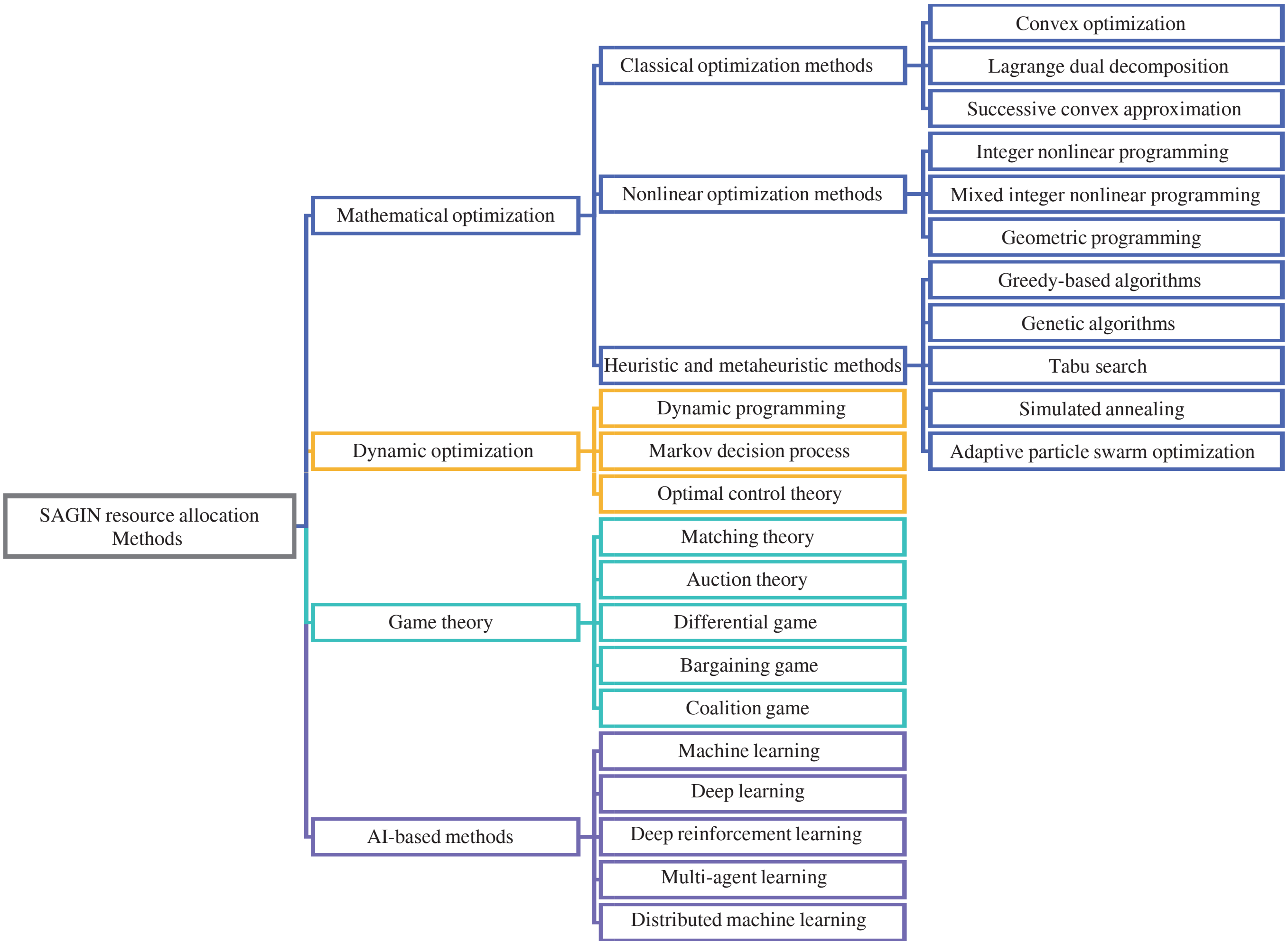

Fig. 2 A taxonomy of resource allocation for SAGIN

resources. To help IoT devices in distant areas communicate and compute effectively, researchers have come up with several optimization strategies. These include CMDP and Lagrange dual decomposition methods. The goal of these methods is to lower the average delay and energy use over time, while making sure that tasks are finished and the system remains stable.

2) CMDP provides a strong setup for making choices in systems that are constantly changing and have elements of randomness and unpredictability. For SAGIN, CMDP is used to make unmanned aerial vehicle (UAV) task-sharing more efficient, aiming to reduce the expected long-term delay in the system, as mentioned in Ref. [36]. These methods look at different aspects, such as how much area the UAV can cover, how much power it uses, and the backlog of tasks waiting to be done. The optimization method in Ref. [36] tackles the CMDP challenge by using linear programming to strike a balance between how often tasks are not completed and the average amount of energy used over time.

3) Lagrange dual decomposition is a method for breaking down complex optimization problems, which is really helpful for dealing with separate parts of the problem. In networks that combine space, air, ground, and the Internet of things (SAG-PIoT), this method helps manage the splitting up of tasks and assigning resources to devices, as discussed in Ref. [15]. It simplifies big, complicated optimization challenges by dividing them into smaller, easier-to-handle pieces. Using this method, the best ways to choose sub-channels and control power are figured out. Based on these approaches, the successive convex approximation (SCA) technique is used to set up UAVs as relays. These two smaller issues are worked on over and over again to get the most energy-efficient system possible, as shown in Ref. [28]. The method is also applied in Ref. [37] to find the best sub-channel choices and power control methods, which are then used to develop a strategy for placing UAV relays using the SCA method.

4) Convex optimization is a method for dealing with optimization problems that possess a specific structure, ensuring

the existence of a global optimum. In Ref. [38], convex optimization is applied to adapt central processing unit (CPU) cyclic frequency, while in Ref. [17], it is used for radio resource allocation issues in vehicular networks. The problem is decomposed into two steps: the first step involves solving with convex optimization, and the second step optimizes radio resource allocation through exhaustive search methods.

5) In graph-based optimization methods, we use graphs to model and solve problems like how to best allocate resources, which is known as bipartite graph matching. In Ref. [39], there's an enhanced version of the Kuhn-Munkres (KM) algorithm, which is designed to effectively distribute resource blocks (RBs) in a network. This is paired with a tiered approach to assigning power, known as multi-level water-filling. By applying what's known as an alternating descent method, this strategy can reach the best possible solution after a certain number of steps. This results in the highest possible total network performance, while also making sure resources are distributed fairly.

6) Successive convex approximation (SCA) is an essential method within the SAGIN for addressing the resource allocation challenges critical to system sustainability and efficiency, especially when involving UAVs and ground users engaged in computational tasks[23]. SCA is instrumental in managing complex non-convex optimization issues, such as bandwidth allocation and UAV trajectory optimization[40]. The strategy involves iteratively linearizing non-convex components at the current solution point and solving the resulting convex subproblems, which leads to finding local optima of the initial non-convex problem. SCA has been effectively utilized in SAGIN contexts, where UAVs perform dual roles as computational task relays for ground users and as autonomous agents with their own operational tasks. It optimizes data offloading decisions to minimize the overall energy consumption, within the constraints imposed by task-related time delays[23]. Additionally, SCA is frequently integrated with other optimization methods such as alternating optimization to address interconnected sub-problems, including user scheduling, partial offloading, computational resource distribution, bandwidth management, and multi-UAV trajectory planning. This iterative process continues until the solution converges to an optimum[41]. Furthermore, the Dinkelbach method is utilized to transform nonlinear fractional objectives into a subtractive form that is more tractable. SCA is then applied to iteratively refine key variables, effectively addressing the maximization of system spectral efficiency[37].

B. Nonlinear Optimization Methods

Nonlinear optimization poses unique challenges within SAGIN, especially when dealing with variables, constraints, and objective functions that do not follow a linear relationship. One particular instance of this is integer nonlinear programming (INLP), which comes into play when orchestrating service function chaining (SFC). Given the intricate nature of INLP, directly approaching its solution can be impractical. Consequently, heuristic methods like the greedy algorithm are commonly implemented to discover workable solutions[42]. MINLP extends the complexity of the problem by considering both integer and continuous variables in the optimization process. In the context of cooperative non-orthogonal multiple access (C-NOMA) heterogeneous air-ground integrated power Internet of things networks (PAGIC HetNets), an optimal task offloading and resource allocation strategy is proposed to minimize the energy consumption of PIoT devices[26]. This problem is a MINLP challenge due to the coupling of long-term queuing delay and short-term constraints. To address this, Lyapunov optimization is employed to decompose the problem into subproblems such as task splitting and local computing resource assignment, queue-aware channel reusing, and optimizing the aerial server resource allocation.

In another study, the issue is formulated as a MINLP problem, aiming to maximize network revenue with the help of matching games and two-tier matching algorithms[43]. Similarly, a MINLP problem is addressed with a block coordinate descent (BCD) method, where the original problem is decomposed into interconnected subproblems[44].

BCD methods are employed to tackle the challenging nonconvex MINLP problems in SAGIN, which encompass issues like scheduling connections for smart devices, managing power, and designing UAV trajectories[35]. For the UAV position optimization subproblem, given its inherently non-convex nature, SCA methods are leveraged to facilitate the solution process[9].

The problem of weight energy minimization considers transmission power control, computing resource allocation, and task offloading decisions, proposing a BCD method to iteratively solve the interconnected subproblems[45].

The objective of maximizing system capacity is expressed as a mixed integer non-convex optimization problem (MINOP). This complex problem involves the scheduling of intelligent device connections, power regulation, and the creation of UAV flight paths. To address this non-convex challenge, a proposed iterative algorithm employs strategies such as variable substitution, successive convex optimization techniques (SCOT), and the BCD algorithm[5].

Geometric programming (GP) is another approach used in optimization problems within SAGIN. A tapped geometric-water-filling algorithm is proposed to schedule traffic relay among satellites based on available service time. Configuration matrices are generated to formulate the relation between relay time and power consumption. Geometric programming with Taylor series approximation is employed to model and solve the collaborative resource allocation problem, maximizing system energy efficiency[46].

In constructing the optimization framework for SAGIN, recognizing the distinguishing features and constraints of the network's constituents, including satellites, UAVs, and ground devices, is vital. These constraints pertain to energy capacity, computational power, and connectivity. Leveraging advanced optimization techniques such as INLP, MINLP, BCD, SCA, and GP is essential in creating effective algorithms that can tackle the nonlinear resource allocation challenges within the extensive and ever-changing SAGIN landscape.

C. Heuristic and Metaheuristic Methods

In the academic community, heuristic and metaheuristic algorithms have been widely applied due to their ability to find near-optimal solutions within a reasonable time frame. This section delves into some of the heuristic and metaheuristic algorithms that have been employed in recent studies for optimizing resource allocation in SAGIN.

1) Greedy-based Solutions: Greedy algorithms, as heuristic methods, adopt locally optimal choices step-by-step in the pursuit of a global optimum. In SAGIN research, these algorithms have been applied effectively to various subproblems. Greedy-based solution for server-side resource allocation[15]: This method employs a straightforward algorithm to tackle the allocation of resources at the server level. Utilizing a greedy approach, it sequentially chooses the best resource allocation on the aerial server, promoting optimal use of computational assets. Greedy algorithm[42]: A heuristic greedy algorithm is proposed to solve the INLP problem associated with SFC planning in SAGIN. This algorithm prioritizes the use of ground network resources and leverages aerial nodes when necessary to balance resource consumption across the network.

2) Genetic Algorithm (GA): GAs are a family of computational models inspired by natural evolution. These algorithms reflect the process of natural selection where the fittest individuals are selected for reproduction to produce offspring of the next generation. Genetic algorithm (GA)[47]: GA has been applied to determine the number of controllers within each subnetwork domain of SAGIN and to establish the corresponding relationships between switch nodes and controllers. This metaheuristic algorithm enhances the global search capability of the optimization process.

3) Tabu Search (TS): TS is a metaheuristic designed to guide local search efforts to move past local optimality and explore more of the solution space. TS for dynamic virtual network function (VNF) mapping and scheduling[13]: Employing TS, this dynamic algorithm tackles the combined challenge of VNF mapping and scheduling. It dynamically adapts its mapping and scheduling strategy to the fluctuating demands of SAGIN services. SFC optimization with TS[48]: This research focuses on optimizing service function chain (SFC) orchestration in the context of SAGIN using TS. The approach specifically aims to achieve a balance in resource usage across the expansive and variable network.

4) Simulated Annealing (SA): SA is a probabilistic technique for approximating the global optimum of a given function. SA-VNA for optimization problem decomposition[49]: This technique breaks down the optimization challenge into discrete tasks of allocation and scheduling. It leverages the SA-VNA combination, which integrates simulated annealing with variable neighborhood adjustment, to progressively improve the allocation of tasks within SAGIN. Iterative algorithm based on SA and SCA[41]: An iterative algorithm based on Dinkelbach's method alternates between SA and SCA techniques to transform a nonlinear fractional objective function into a manageable subtractive form, iteratively updating the non-negative variable λ to solve the maximization problem of system spectral efficiency.

5) Adaptive Particle Swarm Optimization (APSO): APSO is an extension of the particle swarm optimization algorithm that can adapt its parameters during the search process. APSO-based intelligent coordinated scheduling algorithm (APSO-ICSA)[50]: This algorithm reduces scheduling conflicts in SAGIN by dynamically adjusting the global and local search capabilities of particles. It is particularly effective in resolving issues of bandwidth allocation and UAV deployment.

Utilizing heuristic and metaheuristic algorithms, scholars have formulated diverse strategies for refining resource allocation within the intricate and evolving milieu of SAGIN. These algorithms—encompassing greedy-based methods, GA, TS, SA, and APSO—furnish robust frameworks that effectively confront the resource management intricacies of SAGIN, thereby facilitating efficient service delivery and enhanced network performance.

Tab. 2 gives a brief summary of optimization theory based resource allocation methods in terms of the problem objective, network scenarios, performance metrics, and solution approach to get the resource allocation decision variables.

III. DYNAMINC OPTIMIZATION

The exploration of dynamic system approaches for scheduling resources in communication systems can be traced back to the seminal work of Professor S. Haykin from McMaster University, Canada[51]. In his pioneering research, Prof. Haykin was the first to equate the dynamic resource allocation problems of cognitive radio systems to a quest for equilibrium points within a dynamical system framework. By transforming traditional optimization problems into variational inequality problems, he then represented the projection

Tab. 2 A summary of optimization theory-based resource allocation methods

Ref.	Objective	Network scenarios	Performance metrics	Solution method
[36]	Minimize the long-term average system delay	LEO, UAVs, BSs, MEC	System delay, task drop rate, energy consumption	Formulated the problem as a CMDP and employed linear programming to consider stochastic channel conditions, UAV coverage, energy consumption, and task queue backlogs for problem solving
[15]	Minimize the energy consumption	LEO, UAVs, PIoT devices	Energy consumption, queuing delay, convergence performance	Lagrange dual decomposition was used to solve device-side task splitting. A low-complexity greedy-based algorithm was proposed for server-side resource allocation
[37]	Maximize the system energy efficiency	LEO, UAVs, smart devices	System energy efficiency (the total number of bits successfully transmitted to the low-orbit satellite per unit energy consumption)	The problem is formulated as a non-convex MINLP problem, which is solved using an iterative algorithm combining sub-channel selection, uplink transmission power control, and UAV relay deployment
[38]	Maximize the sum-rate	LEO, HAPs, BSs, IoT devices	Remaining battery capacity, energy consumption, maximum average sum-rate	Developed a Lyapunov-assisted multi-agent proximal policy optimization (LAMAPPO) algorithm to handle task scheduling, HAP selection, battery harvesting, and CPU cycle frequency optimization
[17]	Maximize QoS	Satellites, UAVs, edge servers	Average delay of tasks, efficient radio resource allocation	Utilized a brute-force search method for optimizing radio resource allocation
[39]	Maximize the overall capacity	Satellites, Civil aircrafts, BSs	Sum-rate, fairness, access latency, and system capacity	The power allocation subproblem in the resource allocation optimization was addressed using a convex optimization method, employing a multi-level water-filling method that satisfies the Karush-Kuhn-Tucker (KKT) conditions
[23]	Minimize the system energy consumption	Satellites, UAVs, users	System energy consumption, time delay constraint fulfillment, computation resources allocation efficiency	The energy minimization problem with time delay and computation constraints was tackled using a convex optimization strategy through a SCA algorithm to derive closed-form solutions for computation resource allocation
[40]	Minimize the weighted energy consumption	LEO, UAVs, users	Weighted energy consumption of GUs and UAVs, maximum delay constraints fulfillment for computation tasks	SCA method is used to convexify and solve non-convex bandwidth allocation and UAV trajectory control sub-problems
[41]	Maximize the system spectral efficiency	Satellites, UAVs, IoT	System spectral efficiency	Convex optimization with successively convex programming (SCP) and the Dinkelbach method was used to solve the joint optimization problem of gateway selection, bandwidth allocation, and UAV deployment, maximizing system spectral efficiency (SE)
[28]	Maximize the energy efficiency	Satellites, UAVs, BSs or MEC	Energy efficiency, quality of experience (QoE) for users, computation task completion time	Employed SCA to convexify and solve the non-convex parts of the problem related to bandwidth allocation and UAV trajectory control
[42]	Balance the resource consumptions	Satellites, HAPs, BSs, users	Service blockage probability and efficiency of resource utilization	Formulated the SFC planning problem in SAGIN as an INLP and proposed a heuristic decoupled greedy algorithm to address it, leveraging the unique features of aerial and ground nodes while balancing resource consumption
[26]	Minimize the energy consumption	Satellites, HAPs, PIoT	Total energy consumption of PIoT devices, spectrum efficiency, task backlog, and queuing delay	The problem is formulated as a MINLP problem with constraints on long-term queuing delay and multiple short-term parameters
[43]	Maximize the revenue in LEO satellites	LEO, HAPs, ground nodes	Total data priorities (revenue) received by LEO satellites, effectiveness of the proposed algorithms	Formulated the problem as a MINLP problem
[44]	Maximize the network profit	LEO, HAPs, UAVs, ground nodes	Average network revenue, successfully serving probability, and resource consumption	Formulate the joint optimization problem as a MINLP problem
[9]	Minimize the maximum computation delay	LEO, UAVs, IoT devices	Computation delay among IoT devices, fairness in resource allocation, and system energy efficiency	Developed an alternating optimization algorithm based on block coordinate descent and successive convex approximation to solve the formulated problem

Tab. 2 A summary of optimization theory-based resource allocation methods (continued)

Ref.	Objective	Network scenarios	Performance metrics	Solution method
[45]	Minimize the weighted total energy consumption	LEO, HAPs, ground nodes	Weighted energy consumption of the system and maximum task tolerance delay for ground devices	Proposed a low-complexity iterative algorithm using BCD to solve a MINLP problem by converting it into convex form and applying a convex optimization algorithm for efficient solution finding
[5]	Maximize the system capacity	LEO, UAVs, users	System capacity, which is influenced by smart devices' connection scheduling, power control, and UAV trajectory	An efficient iterative algorithm was proposed to solve a mixed-integer non-convex optimization problem. The algorithm employed variable substitution, successive convex optimization techniques, and the block coordinate descent algorithm
[46]	Maximize the network energy efficiency	LEO, hot air balloons acting as relays, inter-satellite laser links	Network energy efficiency, considering the energy consumption of caching, computing, and communication across the TSN	Geometric programming and Taylor series approximation are employed to model and solve the collaborative resource allocation problem, with a focus on maximizing system energy efficiency
[47]	Minimize the average network delay	Satellites, UAVs, users, controller	Average network delay and controller load balance	Employing a multi-objective optimization algorithm based on a genetic algorithm to improve global search capability and solve the multi-objective optimization problem
[13]	Maximize the service acceptance ratio and service provider's profits	LEO, UAVs, IoV services	Service provider's profit, service acceptance ratio, and QoS satisfaction level.	Proposed two TS-based algorithms, namely TS-MAPSCH (TS-based VNF remapping and rescheduling) and TS-PSCH (TS-based pure VNF rescheduling), to find suboptimal solutions to the MILP problem
[48]	Maximize service acceptance and enhance fairness	Satellites, users	Service acceptance ratio, fairness of satellite load, and adaptation to different types of services	Proposed a TS-based algorithm for SFC migration in dynamic LEO satellite networks to minimize service interruption and network resource wastes
[49]	Improve the efficiency of SAGIN	Satellites, UAVs, Earth-observation resources	Load fairness and profit maximization from the observation tasks	Developed a simulated annealing algorithm combined with variable neighborhood adjustment (SA-VNA) for the task allocation subproblem
[50]	Maximize the sum priorities of successfully scheduled tasks	Satellites, UAVs, ground stations	Sum priority of successfully scheduled tasks and guarantee ratio (the ratio of successfully scheduled tasks to total tasks)	Proposed APSO-ICSA, an intelligent scheduling algorithm that dynamically adjusts particles' search capabilities using adaptive inertia weight

dynamical system described by these inequalities with ordinary differential equations. This led to the significant finding that the equilibrium points of the dynamical system described by these differential equations coincide with the optimal solutions of the original optimization problem. This breakthrough paved a novel path for employing dynamic system theory to study resource scheduling issues in communication systems.

A. *Dynaminc Programming*

Dynamic programming (DP) is a method used to solve complex problems by dividing them into smaller subproblems. It is particularly effective when dealing with problems that exhibit the property of overlapping subproblems and optimal substructure, which are common in various dynamic systems such as those found in SAGIN. In the SAGIN field, DP has been utilized to tackle optimization challenges that are time-dependent and involve managing changing network conditions. For example, DP has been applied in low earth orbit (LEO) satellite networks for managing time-varying contact issues[52]. The primary goal is to ensure that the network arrangement adheres to the maximum network transmission capacity (NTC) throughout the mission duration. This is achieved by first establishing a time-varying model for the LEO satellite network and then formulating the network problem as a maximization of NTC at each time slice. Specifically, the application of DP includes constructing a time-varying model of LEO satellites, defining vertices, edges, time, and edge weights to characterize the network, and addressing the maximum NTC problem by seeking optimal satellite network arrangements at each time slice. The contact optimization scheme is then broken down into two phases: the transmission basis depth-first search (TDFS) algorithm to compute the maximum NTC network contact at a specified time slice, and the network performance graph (NPG) to exhibit the NTC performance across different time slice combinations. DP is applied to the NPG to find the optimal sequence of time slices, and together with the CMDP algorithm, it combines DP and TDFS to achieve optimal contact management of the LEO satellite network for faster and higher quality network arrangements during the mission[52].

In another study, DP is used to solve optimization problems in UAV communication within SAGIN[18]. A three-tiered device-to-device (D2D) architecture comprising UAVs, unmanned ground vehicles (UGVs), and satellite network links is proposed to ensure reliable communication links. To accomplish this, reinforcement learning (RL) based on Markov processes is employed for decision-making, and DP is used to compute the optimal strategy or control for real-time reliability of continuous data packet transmission. The application of DP includes calculating optimal strategies using RL based on global information such as flight operations, network traffic monitoring, and extra support messages. It also involves computing state transition probabilities, proposing an RL-based algorithm to calculate state transition probabilities in D2D communication, and employing DP to address the real-time reliability issue in continuous data packet transmission[18].

To address the reliability challenges of UAV communication in SAGIN, a predictive decision-making algorithm is proposed, and DP is used to solve this optimization problem[53]. Specifically, DP is applied to optimize UAV communication resources to ensure quality of service (QoS) for both control and non-payload communication (CNPC) and payload communication. The resource optimization problem is modeled as a knapsack problem, and DP is used to find the optimal solution that maximizes the total link capacity under delay constraints[53].

In an air-based information network, DP is applied to optimize energy efficiency. It is used to select an efficient communication link for each transmission while ensuring time constraints. DP minimizes energy consumption in the communication model, where energy is related to the distance between aircraft and their relative speeds[54].

B. Markov Decision Process

The Markov decision process (MDP) is a mathematical model that is used to assist in making a series of decisions to achieve a certain objective. In an MDP, the decision-maker must start from a state and influence future states by choosing a series of actions. Each action not only leads to a transition of states but may also result in some form of immediate reward or penalty. The MDP serves as a mathematical framework for modeling decision-making in stochastic environments, factoring in potential environmental changes that may affect the outcome. In the context of smart Internet of things (S-IoT) systems, the MDP is employed to optimize packet parameters, consequently minimizing the average age of error information (AoEI). The process involves defining a state space that encapsulates the system's status in each update round, including the AoEI, and an action space that outlines the possible actions at the start of each round, such as the transmission rate selected[55-56].

To address the challenges posed by the instability of inter-satellite links (ISLs) and the unpredictability of user requests in SAGIN, a pre-migration strategy for virtual network function (VNF) has been proposed[57]. This strategy utilizes MDP to model the optimization problem in SAGIN, where the state space defines the network's state at every time slot, encompassing current link status, computational resources, storage resources, and bandwidth resources. The action space, on the other hand, dictates the actions available in a specific state, such as VNF deployment decisions and virtual link mapping[57]. A VNF pre-migration model, based on the software-defined time evolving graph (SDTEG) and MDP, employs a Markov chain to estimate the arrival time of SFC request flows and the corresponding demand for VNF computational resources. By leveraging the MDP framework, the document presents a joint strategy of VNF migration and SFC routing rescheduling. Additionally, a VNF pre-migration algorithm is proposed, incorporating the softmax deep double deterministic (SD3) algorithm and the actor-critic (AC) framework, demonstrating through simulation results the effectiveness of the proposed algorithm in reducing SFC traffic delays caused by satellite topology changes and optimizing network resource load balancing to a certain degree[57].

There's also focused research on the MDP, often used in artificial intelligence (AI), which has led to many studies when combined with AI in SAGIN applications. These research directions cover various aspects of network resource management and optimization. The Monte Carlo Markov decision process (MC-MDP)[58] provides a decision-making framework for SAGIN where there is uncertainty, dynamically adjusting user access to cope with changes in business demands and network conditions, achieving a balanced distribution of network load. Deep risk-sensitive reinforcement learning[6] models the latency-oriented IoT task scheduling problem as an energy-constrained MDP, introducing risk assessment to optimize latency and reduce risk.

Queue-aware actor-critic method (QUARTER)[15] addresses the task offloading problem in SAGIN through the MDP framework, a challenge involving high-dimensional optimization. The load-balancing traffic scheduling scheme based on deep reinforcement learning (DRL)[59] applies the MDP paradigm in the decision-making process, transforming the traffic scheduling problem in SAGIN into an improved max-flow problem. The twin delayed DDPG (TD3) algorithm[60] is used for the joint allocation of subchannels and power in SAGIN, aiming to optimize the system's digital bandwidth resources while ensuring packet latency and reliability.

Furthermore, the task scheduling strategy[8] uses MDP modeling, considering the dynamic nature of IoT device tasks, the mobility of drones, and the computational power differences between drones and LEO satellites. The DRL-G algorithm[61] combines deep reinforcement learning with a greedy algorithm to optimize resource scheduling in SAGIN, enhancing resource utilization and ensuring the continuity and reliability of network services. The multi-agent deep deterministic policy gradient (MADDPG)[7] is used to address cooperation and competition issues in multi-agent environments, minimizing the average energy consumption in task offloading decisions.

In terms of storage resource optimization, distributed deep reinforcement learning[62] uses MDP to describe the resource management process of SAGIN, achieving real-time flexible resource allocation based on user requests and changing resource conditions. These applications demonstrate that MDP provides a solid framework for decision-making scenarios in SAGIN, enabling reinforcement learning and its derivative algorithms to learn optimal resource allocation, task scheduling, and network management strategies under unique challenges such as dynamic conditions, resource scarcity, and real-time decision-making requirements, thereby enhancing the overall performance of SAGIN.

C. Optimal Control Theory

A key challenge in SAGIN is resource allocation, which involves task offloading and assignment of computational resources to PIoT devices. This challenge becomes even more complex when considering the long-term queuing delay and the necessity for real-time decision-making[26]. Addressing this challenge requires advanced optimal control theory approaches, such as Lyapunov optimization, which is adept at handling system stability and optimizing system revenue over time[14].

Lyapunov optimization serves as an essential tool in control theory to maintain the stability of dynamic systems. In SAGIN, the use of Lyapunov optimization facilitates the development of joint online optimization algorithms that aim to minimize the energy consumption of PIoT devices while satisfying long-term queuing delays[30]. By transforming complex, stochastic problems into a series of deterministic subproblems, Lyapunov optimization helps in simplifying the decision-making process, ensuring that the system's stability is not compromised over time. The Lyapunov-assisted multi-agent proximal policy optimization (LAMAPPO) algorithm is an innovative approach that incorporates Lyapunov optimization to manage tasks such as scheduling, high altitude platform (HAP) selection, battery energy harvesting, and CPU cycle frequency optimization[38]. This approach is particularly useful in addressing the coupling between long-term constraints and short-term decision-making, which is a significant hurdle in SAGIN. By integrating control theory with machine learning techniques, LAMAPPO effectively balances the immediate system performance with long-term operational objectives.

Minimizing energy use in PIoT devices is a major concern in SAGIN. The issue becomes more complex with the dynamic nature of task offloading and resource distribution, where long-term queuing delays and immediate needs are interconnected[26]. Using Lyapunov optimization breaks down the problem into smaller parts that can be solved separately, leading to solutions that keep the system stable and reduce energy consumption.

Keeping system stability while maximizing system revenue is a delicate balancing act in SAGIN. The drift-plus-penalty approach, guided by Lyapunov optimization, allows for the original problem to be decoupled into four independent subproblems[14]. Each subproblem can be resolved effectively, leading to a system that adeptly admits and processes a plethora of requests, minimizes UAV dispatching costs, and stabilizes service queues in the long term.

IV. GAME THEORY

Resource allocation in SAGIN poses considerable challenges due to the network's heterogeneous and dynamic elements. Game theory offers a strategic framework to tackle these challenges by representing the interactions among different network actors as strategic games. In these games, each participant, or player, seeks to optimize their respective objectives[34]. While there is extensive literature on game theory within various network contexts, its application in satellite communication networks remains underexplored. This chapter aims to fill that gap by delivering a detailed examination of game-theoretic methods for resource allocation in SAGIN.

A. Matching Theory

Matching theory is a branch of game theory that studies the formation of mutually beneficial relationships[26]. It has been effectively applied to solve the subproblem of queue-aware channel reuse in SAGIN. The three-sided cyclic matching algorithms, including the content-oriented resource allocation algorithm (COR2A) and the user-oriented resource allocation algorithm (UOR2A), are designed to allocate resources efficiently among three entities: content sources, network equipment providers, and users[63-64]. These algorithms rely on the creation of preference lists by each entity and seek a stable matching that optimizes the overall network performance.

Given the ordered preferences of each group of participants for members of other groups, the objective in a matching theory framework is to establish stable pairings among the diverse groups[65]. Matching theory can be categorized into bipartite matching scenarios, such as male-female pairings, and tripartite matching scenarios, such as male-female-pet pairings. Bipartite matching can be further subclassified into one-to-one pairings (e.g., matrimony), one-to-several pairings (e.g., university admissions), and several-to-several pairings (e.g., file-sharing in networks).

Stability in a match implies that none of the paired individuals can find a preferable alternative match over their existing one. The renowned Gale-Shapley procedure, also known as the deferred acceptance method, is a well-established algorithm for achieving a stable match efficiently in polynomial time[66].

Matching theory has been effectively applied to computation offloading and resource allocation in mobile edge networks[67], workload balancing in vehicular edge computing[68], and data dissemination within device-to-device LTE-V2X networks[69]. These applications demonstrate the suitability of matching theory for tackling issues of resource distribution, task assignment, and network selection in satellite communications, offering numerous advantages[70]. In matching scenarios, preferences can reflect a wide spectrum of network attributes and user requirements. Decentralized matching processes and achieving stable matches are crucial for practical implementations. One of the complexities encountered is the customization of preference profiles to fit the theoretical constructs into the specific requirements of satellite communication environments.

In Ref. [71], the issue of simultaneous computation offloading and resource distribution within LEO satellite edge computing environments is explored. The primary goal of the system is to minimize both latency and power usage. This complex optimization challenge is split into a pair of more manageable sub-tasks. For the initial sub-task, a matching game approach is utilized for determining offloading strategies and an iterative approach based on coalition games is introduced to solve it, which ultimately reaches a state of Nash equilibrium. As for the subsequent sub-task, resource allocation is handled through the implementation of the Rosen gradient projection technique alongside the application of the Lagrange multiplier framework, given the offloading decisions already made. When contrasted with a standard uniform allocation model, the methods presented here lead to reduced overall system expenses, particularly in the context of latency and energy expenditure.

In the research presented in Ref. [72], the allocation of resources in satellite-terrestrial networks is formulated as a hierarchical matching problem with two distinct levels. At the upper level, a many-to-one matching framework is utilized to allocate satellite resources to terrestrial ground stations, while at the lower level, a one-to-one matching strategy is applied for linking end-users to these stations. The study proposes an interference-aware algorithm designed to optimize resource allocation with the goal of maximizing the aggregate data throughput for users. This innovative algorithm demonstrates superior performance when compared with conventional strategies, including greedy heuristics, random selection, and different adaptations of the Gale-Shapley algorithm.

Moreover, the study introduces three-sided cyclic matching algorithms—specifically, the COR2A and the UOR2A, as detailed in Ref. [63-64]. These algorithms are structured to efficiently distribute resources among three key players: content providers, network infrastructure operators, and end-users. All entities generate preference lists, which form the basis for achieving a stable match that is aimed at enhancing the overall efficiency and effectiveness of the network system.

B. Auction Theory

Auctions serve as an effective mechanism for allocating resources, using pricing to uncover participants' valuations and assign scarce assets. Single auctions gather bids and award goods to the highest bidder, with payments varying by auction type, such as the top bid in first-price or second-highest in second-price auctions. Double auctions involve both sellers and buyers, allowing for mutual trading.

While ideal auction design aims for properties like truthfulness, efficiency, rationality, and budget balance, these cannot all be achieved concurrently as per the Myerson-Satterthwaite theorem[79].

The auction method has been effectively utilized for assigning spectrum rights in terrestrial networks, favoring long-term leasing. In 2022, Romania and Estonia auctioned off multiple frequency bands, notably for 5G deployments, in the 700 MHz to 3.6 GHz range.

Auction theory addresses the allocation of resources through bidding and pricing mechanisms. In the context of SAGIN, the service-oriented fair (SOF) resource allocation problem is formulated to minimize the discrepancy between the allocated and required data rates[74].

The study in Ref. [74] addresses resource allocation in a sophisticated SAGIN, which serves civil aviation. It proposes a dual-approach solution that combines a service-oriented iterative algorithm for fair resource distribution with a double auction mechanism to optimize profits. The iterative algorithm yields results that closely approximate the optimal balance between network efficiency and fairness. Simultaneously, the auction-based method demonstrates superior profit generation compared to traditional auction approaches, as evidenced by numerical simulations.

The study detailed in Ref. [22] conceptualizes the allocation of CPU resources in satellite-aided mobile edge computing as a double auction. Within this framework, satellites or access points act as auctioneers, while mobile devices participate as buyers, and edge servers function as sellers. The research introduces two innovative double auction strategies. These strategies adhere to key theoretical properties, including computational efficiency, individual rationality, and incentive compatibility, leading to enhanced performance. Compared to existing methods, these approaches show superior results in simulations, achieving higher rates of successful transactions and improved utility.

C. Differential Game

Differential game theory, an extension of dynamic game theory adept at managing continuous-time decision-making in dynamic environments, has garnered significant attention from researchers in the field of communications. This method is especially pertinent for confronting the rapidly advancing wireless communication technologies and the intricate issue of resource sharing among multiple users. Its application facilitates the formulation and analysis of strategic interactions in systems that evolve over time, providing valuable insights into optimal resource allocation and usage in an ever-changing technological landscape.

The use of differential game theory has led to a number of representative studies that showcase its effectiveness. For instance, Su et al. have developed a differential game model for bandwidth allocation in satellite communication networks by combining differential equations with Stackelberg games. The solutions to these games were determined by solving Bellman's dynamic equations, and the methods' validity was confirmed through simulation experiments[80]. Similarly, Liu et al. proposed a model based on Stackelberg differential games for wireless network resource allocation, aimed at optimizing resource distribution in fog computing scenarios. By modeling the system's stochastic dynamics with stochastic differential equations and analyzing feedback Nash equilibria, they enhanced resource utilization and decreased system costs in fog computing networks[81]. Du's team devised mechanisms based on evolutionary and Stackelberg differential games for resource trading between cloud and edge computing service providers[82], while Lyu et al. tackled source selection and resource allocation in wireless energy relay networks through Stackelberg differential game models[83].

These differential game-theoretic approaches form a subset of the broader dynamic game theory framework, which has significantly influenced the telecommunications research landscape. Dynamic game theory is characterized by its consideration of time's role in decision-making. It differs from static game theory in that the decisions of participants are influenced not only by the current environmental state but also by anticipated future states and the decisions of other players. This forward-looking perspective has provided new viewpoints and tools for complex resource scheduling problems.

Pioneering the application of dynamic game theory in communication systems is Professor Ekram Hossain from the University of Manitoba, Canada. His groundbreaking contributions have significantly advanced our comprehension of strategic behavior and decision-making processes in networks, as evidenced by his influential publications[84-89]. Also instrumental in this field is Professor Wei Zhang of the University of New South Wales, Australia, whose notable works include a series of impactful studies[90-95]. From the United States, Professor Zhu Han of the University of Houston has markedly contributed to the literature, offering substantial insights through his research[83,96-101]. And Professor Dusit Niyato from Nanyang Technological University, Singapore, has furthered the application of these theories with a focus on areas such as resource allocation, network security, and wireless signal processing[99,102-106].

D. Bargaining Game

In the context of game theory, the bargaining model is employed to represent the negotiation processes among various entities[107]. This model encourages the entities to collaboratively reach an agreement that enables a mutually advantageous outcome over individualistic, competitive strategies. The goal is to achieve an outcome that is Pareto optimal, where the utility of one party cannot be increased without diminishing that of another, thereby ensuring an equitable distribution. Such bargaining strategies have been effectively adapted for managing resources in cognitive radio systems, promoting an equitable trade-off between system effectiveness and just treatment of both primary and secondary operators[108].

In the study presented in Ref. [75], a novel dynamic bargaining game framework is introduced for the purpose of facilitating the spectrum allocation discussions between satellite entities and ground-based networks. This innovative model is versatile, encompassing various pricing structures that range from exclusive pairwise negotiations to more complex one-to-many interactions, all the while considering the distinct preferences of different users. The study advocates for a well-reasoned pricing strategy that is geared towards securing a singular Nash equilibrium point. The robustness of this approach is supported by a series of numerical tests that validate its practicality.

The study in Ref. [76] investigates the complex task of managing transmission power and bandwidth in cognitive satellite networks capable of serving numerous users and conducting multi-beam operations. It introduces a cooperative bargaining game framework, enhanced by an algorithm that employs subgradient techniques for joint resource management. This dual strategy is carefully crafted to achieve a Pareto efficient resource distribution that balances individual user fairness with overall network capacity. The effectiveness of this innovative approach is validated through rigorous theoretical analysis and comprehensive simulation studies, which demonstrate its enhanced performance in comparison to existing resource management methods.

E. Coalition Game

Coalition game theory focuses on the strategic formation of groups, or coalitions, wherein participants collaborate to attain shared goals. Within the context of SAGIN, coalition game methods can be leveraged to optimize file delivery and sharing across low earth orbit (LEO) satellite-ground integrated networks[77]. By establishing coalitions, smaller satellites within LEO constellations can work in unison to bolster reliability and diminish operational expenses, as demonstrated in[78]. This cooperative approach enables more efficient utilization of resources and improved service quality in satellite communications.

More details of the above mentioned game theory-based resource allocation works are listed in Tab. 3.

V. AI-Based Methods

AI technologies, especially subfields such as machine learning, deep learning, and reinforcement learning, have not only provided robust support in exploring resource allocation strategies for SAGIN but have also paved new ways for optimizing network performance. Despite the continuous, widespread, and scalable nature of satellite communication, there are still pressing issues in managing resources, controlling networks, ensuring security, managing the spectrum, and reducing energy consumption that need immediate attention[33]. Fortunately, AI applications have shown great capability in tackling these problems, covering various parts of satellite communications such as changing frequencies to avoid interference, blocking jamming, predicting traffic, modeling channels, analyzing telemetry data, detecting disturbances in the ionosphere, managing interference, conducting remote sensing, modeling behavior, and managing energy in combined air-space and ground networks[33]. Ref. [29] also highlights the important contribution of deep learning in managing SAGIN's resources.

A. Machine Learning

SAGIN represents a paradigm shift in communication networks by integrating terrestrial, aerial, and space-based components to provide seamless connectivity. Machine learning, particularly AI-based methods, plays a crucial role in efficient resource allocation within these complex and dynamic networks. Here, we delve into various machine learning approaches that contribute to the advancement of resource management in SAGIN.

1) K-means Clustering: The K-means algorithm is a foundational machine learning technique utilized for clustering and classification tasks. In the context of SAGIN, advanced K-means algorithms (AKA) are employed for optimizing slice-level resource management in edge computing satellites (ECS)[19]. By clustering network domains and determining the placement and number of controllers, the k-means clustering algorithm facilitates the division of the network into multiple subnetwork domains, ensuring efficient resource distribution[47].

2) Monte Carlo-Markov Decision Processes (MC-MDP): MC-MDP algorithms offer a robust framework for decision-making under uncertainty, leveraging the Monte Carlo method for improved convergence and performance[58]. These algorithms dynamically adjust user access in SAGIN while considering the user's service requirements and network differences, leading to more balanced network load distribution across multiple networks.

3) Reinforcement Learning: Reinforcement learning techniques, particularly those employing policy networks for node embedding, are pivotal in developing adaptive strategies for traffic offloading and access mode selection (AMS). These methods enable systems to adaptively choose entry points into the network to maximize data rates in space-air-ground integrated vehicular networks (SGIVN)[16,109]. The RL-BA-VNA algorithm is an example that leverages reinforcement learning for bandwidth-aware virtual network resource allocation, prioritizing significant bandwidth requests for embedding[110].

4) Self-organized Resource Allocation Mechanisms (CHERA): Self-organizing mechanisms, such as the CHERA, utilize algorithms like K-means clustering, Greedy base station (BS) sleeping strategies, Lagrange dual methods, and Dinkelbach algorithms to establish multiple independent BS clusters for distributed energy efficiency optimization[111]. These approaches ensure resource allocation caters to the varying needs of different network segments within SAGIN.

5) Safety-oriented Resource Allocation Scheme: safety-oriented resource allocation schemes emphasize the prioritization of resources to ensure the transmission requirements for safety services in high-speed railways (HSRs). Algorithms like Q-learning are applied to solve resource allocation problems in a low-complexity manner, addressing the prioritization of safety services and network handover costs[112].

In summary, machine learning methods are instrumental in addressing the resource allocation challenges in SAGIN. These methods offer a fine-grained approach to manage resources across disparate network segments, ensuring optimal network performance and adherence to service quality requirements. By leveraging machine learning's ability to analyze complex patterns and adapt to dynamic network conditions, SAGIN can achieve the envisioned goal of providing ubiquitous and reliable connectivity.

B. Deep Learning

The SAGIN presents a multi-layered networking environment that significantly benefits from the integration of AI, particularly deep learning techniques, for optimizing resource allocation tasks. Deep learning's potential in handling complex and dynamic network structures makes it an ideal candidate for enhancing the efficiency and performance of SAGIN systems. Here, we explore the application of deep learning meth-

Tab. 3 A summary of game theory-based resource allocation methods

Ref.	Objective	Network scenarios	Performance metrics	Solution method
[26]	Minimize the energy consumption	PAGIC HetNets, communication and computing services	Energy consumption, spectrum efficiency, task backlog, queuing delay	Transform the challenge of MINLP into tractable subproblems by decoupling long-term queuing delay and short-term constraints. Address the problem of queue-aware channel reusing by optimizing subchannel assignment through a many-to-one matching approach
[63]	Maximize the system throughput	SAGINEs (e.g., drones, airships), content sources, and users	System throughput, content service provider (CSP) revenue, user experience	Three-sided cyclic matching approach: A variant of the 3-D stable marriage model with cyclic preferences (3DSM-CYC), termed as three-sided matching with size and cyclic preference (TMSC), is utilized for content service-oriented resource allocation
[64]	Optimal resource allocation strategy	Satellite-ground network scenario: users, GEO, and LEO	Average delay, satellite revenue, number of served users	Three-sided cyclic matching approach: A method that considers all three entities (GEO satellites, LEO satellites, and end users) simultaneously. The distributed nature of the matching algorithm allows for effective alteration of resource allocation in response to changing user demands and the time-varying nature of satellites
[43]	Maximize the revenue (total data priorities)	The cooperation of HAP-based massive access and LEO satellite-based backhaul	Total revenue, number of served users, time complexity	Satellite-oriented restricted three-sided matching (R-TMSC) algorithm: Proposed to handle the matching among users, HAPs, and satellites in each time slot, focusing on a stable matching with maximum cardinality
[73]	Maximize the energy efficiency in SAGIN-IPloT	Maximize the energy efficiency in SAGIN-IPloT	Energy efficiency, subchannel allocation, terminal transmission power control	A system using an LEO satellite for broad coverage and UAVs for improved communication, reusing satellite frequencies. It tackles subchannel assignment with a matching game and power control with the Lagrange dual method for simplicity
[74]	Minimize the difference between allocated and required data rates for users	A CAA-SAGIN system enabling mobile access to land networks, air platforms, and satellites	Difference between allocated and required data rates, system throughput, utility maximization for both network operators and users	Propose a user update mechanism to manage terrestrial network overload and a resource auction model to maximize utility for both network operators and users. This approach involves decomposing the problem into subproblems, applying first-order approximation, and solving it using an alternating descent iterative method
[74]	Ensure fairness in resource allocation for CAA-SAGIN	A multi-layered network architecture consisting of terrestrial networks	Fairness in resource allocation, data rate allocation in comparison to user requirements, utility in terms of economics and telecommunication	A user update mechanism and a resource auction scheme are introduced to manage network overload and maximize utility
[22]	Optimize the rationality of resource allocation in satellite MEC	A satellite MEC	Successful trades, social welfare, computational efficiency, individual rationality, incentive compatibility	Two auction mechanisms, TMF and EMF, are developed for efficient resource allocation between IoT devices and edge servers, ensuring fair distribution and adherence to auction principles
[75]	Efficient spectrum management	Operator trades unused bandwidth	Spectrum efficiency, profit maximization for satellite systems, bandwidth demand satisfaction at an affordable cost	A dynamic bargaining model is adopted where market-based mechanisms are applied to satellite spectrum allocation
[76]	Optimize total capacity	Satellite users and terrestrial networks (primary users)	Total capacity of the network, fairness among users, convergence rate of the allocation algorithm	Formulate the joint transmit power and bandwidth allocation as a cooperative bargaining game based on game theory
[77]	Total cost minimization for file delivery and sharing	LEO satellite distributes files to users, who then share them with terrestrial network users via D2D	Total cost minimization for file delivery and sharing, optimal D2D link establishment for file sharing	Prove that the CFG with group-best order is an exact potential game (EPG), ensuring stable group partition and global optimization
[78]	Optimize total capacity	A multi-beam cognitive satellite network	Convergence rate of the allocation algorithm, fairness among users, total capacity of the cognitive satellite network	Develop a cooperative resource allocation algorithm based on the subgradient method to solve the bargaining game

ods for SAGIN's resource management.

1) Deep Learning for Offloading and Caching: Deep learning has been leveraged to develop intelligent offloading and caching strategies within SAGIN. One such approach is the deployment of deep imitation learning-driven algorithms for offloading and caching[12]. These algorithms are capable of making real-time decisions by learning optimal actions through offline training. The deep imitation learning approach ensures that the resource-intensive training phase is offloaded to more powerful devices like ground stations, allowing for energy-efficient online decision-making on satellites. This is particularly useful in scenarios where satellites have limited energy supply and computing capabilities.

2) Optimizing SAGIN Performance with Deep Learning: The application of deep learning techniques to enhance the performance of SAGIN has also been explored[29]. Deep learning models, with their ability to learn from large datasets and improve over time, can optimize various aspects of SAGIN, including traffic control, handover management, and routing strategies. Such models can potentially outperform traditional optimization methods, especially when dealing with the complexity and dynamics of SAGIN.

3) Deep Learning-based Offloading Optimization Strategies: Deep learning-based strategies have been developed to optimize the computation offloading process in SAGIN[3]. These strategies involve analyzing the energy dynamics, channel conditions, and the heterogeneous computing hardware of IoT devices. By predicting the energy availability and offloading tasks accordingly, deep learning models can significantly improve task success rates and system computation rates, which are crucial for efficient resource management in SAGIN.

In summary, deep learning methods offer promising solutions for resource allocation in SAGIN by addressing its unique challenges. With advanced models and smart decision-making, deep learning can contribute to the advancement of SAGIN, ensuring that resources are allocated efficiently to meet the diverse needs of users and maintain optimal network performance. As SAGIN continues to evolve towards the 6G era, the role of deep learning in its resource management will become increasingly important.

C. Deep Reinforcement Learning

The SAGIN combines satellite, UAV, and terrestrial networks to provide continuous network connectivity for IoT devices. Despite offering widespread connectivity, this integrated network faces challenges related to fast-changing conditions and limited resources, particularly when UAVs are used as mobile computing platforms for gathering and processing IoT data. To overcome these challenges, DRL has become a popular method in academic research, offering effective solutions for autonomously optimizing task scheduling and resource distribution, ensuring service quality, and saving energy. This paper will explore how DRL is applied in the context of SAGIN and its effectiveness in optimizing the scheduling of delay-sensitive IoT tasks.

Zhou et al.[6] proffered a DRL algorithm to tackle the delay-oriented IoT task scheduling conundrum in SAGIN. The algorithm initially models the online scheduling quandary as an energy-constrained MDP. Subsequently, it develops an innovative deep risk-sensitive reinforcement learning algorithm, which, whilst learning optimal policies, appraises the risk associated with each state and searches for the optimal parameters that minimize both delay and risk. Liao et al.[15] conceived a learning algorithm dubbed QUARTER for the joint optimization quandary in SAGIN. Specifically, this algorithm, predicated on a queue-aware actor-critic method, addresses the high-dimensional optimization challenge in task offloading. Lyu et al.[24] amalgamated the actor-critic method to grapple with challenges posed by expansive state and action spaces. Zhang et al.[113] employed DRL to model the heterogeneous resource orchestration issue in SAGIN and introduced a cross-domain VNE algorithm for SAGIN. Here, the DRL method is utilized to unravel resource scheduling dilemmas in SAGIN, specifically via a bespoke policy network serving as an agent, and based on a feature matrix formed from extracted SAGIN network attributes to train the agent. Training yields the probabilities of each substrate node being embedded. Tao et al.[59] designed a DRL-based load-balancing traffic scheduling scheme for SAGIN under an SDN framework. DRL is applied in the decision-making process to enable globally optimal traffic scheduling within SAGIN. In the proposed scheme, the potential transmission capacity of envisaged links between each pair of source and destination nodes is predicted, transforming the traffic scheduling issue into a modified maximum flow problem. Liu et al.[114] resorted to the reparameterized deep deterministic policy gradient (RPDDPG) algorithm to resolve the adaptive transmission strategy problem (ATSP) in SAGIN, aiming to maximize system throughput while satisfying latency and reliability requirements for data packets. Deng et al.[60] proposed a twin delayed DDPG (TD3)-based DRL algorithm for the joint allocation of subchannels and power. This algorithm is applied to tackle the ATSP in SAGIN with the goal of optimizing system throughput while ensuring packet latency and reliability. Conversely, Wu et al.[122] addressed resource allocation issues in cloud-native networks based on TD3. In the study by Wang et al.[8], a task scheduling strategy was put forth through MDP modeling, accounting for the dynamism of task generation by IoT devices, the mobility of UAVs, and the computational disparities between UAVs and LEO satellites. This strategy aims to minimize the average energy consumption of task processing, reduce processing delay, and extend the power lifespan of IoT devices. Another study[61] integrated the DRL-G algorithm, which combines deep reinforcement learning with a greedy algorithm to optimize resource scheduling, reducing energy consumption while ensuring QoS, thereby heightening the resource utilization efficiency of SAGIN and guaranteeing the continuity and reliability of network services. The algorithm adeptly allocates heterogeneous network resources in SAGIN by amalgamating heuristic algorithms and deep reinforcement learning[61]. Moreover, multi-objective optimization issues are employed to consider the QoS requirements for different traffic types simultaneously, especially for enhanced mobile broadband (eMBB) and ultra reliable low latency communications (URLLC) slices[116].

These studies highlight the strong potential and practicality of DRL in solving SAGIN's resource allocation problems. DRL not only effectively handles the dynamic and resource-limited nature of SAGIN but also optimizes task scheduling and resource management in complex decision-making scenarios. From improving system throughput to reducing energy use, from ensuring packet reliability and timeliness to meeting diverse traffic type service quality requirements, DRL is set to drive SAGIN towards a more efficient and smart future.

D. Multi-Agent Learning

Multi-agent learning (MAL) is a subfield of machine learning where multiple agents learn or are trained to understand how to behave in an environment. In the context of SAGIN, MAL is particularly relevant due to the complex and dynamic nature of the network, where multiple agents such as satellites, UAVs, and ground stations must collaborate to optimize resource allocation and task offloading.

1) Lyapunov-assisted Multi-agent Proximal Policy Optimization (LAMAPPO): One of the innovative approaches in MAL for SAGIN is the LAMAPPO algorithm. This method is used for handling tasks such as scheduling, high altitude platform (HAP) selection, battery energy harvesting, and CPU cycle frequency optimization. The LAMAPPO algorithm integrates Lyapunov optimization techniques to ensure the stability and reliability of the network operation while optimizing the policy decisions[38]. The LAMAPPO approach is particularly effective for addressing the real-time constraints associated with energy harvesting and computational offloading without having full knowledge of future network states.

2) Multi-agent Reinforcement Learning for Edge Computing Task Offloading: Task offloading in edge computing networks also benefits from the application of multi-agent reinforcement learning (MARL), where agents learn optimal policies for offloading tasks to minimize energy consumption and completion delay[21]. By formulating the offloading problem as a Markov decision process (MDP), MARL-based schemes can be developed to obtain optimal task offloading policies, taking into account the dynamic computation requests and stochastic time-varying channel conditions.

3) Curriculum Learning-multi-agent Deep Deterministic Policy Gradient (CL-MADDPG): Another notable contribution to the field is the curriculum learning-multi-agent deep deterministic policy gradient (CL-MADDPG) algorithm. This algorithm introduces the concept of curriculum learning to the multi-agent setting, allowing for a structured and gradual learning process that can significantly reduce the average task processing delay. The CL-MADDPG algorithm is adept at learning near-optimal offloading strategies in the face of the complexity and dynamics inherent to SAGIN[8].

4) Multi-agent Deep Deterministic Policy Gradient (MADDPG): The MADDPG algorithm stands out as a robust solution for cooperative and competitive problems within multi-agent environments. MADDPG is well-suited for scenarios involving multiple IoT devices acting as decision-makers, where the task offloading decision problem is modeled as an MDP and solved by minimizing the average energy consumption of processing tasks[7]. This approach enables multiple agents to learn and make decisions that are collaborative and aligned with the overall system objectives. It is used to solve the problem of collaboration and competition in a multi-agent environment.

5) Distributed Deep Reinforcement Learning (DRL): In the optimization of storage resources in SAGIN, the application of distributed DRL offers a novel perspective for addressing highly dynamic and resource-constrained network environments[62]. With the aid of distributed DRL, intelligent agents in each edge physical domain can leverage network attributes to construct a training environment and learn how to efficiently allocate storage resources in SAGIN through interaction with the environment. This approach utilizes the MDP to describe the resource management process, achieving effective management of SAGIN's storage resources. Furthermore, the proposed SAGIN resource management framework, by integrating distributed DRL, provides real-time resource management solutions for each edge server, enabling SAGIN to flexibly adjust resource allocation strategies in response to changes in user requests and resource conditions. Simulation results show that the algorithm improves resource allocation gain and user request acceptance rate by approximately 18.15% and 8.35% respectively compared to other algorithms, demonstrating its effectiveness and flexibility in optimizing SAGIN's storage resources.

In summary, multi-agent learning, particularly through advanced algorithms like LAMAPPO, CL-MADDPG, and MADDPG, offers a pathway to effectively manage the resource allocation challenges in SAGIN. These methods allow for decentralized decision-making, where each agent learns to cooperate with others, leading to improved overall network

Tab. 4 A summary of AI-based resource allocation methods

Ref.	Objective	Network scenarios	Performance metrics	Solution method
[19]	Fine-grained resource management for Edge Computing Satellite	LEO satellite network acting as edge computing nodes	Efficiency of resource division in ECS, terminal demand evaluation on delay, bandwidth, and connection time, load balancing in ECS network	Propose an ECS framework with infrastructure and application management for demand analysis and resource virtualization, and develop an advanced K-means algorithm for optimized slice-level resource management
[58]	Maximum bandwidth resource utilization efficiency	Bandwidth resource utilization efficiency, channel utilization, convergence rate of the algorithm, system blocking rate	Propose an MC-MDP algorithm to dynamically adjust user access networks based on service requirements and network differences.	Propose an MC-MDP algorithm for dynamic adjustment of user access networks based on service requirements and network differences
[47]	Minimize the average network delay and controller load balance	Ground-based primary controllers, space-based secondary controllers, data plane comprising space-based, air-based, and ground-based networks	Average network delay, controller load balance, convergence efficiency of the deployment algorithm	Develop a multiobjective optimization model considering network delay, controller load, and use the K-means clustering algorithm to divide the data plane
[109]	Maximize the network utility function by offloading traffic to satellite	Introduce SAGIN involving satellites, UAVs, and terrestrial networks.	Signaling overhead, channel utilization, algorithm time complexity, number of iterations	Propose an MC-MDP algorithm for heterogeneous network switching, combining Monte Carlo and MDP methods to dynamically adjust user access networks and enhance performance based on service requirements and network differences
[16]	Maximize vehicles' long-term data rate	Base stations, LEO, high-mobility vehicles	Average data rate, network dynamics adaptation	Introducing a reinforcement learning-based algorithm for adaptive AMS decisions in dynamic networks without data packet arrival models
[110]	Maximize acceptance rate, and long-term reward/cost	Ground networks, air networks (UAVs), and space networks (satellites)	Long-term average reward, acceptance rate, long-term reward/cost ratio, bandwidth requirements satisfaction	Propose RL-BA-VNA, a reinforcement learning-based algorithm for virtual network resource allocation that optimizes node embedding and prioritizes high-bandwidth virtual network requests
[111]	Maximize the energy efficiency of SAG IoT Networks	A two-tier SAG IoT HetNets consisting of macrocell base stations and aerial base stations	Energy efficiency, total system data rates, total system power consumption	Propose a cluster-based HetNets energy-efficient resource allocation (CHERA) mechanism that divides the network into independent base station (BS) clusters for distributed EE optimization
[112]	Maximum safety	SAGIN for HSRs, LEO, GEO,terrestrial base stations	Data rate, bit error rate, end-to-end latency	Establish a dual C-plane connection, introduce gain and handover factors for safety service prioritization, and implement a Q-learning algorithm considering train and satellite movements for resource allocation
[12]	Minimize the task completion time and satellite resource usage	Vehicles in remote areas, edge computing-enabled LEO, MEO, GEO, ground cloud servers	Task completion time, satellite resource usage, system reward performance, accuracy of offloading and caching actions	Present a preclassification scheme to reduce the action space and propose a deep imitation learning (DIL)-driven offloading and caching algorithm for real-time decision-making
[29]	Maximum end-to-end QoE	GEO, MEO, LEO, UAVs, ground communication systems	End-to-end QoE, network throughput, packet loss rate	Propose a deep learning-based method to balance satellite traffic and improve traffic control performance
[3]	Improve the task success rate	LEO, UAVs, and 6G IoT devices	Task success rate, system computation rate	Utilize LSTM models for energy harvesting prediction and offloading decision optimization, validating the effectiveness of proposed AI techniques for 6G IoT applications through analysis and evaluation
[6]	Minimizes offloading and computing delay of all tasks	UAV, IoT devices, base station, satellite	Offloading and computing delay of all tasks, UAV energy capacity constraint satisfaction	Formulate the online scheduling problem as an energy-constrained MDP and develop a deep risk-sensitive reinforcement learning algorithm to optimize parameters for minimizing delay and risk while considering energy constraints
[15]	Minimize the energy consumption	PIoT devices, UAVs, satellites	Energy consumption, queuing delay, convergence performance	Propose QUARTER, a learning-based algorithm for queue-aware task offloading and resource allocation, decomposing the optimization problem into device-side task splitting and resource allocation, task offloading, and server-side resource allocation subproblems

Tab. 4 A summary of AI-based resource allocation methods (continued)

Ref.	Objective	Network scenarios	Performance metrics	Solution method
[113]	Long-term average revenue	Satellites, UAVs, intelligent transportation systems	VNE long-term average revenue, virtual network request (VNR) acceptance rate, revenue-cost ratio	Utilize DRL to optimize the multi-domain VNE algorithm for SAGIN, incorporating network modeling, attribute setting, policy network implementation, and evaluating algorithm efficiency through simulations
[59]	Improve global data transmission capacity	LEO, UAVs, SDN architecture	Transmission capacity of SAGIN, network load balancing	Predict the transmission capacity of links in SAGIN, formulate the traffic scheduling problem as a modified maximum flow problem, and employ a DRL model to make global optimal traffic scheduling decisions
[60]	Maximize the sum log spectral efficiency	Multibeam GEO Satcom system	Sum log spectral efficiency	Implement an enhanced DRL algorithm based on TD3 with independent training, prioritized experience replay, scaling factor, and noise rebound to address the bound action problem, and demonstrate its superior performance through simulations compared to baseline schemes
[114]	Maximize the system throughput	LEO, aerial components, base stations, UEs	System throughput, delay and reliability requirements satisfaction for traffic flows	Formulate the adaptive transmission strategy problem (ATSP) as a mixed-integer stochastic optimization problem and propose RPDDPG, a deep reinforcement learning algorithm, to optimize the transmission strategy
[24]	minimize the weighted sum of delay, energy consumption, and server usage cost	Cloud computing satellites , UAVs, IoT devices, near-user edge computing servers	System throughput, total cost, convergence speed of the learning-based computing offloading algorithm	Propose a DRL-based computing offloading and resource allocation approach for UAV edge servers to optimize offloading policies and efficiently manage computing resources and task scheduling
[7]	Minimize the time-averaged tasks processing	IoT devices, UAVs, LEO	Energy consumption, task execution delay	Develop a DRL-based algorithm to solve the problem in the dynamic aerial environment and introduce an adaptive federated DRL-based offloading method that ensures privacy protection and handles communication failures
[8]	Minimize the processing delay	IoT devices, UAVs, LEO	Average task processing delay, utilization of UAV computing resources (UAV utility function)	Model the distributed offloading problem as an MDP incorporating task generation dynamics, UAV mobility, and computing power differences, and propose a CL-MADDPG algorithm to obtain a near-optimal offloading strategy
[115]	Maximize multi-user task completion efficiency	IoT devices, UAVs, LEO, cloud servers, SDN controllers	Task completion time, energy expenditure, financial cost, SLA fulfillment, throughput, and profit	Proactive SDN-based resource management considering user priorities, latency, SLA, and budget constraints in SAGIN
[61]	Minimize energy consumption	Aircraft networks, LEO, HAPs, SDN, NFV, and MEC technologies	Service request reception rate, end-to-end delay, and average energy consumption	Implemented a hierarchical SAGIN-MEC structure and developed a DRL-G algorithm combining heuristics with deep reinforcement learning for resource allocation
[116]	Minimize latency	Satellites, UAVs, terrestrial networks, eMBB and URLLC slices	Network availability, latency experienced by eMBB and URLLC traffic, service costs	Implement a deep reinforcement learning (DRL) approach using the deep deterministic policy gradient (DDPG) algorithm for efficient resource allocation and UAV trajectory optimization
[38]	Maximize sum-rate	LEO, high altitude platforms, base stations	Average sum-rate, remaining battery capacity, energy consumption	Developed a LAMAPPO algorithm for task scheduling, HAP selection, CPU cycle frequency optimization, and energy harvesting
[21]	Minimize the computational cost	Ground users, UAVs, LEO	Average computation cost, energy consumption, and delay	Developed a MADDPG-based task offloading approach considering dynamic computation requests and time-varying channel conditions
[117]	Improve network resource utilization	Satellites, UAVs, ground devices, service providers	Long-term average revenue, SFC request (SFCR) acceptance rate, long-term average revenue-cost ratio	Employed a federated learning (FL)-based algorithm for dynamic SFC embedding, considering node attributes and resource load to balance resource consumption and SFC reconfiguration
[118]	Improve connectivity and QoS	UAVs, LEO, and central and edge learners for distributed learning	Communication delay, QoS requirements, resource management efficiency	Utilize federated learning to manage resource scheduling intelligently in SAGIN while ensuring security and user privacy, with a case study on federated reinforcement learning-based traffic offloading

Tab. 4 A summary of AI-based resource allocation methods (continued)

Ref.	Objective	Network scenarios	Performance metrics	Solution method
[62]	Optimize storage resource management	Satellites, UAVs, ground nodes	Resource allocation revenue, user request acceptance rate, and resource allocation flexibility	Proposed a SAGIN storage resource management algorithm based on distributed DRL, modeled as a MDP with distributed training across edge servers
[119]	Maximum QoS and QoE	Satellites, UAVs, ground nodes	Long-term node utilization, link utilization, long-term average revenue-to-cost ratio, and acceptance ratio	Implement a distributed DRL approach to intelligently manage edge caching capabilities and hot task caching in network nodes, aiming to reduce transmission delays and offloading pressure on space-based networks
[120]	Minimize energy consumption of UAVs	UAVs, basic RANs, and IoT devices	Efficiency of model training, energy consumption of UAVs	Employ machine learning techniques, specifically distributed machine learning, where UAVs facilitate the model training process among multiple terrestrial users
[121]	Multiobjective optimization	Satellites, UAVs, ground nodes	Throughput, service delay, coverage area, long-term node utilization, link utilization, long-term average revenue-to-cost ratio, acceptance ratio	A combined centralized and distributed multi-agent deep deterministic policy gradient (CDMADDPG) algorithm is used to optimize SAGIN slicing, considering different network components, their channel features, and service advantages

performance in terms of energy efficiency, task processing delays, and quality of service (QoS).

E. Distributed Machine Learning

Distributed machine learning is key to tackling the complexities, dynamics, and vast scale of network challenges. We outline the latest research developments, particularly how distributed DRL and federated learning (FL) are integrated into resource optimization for the SAGIN.

Stepwise learning. In the multi-objective optimization of SAGIN resource allocation, Ref. [121] introduces a combined centralized and distributed multi-agent deep deterministic policy gradient (CDMADDPG) algorithm. This algorithm initially utilizes a centralized unit to determine the optimal positioning of virtual unmanned aerial vehicles (vUAVs) and the sub-channel and power sharing among their slices. Subsequently, three independent distributed units optimize the sub-channel and power allocation within each slice, as well as the deployment of virtual base stations (vBS)/vUAVs/virtual low earth orbit (vLEO) satellites, seeking near-Pareto optimal solutions. This method allows distributed agents to independently learn and collaborate in SAGIN, achieving optimal resource allocation for different types of services.

Distributed deep reinforcement learning. Ref. [119] proposes a resource allocation algorithm for SAGIN assisted by distributed DRL. This algorithm focuses on optimizing the caching of hotspot tasks within SAGIN network nodes to reduce transmission delay and alleviate the offloading pressure on space-based networks. The application of DRL allows the network to adapt to complex environments and discover the best resource management strategies through intelligent agents interacting with the environment[120]. DRL is particularly suitable for dealing with complex scenarios involving multiple IoT devices as decision-makers, where deep reinforcement learning (DRL) is employed to handle large-scale intricate connectivity decisions and resource management issues.

Federated learning. Ref. [117] explores the potential applications of FL in SAGIN, highlighting the role of FL as a distributed learning method in managing SAGIN's resource scheduling. Advantages include reducing signaling overhead while ensuring security and user privacy. Potential applications of FL include resource allocation and dynamic node scheduling. Ref. [118] proposes a dynamic service function chaining (SFC) embedding algorithm through federated learning, balancing resource consumption by considering different characteristics and resource loads of nodes, and introduces an SFC scheduling mechanism allowing SFC reconfiguration to reduce service blocking rates. The application of FL permits data sharing and cooperative model training while protecting data privacy, thereby effectively utilizing local data and edge computing resources.

To provide a better illustration, we give a summary of AI-based resource allocation researches in Tab. 4.

VI. Conclusion and Open Research Directions

This work provides a comprehensive review of the latest advancements in resource allocation methods within the SAGIN, covering a range of approaches from mathematical optimization theory, control theory, game theory to Artificial Intelligence methords. The emphasis is on leveraging these methods to overcome the challenges of resource allocation in SAGIN amid growing demands from mobile users and Internet of things (IoT) devices.

In conclusion, resource allocation in SAGIN is a multidimensional, interdisciplinary challenge that requires a synthesis of various methods and techniques to provide solutions. With the upcoming 6G technology, these approaches will be further enhanced to support the expanding service requirements and the more sophisticated network landscape of SAGIN. Future research should concentrate on integrating these diverse methods into SAGIN's resource allocation framework more effectively and on exploiting 6G technology to advance resource management and service quality optimization.

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