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A Survey on Resource Scheduling and Optimization for Space-Air-Ground Integrated Communication-Sensing-Computation Networks

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Abstract. The development of sixth generation (6G) communications is aimed at achieving global connectivity, covering oceans and remote areas with limited ground infrastructure. With the integration of sensing, communication and computing (ISCC) technology, the space-air-ground integrated network (SAGIN) is evolving from a simple data transmission channel to an intelligent task processing platform. This paper uses a narrative review method to analyze the evolution path of resource orchestration technology in heterogeneous environments, and focuses on mathematical programming and data-driven intelligent methods to optimize resources. The existing research is classified according to the method system. This paper also examines the architecture paradigm, multi-dimensional resource modeling and algorithm system. Studies have shown that static methods such as Lagrangian dual decomposition and block coordinate descent provide the necessary performance benchmarks, and deep reinforcement learning can achieve fast response in high mobility links. In addition, this paper discusses the potential of large language model (LLM) as a semantic interpreter, which can accelerate the process of parsing task requirements into technical constraints in specific applications. This study provides a methodological reference for achieving task-centered connectivity, and believes that a hybrid framework that combines the accuracy of deterministic methods and the adaptability of learning methods is a feasible development direction for future space infrastructure.

Keywords: 6G, Space-Air-Ground Integrated Networks (SAGIN), Integrated Sensing, Communication, and Computation (ISCC), Resource Orchestration

1. Introduction

The deployment of the sixth-ground fifth-generation (5G) network has accelerated the global digitization process, but there are still many areas in the ocean, remote land and disaster-stricken areas that are not covered. In order to realize the ubiquitous connectivity vision of the sixth generation (6G) communication, incorporating the non-terrestrial network (NTN) into the unified space-air-ground integrated network (SAGIN) has become the main research direction [1, 2]. Sixth, at present, the SAGIN node has gradually changed from a data channel for simple transmission to an intelligent task processing platform with on-board processing (OBP) and environmental awareness

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capabilities [3]. The evolution has promoted the development of integrated sensing, communication and computing (ISCC) systems, in which multi-dimensional resources such as spectrum, power and CPU cycles are deeply coupled [4, 5]. Under the strict constraints of the space environment. The main goal of this paper is to analyze different resource optimization methods along a systematic approach, covering architecture evolution, decomposition-based mathematical programming, and learning-based dynamic adaptation methods. This paper identifies technical difficulties such as outdated state information, and discusses the potential of intent-driven large models in simplifying complex orchestration [6, 7]. This study aims to provide a possible implementation framework for task-centric connectivity in the 6G era.

2. Architectural systems and multidimensional resource modeling

2.1. Evolution of network architecture

The evolution of SAGIN reflects the transformation from an isolated vertical system to a multi-layer collaborative infrastructure. This shift is mainly driven by the need to support diverse 6G services in a highly heterogeneous environment.

2.1.1. Single cloud-centric architecture

Traditional network resource management relies on a single cloud-centric architecture for unified information processing through terrestrial core networks or geosynchronous orbit (GEO) satellites [8]. The architecture uses a centralized data center to carry out global resource orchestration and maintain a comprehensive grasp of the entire network state. Although this approach has strong computing power and simple management logic, it faces significant challenges in the SAGIN environment. The inherent long propagation delay of the GEO link, coupled with the large amount of signaling overhead required to return data from the network edge, often leads to outdated state information, making the decision lag behind the actual network state. Therefore, although the single cloud center mode is suitable for long-term global resource reservation, it is difficult to meet the response speed requirements of high mobility nodes such as low earth orbit (LEO) satellites and unmanned aerial vehicles (UAVs).

2.1.2. Single edge-node architecture

In order to alleviate the inherent delay problem of the centralized cloud architecture, the single edge node architecture sinks the computing power to LEO satellites and drones at the edge of the network. In this paradigm, each edge node acts as an independent resource provider, providing local computing and storage resources for task offloading. Because the processing location is close to the data source, the round-trip delay is significantly reduced, which can support real-time processing of perceptual data and low-latency communication.

However, the resource capacity of a single edge node is strictly limited by volume, weight and power. In addition, independent edge nodes often face the problem of resource fragmentation. For example, overloaded satellites are difficult to use the idle computing power of adjacent nodes to ease their burden. This architecture is an important step to achieve low-latency autonomous processing, but there are still deficiencies in the cross-domain collaboration required to perform large-scale tasks.

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2.1.3. Integrated cloud-edge-end architecture

Modern cloud edge-end integration architecture uses software defined network (SDN) and network function virtualization (NFV) to achieve cross-layer orchestration. SDN supports the dynamic deployment of controllers by separating the control plane and the data plane to minimize the delay of the control loop. NFV cooperates with virtualized hardware resources to enable the service chain to be deployed across ground, air and space domains. The architecture supports optimizing the controller position to reduce the control loop delay while ensuring global resource visibility. Through the collaboration between cloud centralized intelligence and edge fast execution, the integrated architecture provides reliable support for SAGIN 's transformation from a simple data channel to an intelligent task processing platform.

2.2. Resource allocation dimensions

The resource modeling of ISCC system needs to use a high-dimensional representation to describe the interaction between physical resources and logical resources.

2.2.1. Communication and sensing resources

In the ISCC framework, communication and sensing functions compete to use the same physical resources, including spectrum bandwidth and transmit power. Spectrum resource modeling involves the dynamic allocation of frequency blocks and the optimization of time slot ratio to balance data throughput and target detection frequency. The transmission power needs to be finely allocated, because increasing the perceived pulse power can improve the target resolution, but it will reduce the signal-to-interference-plus-noise ratio (SINR) of the concurrent communication link. In addition, beam pointing and beamforming vectors constitute important spatial resource dimensions; narrow beam and high gain beam are very important for precise positioning and high-speed directional backhaul. The deep coupling between these variables requires a unified modeling method that jointly optimizes space, time, and spectrum resources as a whole.

2.2.2. Computing and storage resources

The computing resources in SAGIN are mainly characterized by the CPU clock frequency allocated to on-board processing and edge execution. Resource modeling must consider the trade-off between local processing and task offloading, because the allocation of CPU cycles directly affects processing delay and node energy consumption. At the same time, edge cache space is an important storage resource, which determines the efficiency of content distribution and the degree of relief of backhaul pressure. An important part of computing resource modeling is virtual network function (VNF) deployment, which maps logical service components to physical nodes with sufficient computing and memory resources. Effective modeling can ensure that computationally intensive sensing algorithms and communication protocol stacks are allocated to the most appropriate nodes in the cloud edge hierarchy, thus ensuring the complete execution of end-to-end tasks.

2.3. Formulation of joint objective functions

The main goal of SAGIN resource orchestration is to maximize the success rate of tasks in complex cost-benefit tradeoffs. Therefore, it is necessary to construct a unified objective function to quantify the multi-dimensional trade-offs between conflicting performance indicators. U is designed to

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minimize end-to-end latency (Di), which encompasses both space-link propagation lag and edge-server processing delays, and system energy consumption (Ei), a critical constraint for power-limited LEO and UAV nodes. Concurrently, the function incorporates the optimization of sensing accuracy (Φi), measured by indicators such as the Position Dilution of Precision (PDOP) or the Cramer-Rao Bound (CRB). To account for varying units and scales, each metric is normalized. The integrated utility function U is represented as:

$$\min_{\mathrm{P,B,C}} \mathscr{U} = \sum\nolimits_{\mathrm{i}\in\mathscr{N}} (\alpha \mathrm{D_i} + \beta \mathrm{E_i}) - \gamma \Phi_{\mathrm{i}} \tag{1}$$

where α, β, γ denote dynamic weighting factors assigned based on real-time task urgency and environmental constraints and $\widehat{\mathrm{D_i}}$, $\widehat{\mathrm{E_i}}$, and $\widehat{\Phi_{\mathrm{i}}}$ denote normalized latency, energy consumption, and sensing accuracy, respectively. This function shifts the network from a fixed scheduling logic to a task-aware orchestration framework by punishing excessive transmit power and inefficient CPU usage while rewarding higher sensing accuracy. This mathematical foundation supports flexible priority adjustment, enabling SAGIN to adjust resource allocation strategies according to different operating scenarios and maintain robust performance in a diverse and highly mobile environment.

3. Methodology of resource optimization algorithms

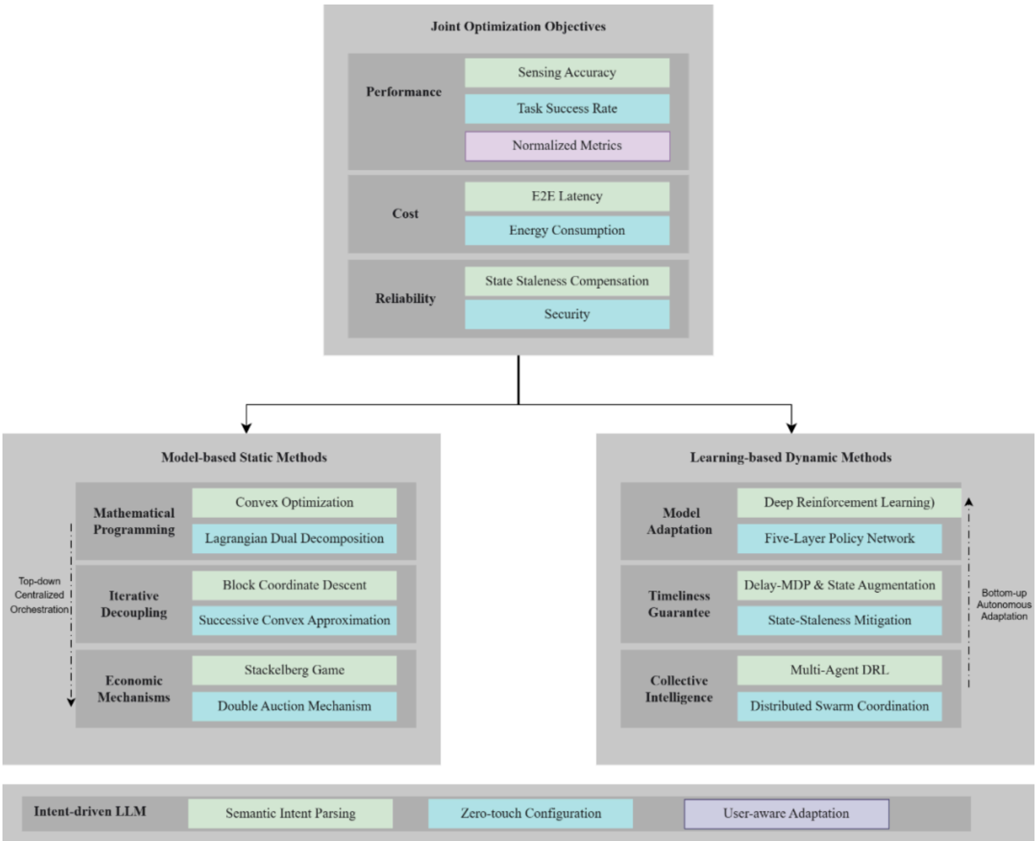

Figure 1. Methodological evolution of resource optimization

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In order to systematically sort out the research in the field of SAGIN resource optimization, Figure 1 shows the method evolution roadmap. The framework describes the technology development process from three dimensions: top-level definition of ISCC joint optimization objectives, covering performance, cost and reliability indicators; the middle part distinguishes two core paradigms. The left side represents top-down centralized management, emphasizing mathematical rigor and global control. The right side represents bottom-up distributed learning, focusing on the autonomous adaptation of edge agents. The horizontal axis represents the path from fixed deterministic planning to fully autonomous intelligent evolution. This chapter will analyze the principle and application of representative algorithms based on the roadmap.

3.1. Optimization methods for quasi-static scenarios

3.1.1. Exact optimization via Lagrangian dual decomposition

In order to achieve the theoretical upper bound of resource utilization efficiency, the exact optimization algorithm transforms the constrained objective function into a solvable dual problem [9]. By introducing Lagrangian multipliers λ and ν for the power and bandwidth constraints, the augmented Lagrangian function $\mathscr{L}$ is formulated as:

$$\mathscr{L}(\mathrm{P},\mathrm{B},\mathrm{C},\lambda,\nu) = U(\mathrm{P},\mathrm{B},\mathrm{C}) + \sum_{\mathrm{j}} \lambda_{\mathrm{j}} \mathrm{g}_{\mathrm{j}}(\mathrm{P},\mathrm{B}) + \sum_{\mathrm{k}} \nu_{\mathrm{k}} \mathrm{h}_{\mathrm{k}}(\mathrm{C}) \tag{2}$$

where g_{j} and h_{k} represent the physical resource constraints defined in Section 2.3. The optimal allocation is reached by iteratively solving the dual function $\mathrm{D}(\lambda, \nu) = \min \mathscr{L}$. In quasi-static scenarios, Lagrangian dual decomposition is used to decouple complex resource constraints. Although this method can approximate the theoretical upper bound in convex problems, in non-convex ISCC environments, it mainly provides performance benchmarks or obtains local solutions with non-zero dual gaps.

3.1.2. Block coordinate descent for variable decoupling

In ISCC systems, variables such as beamforming vectors w and computing offload ratios f are highly coupled, rendering the problem non-convex [10]. The block coordinate descent (BCD) algorithm optimizes one set of variables to find the stationary point while fixing other variables.

$$\mathrm{w}^{(\mathrm{k}+1)} = \arg\min_{\mathrm{w}} \mathscr{U}\left(\mathrm{w},\mathrm{f}^{(\mathrm{k})}\right), \quad \mathrm{f}^{(\mathrm{k}+1)} = \arg\min_{\mathrm{f}} \mathscr{U}\left(\mathrm{w}^{(\mathrm{k}+1)},\mathrm{f}\right) \tag{3}$$

This iterative optimization process continues until the system converges to a stationary point. BCD is an important tool to balance the allocation of sensing and communication resources. It can obtain an approximate optimal solution with low computational overhead under quasi-static network snapshots.

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3.2. Scheduling algorithms for dynamic scenarios

3.2.1. Deep reinforcement learning with policy mapping

In response to the high-dimensionality and time-varying nature of SAGIN, the framework based on deep reinforcement learning (DRL) uses neural networks to map network states directly into resource allocation actions [11]. In the context of virtual network embedding (VNE), the probability p_i of selecting a physical satellite node i is calculated using the Softmax function within a multi-layer policy network:

$$p_i = \frac{\exp(z_i)}{\sum_{n \in \mathscr{N}} \exp(z_n)} \tag{4}$$

Where z_i represents the resource score of the i th physical node, which is extracted by the convolutional layers from a high-dimensional feature matrix containing CPU capacity, bandwidth, and node distance. The mapping mechanism converts the continuous state space into a discrete probability distribution, so that the agent can instantly select the satellite or air node that is most suitable for the deployment task.

3.2.2. State-delay compensation via trajectory prediction

In high mobility LEO satellite-terrestrial networks, there is a significant time difference between state observation and corresponding action execution due to propagation delay and control feedback period. In order to solve the problem of outdated state information, the framework proposed by Xie models resource orchestration as a delay-aware Markov decision process. Its core innovation is the state augmentation technology, which transforms the system with action delay into a standard Markov process. Specifically, the system state is redefined as a combination of current local observations and previously issued but unconfirmed action sequences. The augmented state $\mathscr{S}_t^{aug}$ is formulated as:

$$\mathscr{S}_t^{aug} = \left\{ s_t, a_{t-d}, a_{t-d+1}, \ldots, a_{t-1} \right\} \tag{5}$$

where, s_t represents the current local features such as CPU load, while $\{a_{t-d}, \ldots, a_{t-1}\}$ includes the decisions in transmission within the delay window d. Using this augmented representation as input to a Double Deep Q-Network, the agent learns how pending actions affect future network states. Different from the simple trajectory prediction method that only extrapolates physical coordinates, the state augmentation method considers the cumulative impact of resource allocation decisions that are still in transmission. The results show that the framework can significantly improve the task success rate under high delay conditions and achieve effective closed-loop control a in high-speed rail environment.

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3.2.3. Distributed multi-agent collaborative learning

For a giant constellation containing thousands of satellites, the centralized control architecture faces serious scalability bottlenecks and a large amount of signaling overhead. In order to alleviate these problems, multi-agent deep reinforcement learning (MADRL) can be used to realize distributed intelligent orchestration [12, 13]. Following the Centralized Training and Distributed Execution (CTDE) paradigm, each satellite agent i updates its individual policy θ_i while considering the actions of its neighbors. The gradient of the expected total return $J(\theta_i)$ for agent i is formulated as:

$$\nabla_{\theta_i} J(\theta_i) = E_{s,a\sim\mathbb{D}}\left[\nabla_{\theta_i}\mu_i(a_i s_i)\nabla_{a_i}Q_i^{\mu}(s, a_1, \ldots, a_N)\right] \tag{6}$$

where, μ_i denotes the actor network of the i-th agent, and Q_i^{μ} represents a centralized critic that utilizes the global state s and the joint action vector $\{a_1, \ldots, a_N\}$ to provide feedback. This mechanism enables satellites to form a collective consensus on frequency reuse and interference coordination during the training phase, and make local decisions independently during the operation phase. By mitigating the nonstationarity of the environment, the MADRL framework supports scalable resource management, making the resource orchestration of ultra-large-scale infrastructure both resilient and communication efficient.

4. Conclusion

This study shows that the choice of SAGIN resource orchestration method depends on the specific application scenarios and diverse task requirements. Through the analysis of the integrated perception, communication and computing (ISCC) system, it is found that the model-based solution method can provide performance benchmarks for quasi-static links, while deep reinforcement learning (DRL) has the responsiveness suitable for dynamic LEO environments. For user-centered complex tasks, the large language model (LLM) is expected to speed up the process of parsing task objectives into technical constraints. Therefore, a hybrid framework that combines the accuracy of deterministic methods with the adaptability of learning methods according to operational requirements is a promising development path for resource orchestration management. Despite the above understanding, this paper still has limitations to be improved. Specifically, this study has not yet explored the hardware-level energy trade-offs involved in deploying lightweight LLM on a power-constrained LEO platform, nor has it analyzed the resource competition among different operators in the giant constellation. Filling these research gaps will help strengthen multi-domain coordination to support diversified 6G services. The shift to task-aware orchestration will provide important support for the realization of ubiquitous connections and connections that can perceive user needs.

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