Bridging Terrestrial and Non-Terrestrial Networks: A Novel Architecture for Space-Air-Ground-Sea Integration System

Xin Wang, Bo Yi, Saru Kumari, Chien-Ming Chen, Shalli Rani, Keqin Li, and Jianhui Lv

Abstract

With the rapid evolution of wireless technology and the expansion of human activities, the integration of terrestrial and non-terrestrial networks, encompassing 5G/6G and the Internet of Things (IoT), is becoming essential for future networking paradigms. These integrated networks must support extensive spatial and content coverage, serving diverse environments from urban landscapes to remote regions such as mountains, deserts, oceans, underground areas, and airspace. While 5G/6G technologies offer significant improvements, their widespread deployment faces challenges, including high infrastructure costs and difficulties in covering extremely remote or inaccessible areas. To address these challenges, we design and propose a novel space-air-ground-sea (SAGS) integration architecture that builds upon terrestrial networks and supplements them with non-terrestrial networks, aiming to provide ubiquitous, intelligent, collaborative, and efficient information support across vast spatial domains. Our approach focuses on three critical aspects: global situation awareness, leveraging reinforcement learning, graph convolutional networks, and multi-modal data fusion to enhance situational awareness and decision-making; reliable transmission, ensuring robust data transmission by mitigating environmental conflicts and optimizing communication pathways across space, air, ground, and sea; and dynamic time-varying scheduling, formulating a multi-objective scheduling optimization model to minimize uncovered areas, energy consumption, and operational spans, adapting to the time-varying nature of services in the SAGS environment. Key contributions of this work include a comprehensive SAGS architecture that integrates advanced AI techniques to optimize network performance and experimental validation, demonstrating that our proposed SAGS outperforms state-of-the-art methods by specific percentages in terms of convergence efficiency, latency, and throughput, which highlights the system's feasibility and effectiveness.

Introduction

With the advancement of wireless technology and the expansion of human activity spaces, novel network technologies such as 5G/6G and the Internet of Things (IoT) are gradually becoming the primary focus of future terrestrial and non-terrestrial networking. Compared to the communication needs of ordinary individuals, communications for both terrestrial and non-terrestrial networks will experience significant expansion in terms of spatial and content coverage [1]. A diverse array of IoT devices and services will span a broader range of areas, including spaces, mountains, deserts, oceans, underground locations, and skies, which can be divided into either terrestrial networks or non-terrestrial networks. Aiming at such principle, the bridging between terrestrial and non-terrestrial networks becomes vitally important, where the final goal is to fulfill their deep integration [2].

Targeting such diverse environments and goals, 5G/6G and IoT have provided more flexible services, greater capacity, and higher efficiency for emerging applications such as virtual reality, autonomous driving, and smart cities, using specific technologies such as the Ultra-Reliable and Low-Latency Communication (URLLC) and massive Machine-Type Communication (MTC). In addition, the Narrowband IoT (NB-IoT), beamforming, and uplink/downlink decoupling that are actively promoted by 5G/6G can naturally address the emerged challenges of wide-area coverage, high energy consumption, and large-scale connectivity when fulfilling the bridging between terrestrial and non-terrestrial networks [3]. While 5G/6G technologies promise significant advancements, their extensive deployment comes with substantial financial and logistical challenges. The rollout requires considerable investment in infrastructure, including dense base station deployments and backhaul network construction. Additional costs include the installation, leasing, and maintenance of optical fibers, all of which contribute to high capital expenditures. Moreover, terrestrial networks face limitations in covering extremely remote areas such as oceans, deep underground locations, skies, and deep space. These geographical constraints make it difficult to bridge terrestrial and non-terrestrial networks, thereby hindering the achievement of ubiquitous communica-

Xin Wang and Bo Yi (corresponding author) are with Northeastern University, China; Saru Kumari is with Chaudhary Charan Singh University, India; Chien-Ming Chen is with Nanjing University of Information Science and Technology, China; Shalli Rani is with Chitkara University, India; Keqin Li is with State University of New York, New Paltz, NY; Jianhui Lv (corresponding author) is with The First Affiliated Hospital of Jinzhou Medical University, China.

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tion across an expanded network space [4].

The focus has increasingly shifted toward integrating terrestrial and non-terrestrial networks to achieve seamless connectivity across space, air, ground, and sea. This integration aims to build a comprehensive infrastructure that leverages both terrestrial and non-terrestrial components to provide ubiquitous, intelligent, collaborative, and efficient information support for various network applications across vast spatial domains [5]. Terrestrial networks, primarily consisting of the Internet and mobile communication networks, cover ground and sea environments and deliver services in densely populated areas. Non-terrestrial networks, comprising high-altitude communication platforms, Unmanned Aerial Vehicles (UAVs), and satellite systems, extend coverage to space and air, enabling global connectivity and broadband access [6]. The Space-Air-Ground-Sea (SAGS) integrated network builds on existing terrestrial infrastructure, supplemented by non-terrestrial components, to offer comprehensive support for diverse applications.

However, achieving deep integration between these layers presents significant challenges [7]. Environmental variability in space, air, and sea can affect communication reliability, making it crucial to ensure robust performance under changing conditions [8]. Covering such a vast expanse—from space to ground and sea—requires sophisticated environmental perception and coordination across different layers. Inadequate cooperation can hinder decision-making and lead to significant losses [9]. Moreover, the services within the SAGS system are subject to temporal changes; delays in perception and reliability assurance can render previous decisions obsolete, leading to increased time and energy costs [10]. To overcome these challenges, the integration process must break down barriers between space, air, ground, and sea, fostering seamless interoperability and ensuring reliable and efficient communication across all domains.

Therefore, according to the above consideration, the design of the space-air ground and sea integrated network architecture for the new-type air-space-ground-sea collaborative scenario not only necessitates multi-dimensional and distributed sensing and detection but also requires real-time and stable communication transmission. In this point, we propose a novel Space-Air-Ground-Sea (SAGS) integration architecture, in which the global perception, reliability guarantee, and dynamic time-varying scheduling services are essentially achieved to meet the demands of multi-dimensional sensing, collaborative transmission, and intelligent computing, thereby enabling intelligent processing, decision-making, and control of perceived information to better support the development of novel intelligent services.

The rest of this work is summarized as follows: The next section introduces the main motivation and contributions. After that, we propose the integration system and methods. We then present the experimental results and finally conclude this work.

Motivations and Contributions

Motivations

The integration of space, air, ground, and sea poses new demands for global, all-domain, and all-time information services. Key issues such as inadequate network coverage, rigid network structures, and slow service responses are pressing matters that require immediate attention [11]. On the one hand, such integration can provide continuous support for full-time and full-space information, enabling coverage in the global areas and thereby satisfying the information service demands of vital land-based economic belts and overseas hotspot regions. On the other hand, satellite systems, particularly Low-Earth-Orbit (LEO) satellite constellations, possess significant potential challenges in terms of communication coverage and broadband access [12]. The scarcity of resources such as satellite orbital slots and space communication spectrum has intensified the international competition for these resources.

In addition, the integration of these networks presents a well-known challenge: the resulting system is a heterogeneous and multi-dimensional network characterized by extreme complexity in its structure. This complexity arises from the fusion of multiple networks and the diversity of available resources. The distinct dynamic characteristics of space, air, ground, and sea networks further complicate overall network mobility compared to terrestrial-only networks, making it difficult to accurately describe and model the integrated system [13]. Moreover, the integrated system must support a wide range of services for space-based, air-based, ground-based, and marine information operations. The diverse service characteristics and stringent Quality of Service (QoS) requirements pose significant challenges for network resource allocation and service orchestration. Traditional optimization methods struggle to meet these demands, often leading to inefficiencies and slow response times.

Intelligent methods, such as artificial intelligence (AI) based ones, are considered highly potential solutions for complex and dynamic problems that are difficult to model, for example, in the space, air, ground, and sea integration scenario. By extracting and analyzing vast amounts of data, AI can establish optimal mapping models for network environments and network control, enabling efficient and intelligent network design, control, management, and optimization. Using reinforcement learning as an example can help us learn the optimal action strategies through feedback from the agent's interactions with the environment. It can also handle learning decisions in unknown network environments, making it well-suited to the complex and high cost of network data collection in such an integration system. However, reinforcement learning is not enough to address optimal network control, resource allocation, service orchestration, and other similar challenges that are closely related to the dynamically changing characteristics faced by space, air, ground, and sea environments [14].

Moreover, the influence of the space and marine environment leads to the sudden mobility of nodes in the sky or ocean, posing significant challenges to network communication services and business data transmission [15]. In this regard, the unreliability of network communication services and data transmission can result in the unobservability of system states and loss of partial control command information, which not only severely impacts system performance but also significantly degrades user experience. These challenges are

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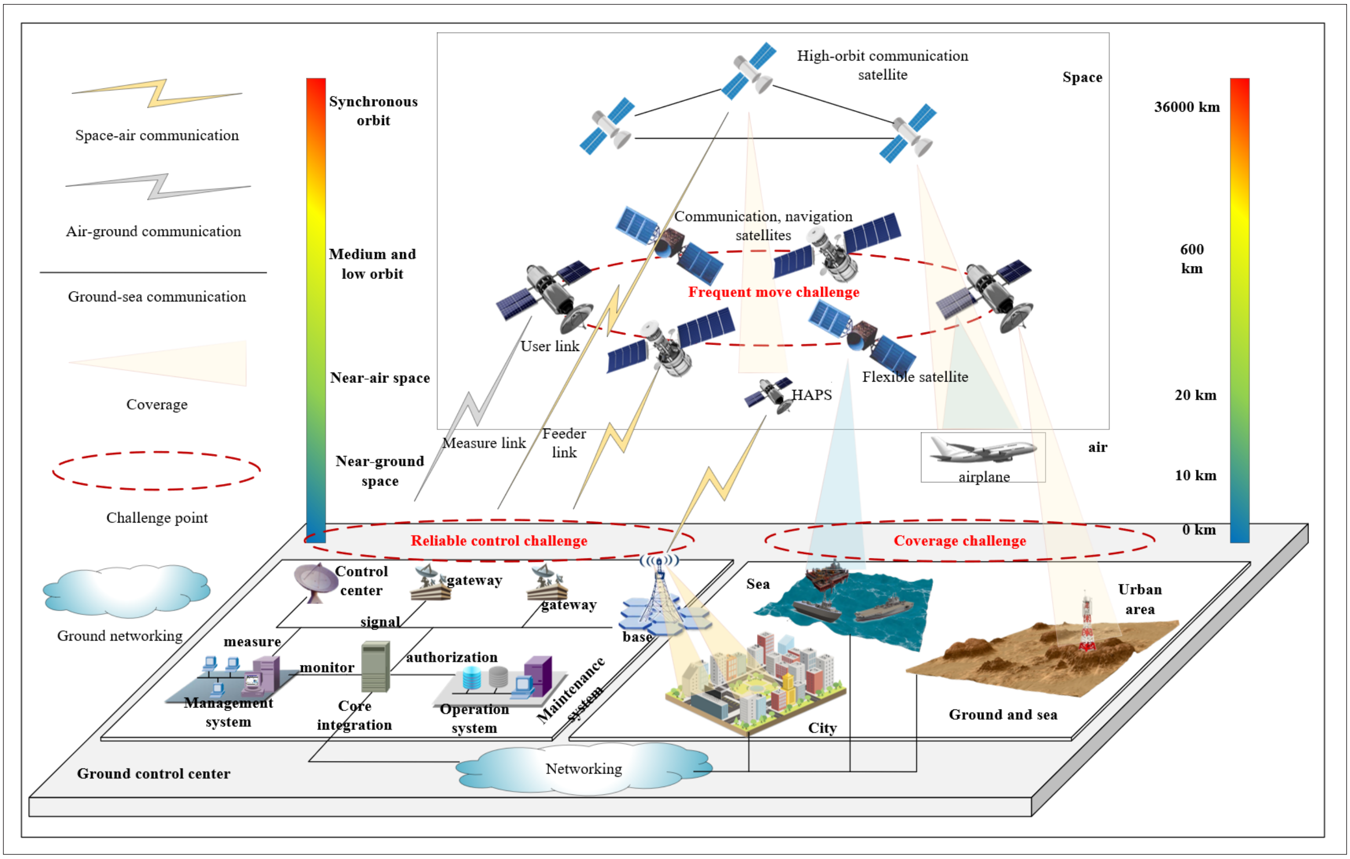

FIGURE 1. Motivation and contribution illustration.

illustrated in Fig. 1.

Contributions

To address the above challenges faced by the integration of space, air, ground, and sea, this work proposes a novel integration architecture (i.e., SAGS), in which the space, air, ground, and sea can be connected smoothly in which the unique abilities and contributions of global situation awareness, heterogeneous reliable transmission, and time-varying service scheduling are enabled as indicated in Fig. 1, as follows:

- Firstly, we design a comprehensive SAGS integration architecture to optimize the communication among devices from space, air, ground, and sea, in which the abilities of global situation awareness, communication reliability guarantee, and time-varying service scheduling are achieved all around the domain.
- Secondly, global situation awareness is implemented in SAGS, where it employs federated reinforcement learning techniques, in conjunction with graph convolution networks and multi-modal data fusion methods, to fulfill the perception requirements for network environments, traffic, and time-varying services in the wide-area coverage network scenarios, which then can be used to make the decision toward the reliability guarantee and scheduling, while satisfying various application requirements.
- Thirdly, to guarantee data transmission reliability across space, air, ground, and sea zones with wide-area coverage, we propose a reliable transmission mechanism tailored to the mobile characteristics of the space-air-ground-sea network. Leveraging artificial intelligence techniques, it computes reliable transmission paths for various types of services within the integrated space-air-ground-sea network. During this, the objective is to maximize communication reliability and resource utilization while avoiding external environmental conflicts at the same time.
- Lastly, due to the uncertain impacts of wireless sensors in space, air, or even sea, the corresponding services become time-varying. Targeting this, we formulate a multi-objective scheduling optimization model with the objectives of minimizing the uncovered area, energy consumption, and energy span. Due to the time-varying nature of the SAGS environment and accounting for the uncertainty in sensor node positions within the SAGS network, we build the connection between uncertain parameters and the internal multi-objective optimization model so that the decision-makers may only need to concern the main sub-objective spaces.

Space-Air-Ground-Sea Integration Architecture Bridging Terrestrial and Non-Terrestrial Networks

Space-Air-Ground-Sea Integration Architecture

The proposed SAGS architecture necessitates a deep fusion of space-based, air-based, ground-based, and sea-based networks, with mobile information serving as a crucial component for achieving comprehensive network integration.

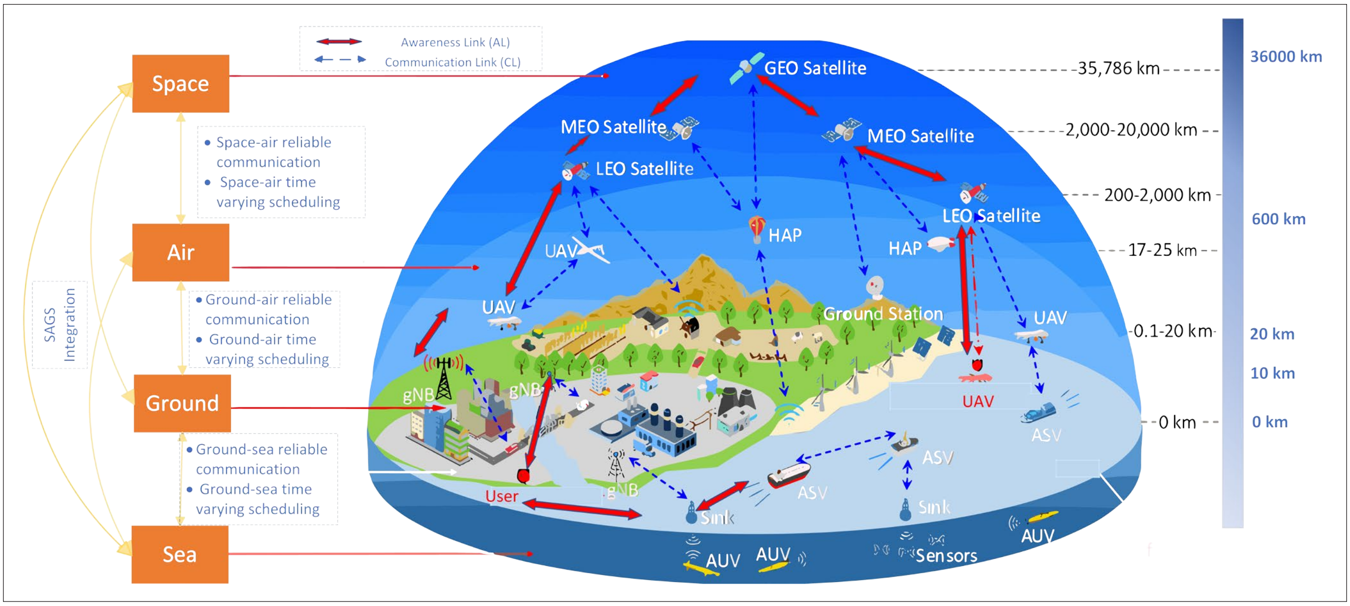

FIGURE 2. Air-space-ground-sea integration architecture.

This study focuses on intelligent data transmission and scheduling optimization based on proactive perception of space, air, ground, and sea information.

By enabling cooperative environment perception for comprehensive coverage across global zones, the integrated SAGS collaborative architecture is established, as shown in Fig. 2. This figure illustrates how global situation awareness helps capture the conditions of the SAGS environment, traffic patterns, and time-varying services. Using perceptive information from the global domain, reliability-focused transmission within the SAGS framework is achieved through an enhanced Graph Convolutional Network (GCN). Subsequently, multi-objective optimization-based adaptive scheduling is implemented to address the time-varying characteristics specific to environments such as space, air, and sea.

Global Situation Awareness

To respond to the requirement for global situation awareness in the SAGS wide-area coverage network, we divide it into the aspects of SAGS traffic awareness, security awareness, and time-varying service awareness.

Graph Convolution Network Based SAGS Traffic Awareness: Given the unique characteristics of the integrated SAGS network, which inherently involves both terrestrial and non-terrestrial traffic data, a comprehensive spatio-temporal fusion framework is proposed for accurate network traffic sensing and prediction. In particular, it encompasses three core modules: temporal feature extraction, topological feature extraction leveraging GCN, and bidirectional gated recurrent unit (Bi-GRU) for transfer learning. Feature extraction utilizes historical data as input and adaptively integrates information to capture temporal characteristics of diverse SAGS traffic patterns. To address the need for considering interactions among various network communication devices positioned across different spatial locations, GCN is applied to capture the topological features of the extensive network, treating each device as a node and their communication links as edges, so as to transform SAGS network into a large-scale graph. Within this graph, GCN employs spectral graph analysis through Laplacian matrices to understand inter-node influence relationships. Enriched with spatial features by GCN, the traffic feature sequences then undergo transfer learning through the Bi-GRU, which comprises forward and backward-gated recurrent units to consider the impact of future traffic variations and enhance long-term dependency learning. Finally, an adaptive fusion layer with an attention mechanism dynamically adjusts the weights of the outputs from these three components, generating SAGS traffic prediction outcomes. It is aware that the model will continuously refine its parameters through backpropagation based on the loss between predicted and actual values, ensuring accurate and adaptable prediction.

D-S Policy and GAN-Based Security Situation Awareness: Given the heterogeneity of the integrated SAGS network, achieving comprehensive security situation awareness depends on synthesizing information from diverse security devices within this environment. Traditional methods relying on mathematical logic models and knowledge-driven reasoning struggle to handle the massive volume of network traffic and complex attack scenarios prevalent in such an intricate architecture. To address these challenges, we propose integrating Dempster-Shafer (D-S) evidence theory with Generative Adversarial Networks (GANs), leveraging the strengths of both methodologies. D-S evidence theory aligns well with the inherent attributes of SAGS nodes and their surrounding environments, providing a robust framework for managing uncertainty, while GANs offer adaptive adjustment capabilities that enhance the precision of network attack identification through dynamic reasoning models. This combined approach commences by collecting network traffic data, where the initial 80 percent of results from multi-modal data fusion using D-S rules form the foundational dataset. After preprocessing, this data is fed into a U-Net model for training, followed by inputting the residual multi-modal fusion

By incorporating advanced techniques like D-S theory and GANs, the proposed method significantly enhances the security posture of the SAGS network, effectively handling uncertain and incomplete information through multi-source evidence combination.

data into the trained model to yield binary and multi-class classification results essential for calculating the security situation value. These classifications are then used to compute attack probabilities and their respective impacts, enabling a comprehensive assessment and evaluation of the overall security situation. By incorporating advanced techniques like D-S theory and GANs, the proposed method significantly enhances the security posture of the SAGS network, effectively handling uncertain and incomplete information through multi-source evidence combination. The adaptive nature of GANs allows continuous learning and adjustment to new attack vectors, ensuring that security measures remain effective against evolving threats. Additionally, the method ensures scalability by efficiently processing large volumes of network traffic without compromising performance, which is crucial for maintaining operational efficiency in extensive SAGS networks. Advanced encryption and anonymization techniques can be integrated to protect sensitive data during transmission and storage, ensuring compliance with privacy regulations such as GDPR and CCPA, while differential privacy mechanisms safeguard individual user data while enabling collaborative computations across the network. Ultimately, this comprehensive strategy not only enhances the accuracy and reliability of security situation awareness but also ensures robustness against a wide range of threats, facilitating safe and reliable operations in various applications.

SAGS Time Varying Service Awareness: The graph neural network is leveraged and integrated with a spatio-temporal convolution model to perceive time-varying service characteristics in SAGS, based on which we propose an unsupervised framework to overcome the challenges of assigning fixed labels to vary traffic flows. In particular, it leverages contrastive learning to learn similarities and differences between graph signals across time steps or nodes in SAGS so as to enable the perception of temporal dynamics. In addition, the dynamic spatio-temporal graph construction discretizes the evolving SAGS network topology, with each time period represented as a static graph, forming a sequence reflecting the network's temporal dynamics. Within this design, the spatial feature extraction employs GCN to learn node feature vectors, capturing structural information influenced by neighbors at each time slice. The temporal feature extraction, on the other hand, utilizes a temporal convolutional network to model nodes' changing trends across time for future predictions based on current and historical information. Finally, node representation learning on these dynamic graphs, optimized through unsupervised contrastive learning, learns low-dimensional vector mappings that preserve node information, enhancing the perception of time-varying traffic characteristics by clustering similar nodes and separating dissimilar ones in the SAGS space.

Space-Air-Ground-Sea Oriented Reliable Transmission

The reliable data transmission tailored for the mobile characteristics of the SAGS environment often necessitates considerations from two primary aspects: the spectrum resources on the non-terrestrial side spanning air, space, and sea, as well as the network capabilities on the terrestrial wired side. These two factors are major constraints in reliable data transmission and interaction. To promptly identify resource bottlenecks and avert unreliable transmission channels in SAGS, we propose a link bottleneck detection mechanism under the wide-area coverage of SAGS to avoid unreliable cases. Specifically, it first models the wide-area coverage network, encompassing a node set (comprising terminals and transmission nodes positioned across air, space, ground, and sea) and an edge set (representing communication links and channels). Subsequently, GCN is introduced to identify anomalous data from edges or nodes within the graph. In an anomalous network, normal nodes tend to share common features with their neighbors, whereas anomalies exhibit distinct features from their neighbors. The core idea lies in learning node function mappings to complete node embedding within the graph, aggregating features from a node and its neighbors, and thereby generating new representations of the nodes.

Building on this foundation, we introduce an active solution for bottleneck detection across the integrated SAGS environment. Specifically, we incorporate AI-based transmission and decision-making to customize routing attributes during data transmission in SAGS, aiming to achieve reliable link scheduling that maximizes path reliability. Initially, traffic data transmitted over links is classified into categories such as management, monitoring, and control, with further subdivisions based on content types like video, voice, and control traffic. Different traffic categories in various SAGS scenarios have distinct minimum performance requirements to ensure reliable interaction. Based on this, we introduce an AI-driven policy customization model that outputs tailored routing strategies according to the interaction demands of intelligent nodes, aligned with the actual conditions of the integrated SAGS channel model.

To enhance this approach, we design a customized bottleneck detection and reliable routing algorithm leveraging the tailored data transmission strategy. The communication path in the SAGS environment is determined by adhering to the strategic attributes within the integrated SAGS reliable transmission model. During the path determination process, path reliability is evaluated using a full probability equation to maximize reliability, ensuring optimal data transmission reliability within the integrated SAGS network.

Time-Varying Adaptive Scheduling for Space-Air-Ground-Sea Integration System

For the SAGS environment, a three-dimensional spatial model is established, where all nodes are categorized into three distinct types: intra-cluster nodes, cluster head nodes, and sink nodes, which aggregate data from cluster head nodes. The sink nodes transmit all collected data to surface base stations. Except for the continuously operational sink nodes, the other two types of nodes each have three states, which are dead, sleeping, active, and clustering. Both the intra-cluster node and head node can have these three states, and their roles can also be interchangeably transformed.

Initially, a specified number of sensor nodes are randomly deployed in the monitoring area using methods such as satellites, aircraft, or submarines. Following deployment, an election process generates a set number of cluster head nodes. In the complex environments of satellite, aircraft, and marine operations, node positions may shift slightly after deployment, leading to inter-node distances that are represented as intervals with upper and lower bounds. Next, the remaining sensor nodes calculate the lower bounds of their Euclidean distances to all cluster head nodes and join the nearest cluster head, becoming intra-cluster nodes. These intra-cluster nodes transmit their collected data to their respective cluster heads. The cluster head nodes then calculate their distances to the sink node and categorize themselves into different levels based on the lower bounds of these distance intervals. Cluster heads at lower levels (farther from the sink node) cannot directly transmit data to the sink node and must relay their data through higher-level cluster heads. Higher-level cluster heads can directly transmit both their own collected data and data received from other cluster heads to the sink node. Finally, the sink node transmits the aggregated data to a base station or surface control center for centralized processing.

Moreover, when tackling the intricate coverage challenges posed by wireless sensor networks spanning the sky, ground, and ocean, a deterministic sensing model is employed for target point coverage, while an acoustic-based communication model addresses interval energy consumption, predominantly attributed to data transmission between nodes. Given that cluster head nodes' heightened energy consumption may precipitate premature node failure, a strategy is enacted to re-select cluster heads post-operational rounds, recalculating node and regional energy reserves to balance consumption, forestall coverage holes, and thereby bolster network reliability and performance.

To address these issues and environmental uncertainties — such as space conditions, wind, and ocean tides — which significantly impact SAGS networks in both terrestrial and non-terrestrial domains, we propose an interval multi-objective SAGS integrated network scheduling and optimization model. This model incorporates key metrics such as uncovered rate, energy consumption, and energy span for optimization. Furthermore, recognizing the importance of decision-maker preferences in practical multi-objective optimizations, our interval multi-objective model employs an evolutionary algorithm that considers reference points and angular preferences from the perspectives of satellites, aircraft, and stations. Hence, this innovative approach preprocesses preference information and then adaptively adjusts the preference radius to tailor the searching area so as to establish a preference-based interval dominance relation and foster a targeted search toward solutions within the preferred region of the objective space.

Performance Evaluation

Simulation Environment

We performed comprehensive experiments leveraging the Starlink as well as extended Walker-Delta comprising 24 satellites. In addition, the simulation also utilizes the 100 most populous cities (e.g., Beijing and London) globally as Ground Stations (GSs) to evaluate all potential GS-to-GS connections. In particular, the air layer between space and ground is simulated via 100 UAV nodes, which compose the middle layer network to seamlessly bridge the gap between satellites and GSs. These drones are set to fly routes following the objectives of maximizing coverage and minimizing latency, thereby enhancing the overall network's resilience and flexibility. In particular, to simulate the heterogeneous pattern in SAGS, three kinds of packet modes are introduced in experiments, which are Segment Routing (SR), Multi-Protocol Label Switching (MPLS), and Geo-Tagging (GEO) [4]. For comparative purposes, on the one hand, the proposed work is compared with the other state-of-the-art methods, including OSPF [11] and GNN [10], that build communication across nodes in space, air, ground, and sea. On the other hand, these comparative methods are all evaluated comprehensively toward the metrics of routing convergence iteration, end-to-end delay, packet delivery rate, and throughput so that we can fully show the benefits and limitations of the proposed SAGS architecture and methods.

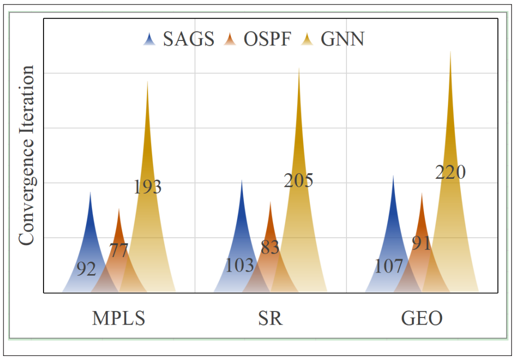

FIGURE 3. Convergence iteration count.

Simulation Results

Convergence Iteration: The convergence iteration is shown in Fig. 3 for three different methods of the proposed SAGS, OSPF, and GNN across three packet modes, that is, MPLS, SR, and GEO. In particular, the y-axis represents the convergence iteration, indicating the number of iterations required for each method to reach convergence in each packet scenario. Therefore, firstly, for the MPLS scenario, SAGS required 92 iterations, OSPF required 77 iterations, and GNN required 193 iterations. This suggests that OSPF is the most efficient method in terms of convergence speed in the MPLS scenario, followed by SAGS, with GNN being the least efficient. In addition, for the SR scenario, SAGS required 103 iterations, OSPF required 83 iterations, and GNN required 205 iterations. Again, OSPF is the most efficient method, followed by SAGS, with GNN requiring the most iterations to converge. Finally, for GEO, SAGS required 107 iterations, OSPF required 91 iterations, and GNN required 220 iterations. OSPF is the most efficient method in this scenario as well, followed by SAGS, with GNN being the least efficient. Overall, OSPF consistently outperforms both SAGS and GNN in convergence speed across all three scenarios. This advantage stems from OSPF's distributed and scalable strategy, which enables rapid convergence. In

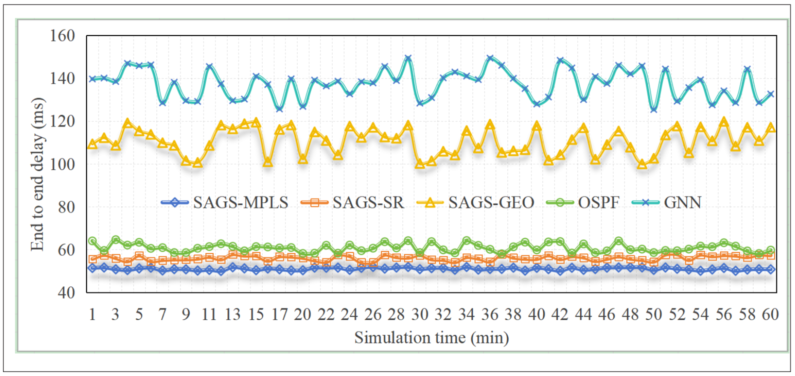

FIGURE 4. End to end delay.

contrast, GNN requires the most iterations to converge, suggesting it may not be the most efficient method for these scenarios. However, the iteration gap between the proposed SAGS approach and OSPF is relatively small, placing SAGS within an acceptable range of performance.

End-to-End Delay: To compare the performance of different methods toward the end-to-end delay, we evaluate and show the proposed SAGS with different packet modes, while the compared methods are evaluated with the most suitable one as indicated in Fig. 3. The corresponding results are presented in Fig. 4, where we can see that the end-to-end delay is captured against the simulation time (i.e., 60 minutes).

Apparently, SAGS-MPLS and SAGS-SR exhibit the lowest end-to-end delays, with SAGS-MPLS consistently outperforming SAGS-SR. This superior performance is primarily due to the MPLS protocol operating at the link layer, which enables faster processing. In contrast, SAGS-GEO performs moderately, ranking between OSPF and GNN in terms of end-to-end delay, with OSPF showing the third-lowest delay. The higher delays in SAGS-GEO can be attributed to its multi-layer routing and forwarding decisions, which increase processing time and complexity. Additionally, calculating global geographical coordinates involves handling heterogeneous expressions and adding transformation overhead. Moreover, in our simulated space-air-ground-sea integration environment, objects such as UAVs and satellites frequently change positions, complicating GEO coordinate calculations and naturally increasing end-to-end delays.

Packet Delivery Rate: The packet delivery rate in such space, air, ground, and sea integration environments is tested and shown in Fig. 5, where the results are obtained against the bit rate ranging from 10Mb/s to 80Mb/s. Obviously, at lower bit rates (e.g., 10 Mb/s to 20 Mb/s), all methods exhibit high packet delivery rates, with SAGS-MPLS and SAGS-SR performing slightly better than the others. As the bit rate increases (i.e., after 20 Mb/s), the packet delivery rate for all methods decreases, but the rate of decrease varies. In specific, SAGS-MPLS and SAGS-SR maintain relatively high packet delivery rates even at higher bit rates, with SAGS-SR consistently outperforming SAGS-MPLS. Meanwhile, SAGS-GEO and GNN show a more significant decline in packet delivery rate as the bit rate increases, with SAGS-GEO performing slightly better than GNN. OSPF exhibits the lowest packet delivery rate across all bit rates, indicating that it may not be as efficient as the other methods in terms of packet delivery. The differences in packet delivery rates are largely due to the distinct routing and forwarding mechanisms of each method. SAGS-MPLS and SAGS-SR, designed for efficient handling of high bit rates, consistently maintain higher packet delivery rates even as bit rates increase. In contrast, OSPF always selects the shortest path for packet routing across space, air, ground, and sea nodes, regardless of link congestion. This approach leads to lower packet delivery rates, especially at higher bit rates, as it does not account for network congestion effectively. While GNN leverages an intelligent neural network for routing decisions, offering potentially efficient paths, it incurs higher convergence times. This trade-off results in a packet delivery rate that, although competitive, does not match the performance of SAGS-MPLS and SAGS-SR.

Throughput: The throughput is also calculated against the bit rates from 10 Mb/s to 80 Mb/s, as shown in Fig. 6. First of all, at the lower bit rates (10 Mb/s to 20 Mb/s), all methods exhibit relatively low throughput, with SAGS-MPLS and SAGS-SR performing slightly better than the others. As the bit rate increases, the throughput for all methods increases, but the rate of increase varies. That is because the smaller the bit rate, the smaller the number of packets, which naturally leads to smaller throughput.

Then, SAGS-MPLS and SAGS-SR demonstrate a significant increase in throughput as the bit rate rises, with SAGS-SR consistently outperforming SAGS-MPLS. This trend aligns with the observations in Fig. 5. While SAGS-GEO and GNN also show increased throughput, their growth rate is slower compared to SAGS-MPLS and SAGS-SR. OSPF exhibits the lowest throughput across all bit rates, indicating its lower efficiency in data transmission. This is consistent with OSPF's lower packet delivery rate, as previously explained.

Conclusion

The advent of 5G/6G and IoT technologies marks a significant shift in networking paradigms, necessitating the seamless integration of terrestrial and non-terrestrial networks to support extensive spatial and content coverage. To address the inherent challenges of high infrastructure costs and coverage limitations in remote or inaccessible areas, this work introduces a novel SAGS integration architecture that aims to provide ubiquitous, intelligent, collaborative, and efficient information support across a broad spectrum of environments by leveraging technologies such as reinforcement learning, graph convolution networks, and multi-modal data fusion to enhance situational awareness and decision-making. Furthermore, a multi-objective scheduling optimization model is formulated to minimize uncovered areas, energy consumption, and operational spans, thereby ensuring reliable data transmission and effective resource utilization. Future work includes exploring the distributed control center placement in space, air, ground, and sea, as well as their seamless interactions.

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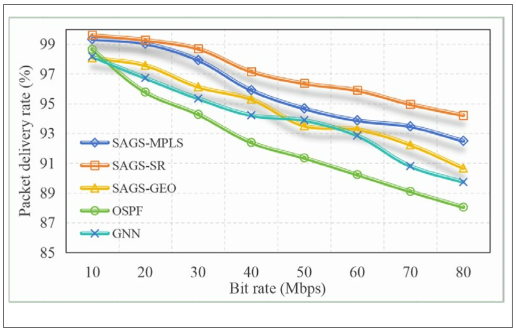

FIGURE 5. Packet deliver rate.

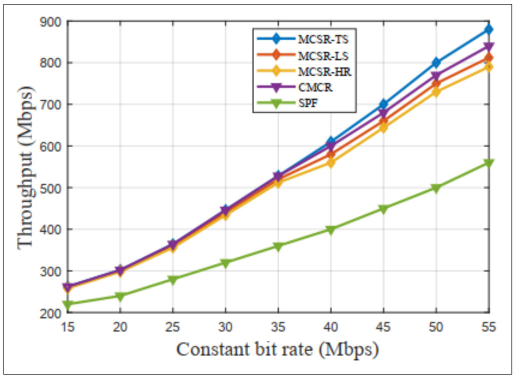

FIGURE 6. Throughput.

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References

[1] Y. Liu *et al.*, "Deep Learning Empowered Trajectory and Passive Beamforming Design in UAV-RIS Enabled Secure Cognitive Non-Terrestrial Networks," *IEEE Wireless Commun. Letters*, vol. 13, no. 1, Jan. 2024, pp. 188–92.

[2] S.-Y. Lien and D.-J. Deng, "Autonomous Non-Terrestrial Base Station Deployment for Non-Terrestrial Networks: A Reinforcement Learning Approach," *IEEE Trans. Vehicular Technology*, vol. 71, no. 10, Oct. 2022, pp. 10,894–909.

[3] S. Ammar, C. Pong Lau, and B. Shihada, "An In-Depth Survey on Virtualization Technologies in 6G Integrated Terrestrial and Non-Terrestrial Networks," *IEEE Open J. Commun. Society*, vol. 5, 2024, pp. 3690–3734.

[4] M. M. Azari *et al.*, "Evolution of Non-Terrestrial Networks From 5G to 6G: A Survey," *IEEE Commun. Surveys & Tutorials*, vol. 24, no. 4, 4th Qtr. 2022, pp. 2633–72.

[5] Z. Wu and L. Dai, "Focusing Ability Enhancement in Broadside Direction of Array: From UCA to UCCA," *Tsinghua Science and Technology*, vol. 29, no. 5, Oct. 2024, pp. 1593–1603.

[6] M. N. Dazhi *et al.*, "Energy-Efficient Service-Aware Multi-Connectivity Scheduler for Uplink Multi-Layer Non-Terrestrial Networks," *IEEE Trans. Green Commun. and Networking*, vol. 7, no. 3, Sept. 2023, pp. 1326–41.

[7] S. Ammar, C. Pong Lau, and B. Shihada, "An In-Depth Survey on Virtualization Technologies in 6G Integrated Terrestrial and Non- Terrestrial Networks," *IEEE Open J. Commun. Society*, vol. 5, 2024, pp. 3690–3734.

[8] Y. J. Guo, M. Ansari, and N. J. G. Fonseca, "Circuit Type Multiple Beamforming Networks for Antenna Arrays in 5G and 6G Terrestrial and Non-Terrestrial Networks," *IEEE J. Microwaves*, vol. 1, no. 3, July 2021, pp. 704–22.

[9] Y. Cao, S. -Y. Lien, and Y. -C. Liang, "Deep Reinforcement Learning For Multi-User Access Control in Non-Terrestrial Networks," *IEEE Trans. Commun.*, vol. 69, no. 3, Mar. 2021, pp. 1605–19.

[10] M. Khalid, J. Ali, and B. -h. Roh, "Artificial Intelligence and Machine Learning Technologies for Integration of Terrestrial in Non-Terrestrial Networks," *IEEE Internet of Things Mag.*, vol. 7, no. 1, Jan. 2024, pp. 28–33.

[11] S. Liu *et al.*, "A Dynamic Beam Shut Off Algorithm for LEO Multibeam Satellite Constellation Network," *IEEE Wireless Commun. Letters*, vol. 9, no. 10, Oct. 2020, pp. 1730–33.

[12] X. Wang, X. Shi and J. Wang, "Sparse Bayesian Learning Based Off- Grid Estimation of OTFS Channels with Doppler Squint," *Tsinghua Science and Technology*, vol. 29, no. 6, Dec. 2024, pp. 1821–28.

[13] C. -Q. Dai *et al.*, "QoE-Aware Intelligent Satellite Constellation Design in Satellite Internet of Things," *IEEE Internet of Things J.*, vol. 8, no. 6, 15 Mar., 2021, pp. 4855–67.

[14] Dogra, Roopali et al., "Essence of Scalability in Wireless Sensor Network for Smart City Applications," *Proc. IOP Conf. Series: Materials Science and Engineering*, vol.1022, no.1, 2021, pp. 1–12.

[15] R. Radhakrishnan *et al.*, "Survey of Inter-Satellite Communication for Small Satellite Systems: Physical Layer to Network Layer View," *IEEE Commun. Surveys & Tutorials*, vol. 18, no. 4, 4th Qtr. 2016, pp. 2442–73.

Biographies

Author biographies unavailable at press time.V