International Journal of Advanced Smart Convergence Vol.13 No.2 7-15 (2024)
http://dx.doi.org/10.7236/IJASC.2024.13.2.7

IJASC 24-2-2

Game Theory-Based Scheme for Optimizing Energy and Latency in LEO Satellite-Multi-access Edge Computing

Ducsun Lim* and Dongkyun Lim

**Post-Doc, Department of Computer Software, Hanyang University, Korea*
Professor, Department of Computer Science Engineering, Hanyang Cyber University, Korea
**imcoms@hanyang.ac.kr, eiger07@hycu.ac.kr*

Abstract

6G network technology represents the next generation of communications, supporting high-speed connectivity, ultra-low latency, and integration with cutting-edge technologies, such as the Internet of Things (IoT), virtual reality, and autonomous vehicles. These advancements promise to drive transformative changes in digital society. However, as technology progresses, the demand for efficient data transmission and energy management between smart devices and network equipment also intensifies. A significant challenge within 6G networks is the optimization of interactions between satellites and smart devices. This study addresses this issue by introducing a new game theory-based technique aimed at minimizing system-wide energy consumption and latency. The proposed technique reduces the processing load on smart devices and optimizes the offloading decision ratio to effectively utilize the resources of Low-Earth Orbit (LEO) satellites. Simulation results demonstrate that the proposed technique achieves a 30% reduction in energy consumption and a 40% improvement in latency compared to existing methods, thereby significantly enhancing performance.

Keywords: *6G, Multi-access Edge Computing, Low-Earth Orbit, Game Theory*

1. Introduction

With the recent advancements in information and communication technology, our life patterns have become increasingly data-oriented. Numerous technologies, such as big data and deep learning, are evolving based on accumulated data. Although 4G and 5G networks have significantly advanced in providing fast and efficient communication services, more than half of the world's population still lacks access to smooth Internet services due to geographical constraints or outdated infrastructure [1]. The emerging 6G network aims to address these problems by changing the communication paradigm and demanding high-quality Quality of Service (QoS).

6G networks represent the next generation of communication technologies, enabling ultra-high speed, ultra-connectivity, and ultra-low latency. They integrate various cutting-edge technologies, such as the Internet of Things (IoT), virtual reality, and autonomous vehicles. These developments have fostered applications that

Manuscript Received: April. 2, 2024 / Revised: April. 8, 2024 / Accepted: April. 14, 2024
Corresponding Author: eiger07@hycu.ac.kr
Tel: +82-2-2290-0301, Fax: +82-2-2290-0600
Professor, Department of Computer Science Engineering, Hanyang Cyber University, Korea

enable devices to perform increasingly complex tasks. One of the essential technological approaches to satisfy the high-quality QoS required in 6G communication services is Multi-access Edge Computing (MEC) [2]. MEC plays a crucial role in minimizing latency in data processing and reducing network traffic, thereby significantly enhancing the user experience. This technology shifts cloud-computing capabilities to the edge of the network and executes data-processing tasks on geographically distributed servers rather than centralized data centers. This shift reduces the need for data to travel long distances, shortens response times, and decreases the load on communication networks. The primary advantage of MEC is its ability to enable real-time data processing and immediate responses along with improved storage services.

Low-Earth orbit (LEO) satellites significantly reduce delay times and provide high data transmission rates owing to their proximity to Earth [3]. These characteristics help to overcome the limitations of ground-based networks and enable fast and reliable communication services across broad areas. MEC technology has been actively discussed in the field of satellite communication to leverage the benefits of LEO satellites. However, the dynamic nature of LEO satellites complicates the application of existing MEC technologies. The continuous movement of satellites creates a fluctuating communication environment that is challenging to address using static optimization methods.

In this study, we propose a game theory-based optimization technique that strategically models and optimizes the interactions between satellites and terrestrial networks. This approach considers the actions of each user and low-orbit satellite as game participants and derives optimal strategies for all interacting parties, thereby enhancing resource allocation and energy efficiency of the overall system. This methodology allows for more stable and efficient communication services and maximizes effectiveness, particularly in sectors that require large amounts of data.

2. Related Work

2.1 Advances in LEO Satellite Communication

Recent advancements in LEO satellite technologies have led to significant improvements in the global communication infrastructure, particularly in underserved and remote areas. The literature reviews various initiatives, notably Amazon's Project Kuiper and Telesat, which aim to deploy vast constellations of satellites to provide broadband services globally [4]. Bhattacherjee et al. [5] and Johnson et al. [6] highlights the reduced latency and increased bandwidth capabilities of LEO satellites compared with traditional geostationary satellites, addressing the need for high-speed Internet access in geographically challenging regions.

2.2 Enhancements in MEC for Networks

The integration of MEC into modern telecommunications has been detailed in several key studies exploring how edge computing enhances data-processing speeds and reduces latency. A pivotal study by Lim and Joe discusses the deployment of edge servers close to end-users, which significantly minimizes delays in data-intensive applications, such as augmented reality (AR) [7]. Furthermore, Zhou et al. provides insights into how MEC optimizes network traffic management and supports the burgeoning demands for IoT devices and smart city infrastructures [8].

2.3 Combining LEO Satellite with MEC

The intersection of LEO satellite systems and MEC is a novel area of research that promises to revolutionize remote connectivity. In [9], a deep learning-based scheme combined LEO satellite systems with maritime MEC settings to reduce latency and energy use, as demonstrates through simulations. Their model addressed the dynamic nature of satellite movement and suggested adaptive algorithms for maintaining consistent service quality. This study aligns with our focus on utilizing deep learning to dynamically optimize resource allocation as satellites alter their positions and network conditions fluctuate.

2.4 Application of Game Theory in Network Optimization

The application of game theory to optimize network resources offers a strategic framework for analyzing the interactions between multiple network agents. In [10], seminal work applied game-theoretical models to wireless networks to enhance the understanding of competitive and cooperative behaviors in resource allocation. Their findings are crucial for formulating our approach to dynamic optimization, where each satellite and user agent acts as a game participant striving for optimal resource utilization.

2.5 Dynamic Optimization Techniques in Fluctuating Environments

The dynamic nature of satellite networks with continuously changing positional data necessitates innovative approaches for system optimization. Research by [11] delves into dynamic optimization algorithms that adapt to environmental changes in real time, ensuring efficient resource distribution and minimizing latency in satellite communications.

This body of work lays a comprehensive foundation for our research, highlighting the existing gaps in integrating MEC with LEO satellite systems, and the potential of game theory to address these challenges. Our study builds on these concepts to propose a novel algorithm that dynamically adjusts to a satellite's positional variations, optimizing network performance and service reliability across varying geographic and infrastructural landscapes.

3. System Model and Proposed Scheme

3.1 System Model

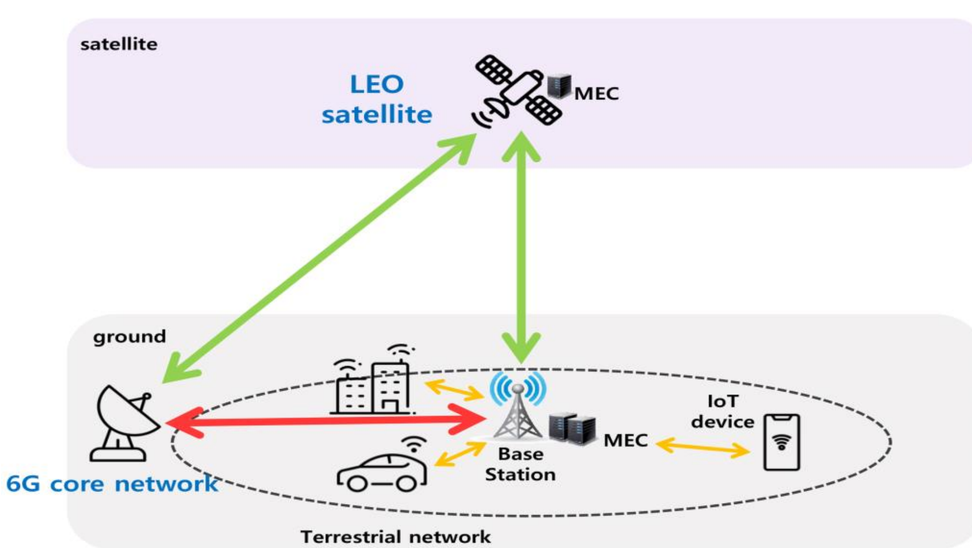

Figure 1. Architecture of System Model

This study addresses the interaction between smart-device users and nearby LEO satellites. This interaction emphasizes the importance of optimizing data processing and energy use within the 6G network environment. Instead of handling computationally intensive tasks directly, users' smart devices can offload tasks to an edge-computing system onboard nearby LEO satellites.

To analyze this process quantitatively, a queuing model was used to represent the workloads of the smart devices and satellite edge servers. The model includes two queues: one for smart-device workloads and the other for satellite workloads. Changes in these queues at each time slot enhance the efficiency of data processing and transmission.

In a 6G network environment, satisfying the high-quality QoS demanded by users is a key objective. Improving data-processing speed and response time is a critical requirement of 6G, and integration with LEO satellites provides an innovative way to achieve this level of service quality. The model and algorithms proposed in this study present optimal resource allocation and task-processing methods in a 6G environment, enabling sustainable and efficient communication services, particularly for smart devices that support applications with high computational demands.

The queues in the model represent the workload processing status between the users and satellite servers. Each equation models the changes in the queue length at a specific time slot. The user queue update equation is defined in (1).

$$Q_u(t+1) = \max(Q_u(t) - (1-\theta(t))c_u(t) - \theta(t)b(t) + a(t), 0) \tag{1}$$

where $Q_u(t)$ represents the length of the user queue at time slot t, $\theta(t)$ is the task offloading decision ratio, $c_u(t)$ is the CPU clock speed of the user's smart device, $b(t)$ is the amount of data offloaded, and $a(t)$, represents the volume of new task arrivals. The update to the satellite server queue is defined in (2).

$$Q_s(t+1) = \max(Q_s(t) - \mathrm{C}(t) + \theta(t)b(t), 0) \tag{2}$$

where $Q_s(t)$ denotes the queue length of the satellite server at time slot t and $C_s(t)$ represents the CPU clock speed of the satellite edge server. These equations are essential for managing data flow and workload, and are used to determine the tasks that should be processed on the user's device or offloaded to the satellite. The accuracy of the model and effectiveness of the simulation depend heavily on the precise configuration of each variable and parameter which can maximizing efficiency in computing environments where energy consumption and processing time are critical.

The aim of this study is to minimize the overall energy consumption and latency in systems involving satellites and smart devices. To achieve this, we propose a new approach by redefining and improving the power and latency models. The following power models were used to model the energy consumption of smart devices and satellite edge servers. The power consumed by smart devices is defined in (3), and the power consumed by the satellite edge servers is defined in (4).

$$P_{dev}(\mathrm{C}(t)) = \eta C_{dev}(t)^3 + \beta \tag{3}$$

$$P_{sat}(C_{sat}(t)) = \eta' c_{sat}(t)^3 + \beta' \tag{4}$$

where $C_{dev}(t)$ and C_{sat} represent the CPU clock speeds of the smart device and satellite edge server at time slot t, respectively. The constants $\eta, \eta', \beta\ and\ \beta'$ are used to adjust the energy efficiency system. The total power of the system is defined in (5).

$$P_{sys}(\mathrm{t}) = P_{dev}(t) + \theta(t)P_{\sigma}(t) + \omega P_{sat}(t) \tag{5}$$

where $P_{\sigma}(t)$ represents the transmission power of the smart device at time slot t, and ω denotes a weighting constant. The latency model considers only the propagation delay and is defined in (6), whereas the total system latency is defined in (7)

$$L_p(t) = 2d(t)\theta(t) \tag{6}$$

$$L_{sys}(t) = L_p(t) \tag{7}$$

where $d(t)$ represents the distance between the satellite and smart device at time slot t. Ultimately, all these elements are combined to define the objective function, as shown in (8).

$$\min\,(k_1 P_{sys}(t) + k_2 L_{sys}(t)) \tag{8}$$

where k_1 and k_3 are weights that determine the relative importance of the energy consumption and delay time, respectively. Using this model, the proposed system can support network operations with enhanced energy efficiency and minimal latency. This model is crucial for maximizing the communication efficiency and responsiveness, particularly in 6G network environments.

4.2 Proposed Scheme

The proposed system utilizes game theory [12-14] to optimize the interactions between satellites and smart devices. The following pseudocode illustrates how the decisions are automated to minimize the overall energy consumption and latency of the system.

Table 1. Proposed Scheme

Step	Description	Details
Initialization	Initialize all variables and parameters for each time slot t	Set θ(t), $C_{dev}(t), C_{sat}(t), d(t), etc,$
Game Setup	Define possible actions for each player (smart device and satellite edge server)	Set utility functions considering energy costs and latency weights.
Strategy Decision	Compute Nash equilibrium to enable each player to select their optimal strategy	Conduct negotiations and iterative calculations to derive optimal actions for each player.
Update and Iterate	Update the system state for each time slot and adjust parameters as necessary	Evaluate and optimize the system according to the objective function $\min\,(k_1 P_{sys}(t) + k_2 L_{sys}(t))$
Termination Check	*Terminate the process once all time slots have been computed*	Ensure all calculations are complete.

Based on game theory, each player strives to minimize their energy usage and reduce the overall latency of the system. At each time slot, smart devices and LEO edge servers adjust their strategies, which significantly affects the overall performance of the network. In particular, the determination of $\theta(t)$ plays a crucial role in effectively adjusting the offloading ratio to balance energy consumption and latency.

By leveraging game theory, this system can maximize efficiency and responsiveness in a 6G network environment through an automated decision-making process, maintaining optimal performance even in complex network configurations.

5. Simulation Results

The simulation results of the game-theory-based scheme proposed in this study were analyzed to evaluate the energy efficiency and latency minimization performance. Simulations were conducted under various hyper-parameter settings, with a specific focus on the impact of the offloading decision ratio, $\theta(t)$, on the overall system performance. Table 2 summarizes the main simulation parameters.

Table 2. Simulation parameters

Parameter	Values
$\theta(t)$	0.1 to 0.9, step 0.1
$C_{dev}(t)$	1.0 to 3.0 GHz
$C_{sat}(t)$	1.0 to 3.0 GHz
d(t)[14]	100 to 1000 km
k_1, k_2	0.5 (Energy), 0.5 (Latency)

We compared our proposed model with the Traditional Load Balancing (TLB) method. TLB distributes network traffic evenly across available resources without considering real-time network conditions, ensuring uniform use of all network paths but lacking dynamic adaptation to changing network loads or conditions. This often results in suboptimal performance in dynamic environments due to the continuously changing positions of LEO satellites and fluctuating traffic demands, leading to inefficient resource utilization, higher energy consumption, and increased latency. Our game-theory-based optimization technique significantly outperforms TLB by dynamically adapting to real-time conditions and satellite movements. By treating each user and satellite as game participants, our model derives optimal strategies considering both current and anticipated network states, resulting in more efficient resource allocation and task offloading decisions.

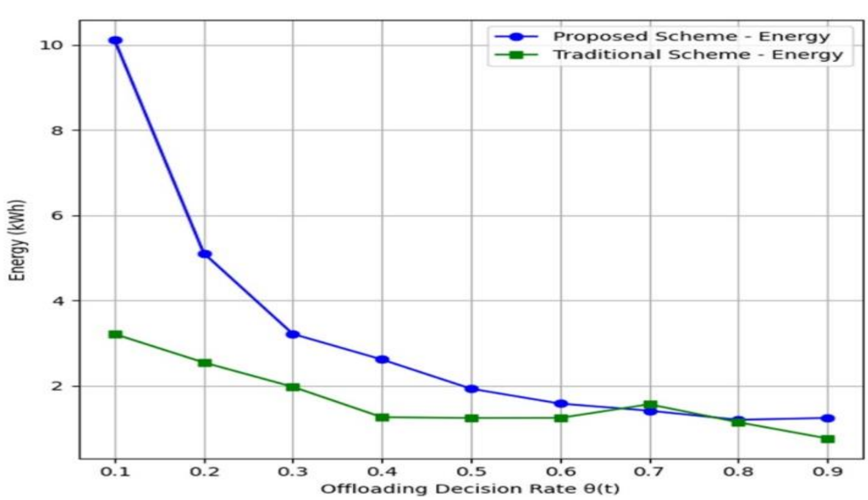

Figure 2. Energy Consumption

Figure 2 demonstrates that the proposed technique exhibits a continuous decrease in energy consumption as the offloading decision ratio, $\theta(t)$, increases. This reduction is attributed to the proposed technique, which effectively reduces the computational load on smart devices and optimizes data processing using satellites, thereby conserving energy. n contrast, the traditional technique maintained relatively high energy consumption levels with a less significant energy-saving effect as the offloading ratio increased. According to the simulation results, the proposed technique reduced energy consumption by 30% compared to the existing method. However, at an offloading decision ratio $\theta(t)$ of 0.7, the traditional approach outperformed the proposed approach in terms of energy consumption. This anomaly can be attributed to the specific characteristics of the network and workload distribution at that particular offloading ratio, where the traditional approach may temporarily align better with the network's current load conditions, leading to more efficient resource utilization. Despite this specific instance, the overall performance of the proposed technique remains superior, as evidenced by the consistent reduction in energy consumption across other offloading ratios and the average 30% reduction compared to the traditional method. The long-term benefits of the adaptive, game-theory-based optimization become more apparent when considering the overall energy savings and efficiency improvements across various network conditions.

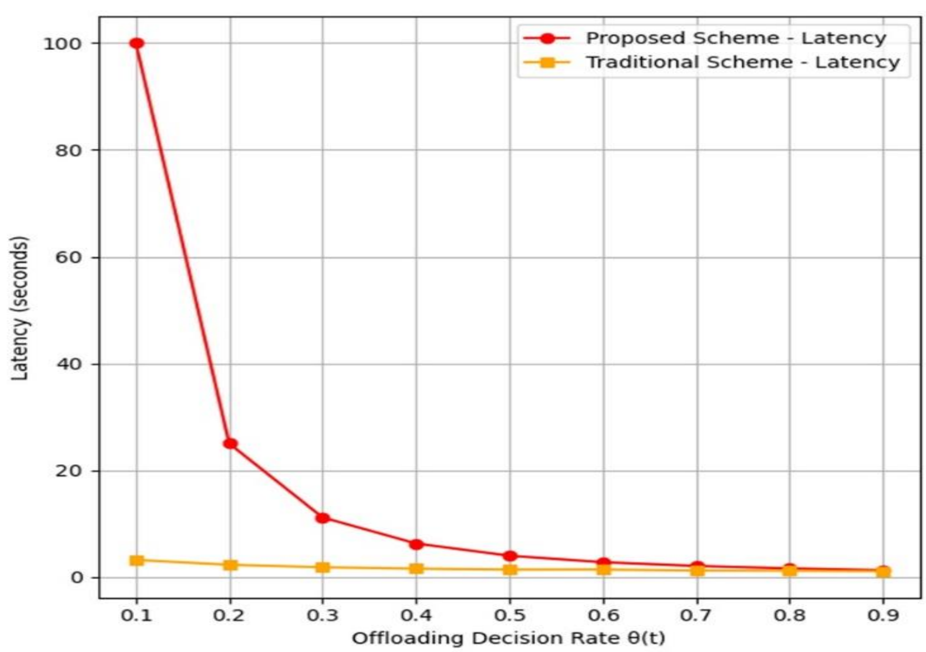

Figure 3. Latency

Figure 3 focuses on latency. The proposed technique showed a notable decrease in latency as the offloading decision ratio $\theta(t)$ increased. This reduction is owing to the efficient offloading of data processing tasks to nearby satellites, which decreases the network load on terrestrial infrastructure and smart devices, allowing for faster data processing and transmission. The proposed technique dynamically adapts to current network conditions and optimizes resource allocation, ensuring that data is routed and processed through the most efficient paths. In contrast, the traditional technique, which does not utilize offloading as effectively, exhibited only limited reductions in latency due to its static nature and inability to adapt to changing network conditions. The traditional method often leads to congestion and delays as it cannot leverage the benefits of real-time optimization and satellite resources as effectively as the proposed model.

The latency improvement observed with the proposed technique, quantified at 40%, demonstrates significant performance enhancement over the traditional approach. This improvement is particularly crucial for applications requiring real-time processing and low-latency communication, such as IoT, virtual reality, and autonomous vehicles. The reduced latency ensures that data is processed and delivered promptly, enhancing user experience and system efficiency.

These results confirm that the proposed technique effectively achieves the primary goals of enhancing energy efficiency and reducing latency. By leveraging game-theory-based optimization and dynamic offloading strategies, the proposed model not only improves overall network performance but also addresses the critical challenges of energy consumption and latency in next-generation communication networks.

6. Conclusion

In this study, we present a game-theory-based scheme for minimizes energy consumption and reducing latency by optimizing the interactions between satellites and smart devices within 6G networks. The simulation results demonstrate that this scheme outperforms existing methods in terms of energy efficiency and processing speed. As the offloading decision ratio increases, energy consumption decreases, allowing smart devices to maintain high processing capacity with lower energy consumption by effectively offloading the workload to satellites. Furthermore, reductions in energy and latency enhance data-processing efficiency and user experience. This underscores the potential of integrating game theory into the design and operation of 6G networks, which could significantly advance network technology in the future.

Acknowledgement

This work was partially supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korean government (MSIT) (No.2020-0-01373, Artificial Intelligence Graduate School Program (Hanyang University)) and the research fund of Hanyang University (HY-2024)

References

[1] A. Gupta and R. K. Jha, "A survey of 5G network: Architecture and emerging technologies," *IEEE Access*, Vol. 3, pp. 1206-1232, 2015. DOI: 10.1109/ACCESS.2015.2461602

[2] D. Lim et al., "DRL-OS: a deep reinforcement learning-based offloading scheduler in mobile edge computing," *Sensors*, Vol. 22, no. 23, pp. 9212, 2022. DOI: https://doi.org/10.3390/s22239212

[3] T. Kim, J. Kwak, and J. P. Choi, "Satellite edge computing architecture and network slice scheduling for IoT support," *IEEE Internet of Things Journal*, Vol. 9, no. 16, pp. 14938-14951, 2021. DOI: 10.1109/JIOT.2021.3132171

[4] P. A. Iannucci and T. E. Humphreys, "Economical fused LEO GNSS," *2020 IEEE/ION Position, Location and Navigation Symposium (PLANS)*, 2020. DOI: 10.1109/PLANS46316.2020.9110140

[5] [5] D. Bhattacherjee et al., "In-orbit computing: An outlandish thought experiment," in *Proc. 19th ACM Workshop on Hot Topics in Networks*, 2020. DOI: https://doi.org/10.1145/3422604.3425937

[6] J-C. Liou and N. L. Johnson, "Instability of the present LEO satellite populations," *Advances in Space Research*, Vol. 41, no. 7, pp. 1046-1053, 2008. DOI: https://doi.org/10.1016/j.asr.2007.04.081

[7] D. Lim and I. Joe, "A DRL-Based Task Offloading Scheme for Server Decision-Making in Multi-Access Edge Computing," *Electronics,* Vol. 12, no. 18, pp. 3882, 2023. DOI: https://doi.org/10.3390/electronics12183882

[8] P. Zhou et al., "5G MEC computation handoff for mobile augmented reality," *arXiv preprint* arXiv:2101.00256, 2021. DOI: https://doi.org/10.48550/arXiv.2101.00256

[9] D. Lim and D. Lim, "Deep Reinforcement Learning-Based Task Offloading in Multi-access Edge Computing for Marine IoT," *in Proc. Computational Methods in Systems and Software,* Cham: Springer International Publishing, pp. 233-244, 2023. DOI: 10.1007/978-3-031-53549-9_23
[10] S. Lasaulce and H. Tembine, *Game Theory and Learning for Wireless Networks: Fundamentals and Applications,* Academic Press, 2011. DOI: 10.1016/C2009-0-62852-X
[11] H. Huang et al., "Fusion of building information modeling and blockchain for metaverse: a survey," *IEEE Open Journal of the Computer Society*, Vol. 3, pp. 195-207, 2022. DOI: 10.1109/OJCS.2022.3206494
[12] R. Gibbons, *A Primer in Game Theory*, Pearson Education Limited, 1992.
[13] J. Moura and D. Hutchison, "Game theory for multi-access edge computing: Survey, use cases, and future trends," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 1, pp. 260-288, 2018. DOI: 10.1109/COMST.2018.2863030
[14] E. Calvanese Strinati et al., "6G in the sky: On-demand intelligence at the edge of 3D networks," *arXiv preprint* arXiv:2010.09463, 2020. DOI: https://doi.org/10.48550/arXiv.2010.09463
[15] Y. Su et al., "Broadband LEO satellite communications: Architectures and key technologies," *IEEE Wireless Communications*, Vol. 26, no. 2, pp. 55-61, 2019. DOI: 10.1109/MWC.2019.1800299