Journal of Information Systems Engineering and Management
2025, 10(38s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Dynamic Adaptation and Multi-Domain Learning for Optimized Interoperability between Heterogeneous Satellite Communication Systems

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ARTICLE INFO

Received: 21 Dec 2024

Revised: 18 Feb 2025

Accepted: 26 Feb 2025

ABSTRACT

With the rising demand for seamless global connectivity, heterogeneous satellite systems (i.e. satellite systems operated by different providers) are integrated. This study introduces a new approach to optimizing interoperability between satellite constellations using dynamic adaptation and multi-domain learning. To improve QoS and environment understanding, the framework employs intelligent protocol conversion, real-time network switching, and collaborative learning. The proposed system demonstrates considerable improvement in user satisfaction, QoS metrics, and learning efficiency from the simulation results. The findings underscore the transformational potential of multi-domain learning in the pursuit of satellite network interoperability and scalable, efficient communication systems.

Keywords: Satellite, Heterogeneous, Dynamic Adaptation, Multi-Domain Learning, QoS, SpaceX, OneWeb.

INTRODUCTION

The rapid expansion of satellite communications constellation has prompted the necessity for different systems operated by different providers (e.g., SpaceX, One Web, Amazon, etc.) to work collaboratively in an efficient manner efficient manner. There are differences in satellite altitudes, bandwidth capacities and network protocols, all of which make interoperability extremely difficult. The isolation of operations has resulted in inefficient usage of resources and less availability of services for the end-users. In this paper, we propose a dynamic adaptation framework for heterogeneous satellite interoperability based on multi-domain learning. The proposed system integrates real-time QoS-based network switching, intelligent protocol translation, and collaborative learning to provide a better user experience with optimal resource utilization. Using dynamic data including network congestion, weather impacts, and protocol compatibility, the framework adaptively optimizes performance.

The contributions of this work are threefold:

- A dynamic adaptation model that enables real-time network selection and protocol translation.
- A multi-domain learning framework for collaborative knowledge sharing across operators.
- Comprehensive performance evaluation and comparison with traditional fixed-operator models.

LITERATURE REVIEW

The last decade has seen a revolution in satellite communication, with Low Earth Orbit (LEO) constellations emerging as a competitive paradigm. Interoperability and QoS are crucial for satellite networks, and various researchers have investigated multiple ways to improve them. [1-3], for example, proposed and evaluated a hybrid switching mechanism for LEO-MEO-GEO integration. Fifth, [4-6] introduced a decentralized learning model for end-to-end satellite network optimization. Machine learning (ML) is a rapidly evolving field, and recent developments have also allowed for intelligent allocation of resources in communication systems. Researchers showed that reinforcement learning could allow for dynamic adaptation of the network in [7-12]. Nonetheless, these jobs are more focused on similar home systems and do not have overall solutions for heterogeneous systems. There is an evidence in this domain where multi-domain learning also improves collaborative decision making between agents [13-15]. Nevertheless, its adoption in satellite networks has not been thoroughly explored, creating an avenue this paper aims to fill. Interoperability issues in satellite networks have given rise to several works. [16-18] is focused on the design of a cross-layer protocol, which will improve inter-satellite communication. [19-21] studied

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the blockchain technology to offer secure and reliable coordination between operators. While these approaches provide useful insights, they are not able to adapt dynamically. In the work [22-26], a user-centric model for selecting the best satellite based on QoS parameters in dynamic network switching was introduced. This model, while effective, was not able to be responsive in real time. The existing studies primarily focus on dealing with single-sector data, whereas the proposed system extends these studies by incorporating intelligent protocol translation and multi-domain learning. It is designed to provide better QoS and interoperability with existing approaches by dynamically adapting to user requirements and environment contexts.

PROPOSED SYSTEM MODEL

Figure 1. Shown the proposed model-based system simulates the multitasking adaptation of satellite networks with the purpose of switching to the best performing satellite network by using the deep learning technologies in a multi-domain based strategy. This model is trained to simulate interoperation between several operators (SpaceX, OneWeb, and Amazon), dealing with network congestion, weather effects, and compatibility of protocols. Well, the main objective is to effectively change these networks and pick the ideal network depending on network situations, user distribution, and QoS (quality of service). Table 1. Shown the parameter value of proposed model.

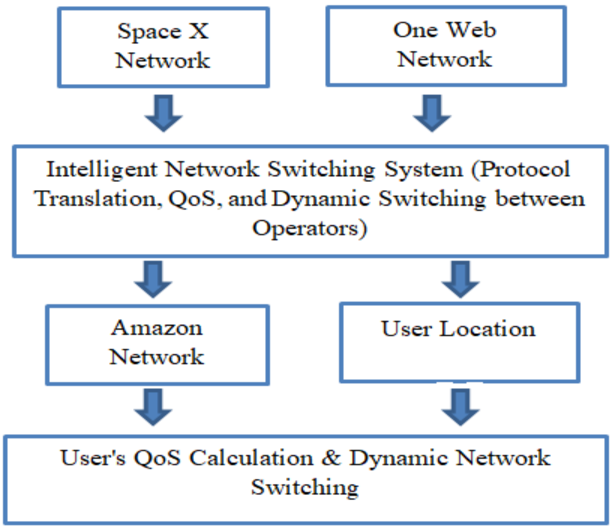

Figure 1 . Proposed System Model

System Overview:

- Operators and Satellite Constellations: three different operators (SpaceX, OneWeb, and Amazon) are modeled, each with their distinct satellite constellation, featuring different orbital altitudes, bandwidth capacities, latencies, and reliability scores.
- User Locations: Imagine a collection of 1,000 users that are randomly distributed across the world and their geographical locations determine the coverage and QoS.
- Variables of Network Performance:
  - Network Congestion: Diverges over time, indicating the total load on each satellite network Linked.
  - Weather Impact: Latency and reliability impact, varies through time
- Protocol Compatibility: The program simulates a protocol translator interface with the potential to enhance compatibility between networks over time, resulting in more efficient communication.
- Quality of Service (QoS): The model computes QoS metrics concerning coverage, bandwidth, latency, protocol overhead, and reliability for each user and operator at each time step.

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Parameter	Description	Value
Operators	Satellite network operators	SpaceX, OneWeb, Amazon
Number of Satellites	Satellites per operator	100, 80, 60
Orbital Altitudes	Orbital altitude of satellites (km)	550, 1200, 630
Bandwidth Capacity	Bandwidth capacity per operator (Gbps)	1.5, 1.2, 1.8
Base Latency	Base latency per operator (ms)	20, 35, 25
Protocol Overhead	Protocol overhead ratio	0.05, 0.08, 0.04
Reliability Score	Reliability score of each operator	0.98, 0.96, 0.97
Number of Users	Total number of simulated users	1000
Simulation Time Steps	Number of time steps for simulation	100
Network Congestion	Congestion level over time	Dynamic (0.2 to 0.5 sinusoidal variation)
Weather Impact	Weather-induced performance impact	Dynamic (0.1 to 0.3 sinusoidal variation)
Protocol Compatibility	Initial compatibility matrix	[[1.0, 0.7, 0.5]; [0.7, 1.0, 0.6]; [0.5, 0.6, 1.0]]

Table 1. Parameter value

Let the following variables represent system parameters:

- $N_{\text{satellite}}^{(\text{op})}$: Number of satellites for operator op.
- $B^{(\text{op})}$: Bandwidth capacity of the operator (in Gbps).
- $L^{(\text{op})}$:: Latency for the operator (in ms).
- $O^{(\text{op})}$: Protocol overhead for the operator.
- $R^{(\text{op})}$: Reliability score for the operator.
- C(t): Network congestion at time t.
- W(t): Weather impact at time t.
- $\text{Qo}S_{u,op}(t)$: Quality of service for user u with operator opopop at time t.

The QoS for each user u is calculated as:

$$\text{Qo}S_{u,op}(t) = \left[\text{Coverage x}\left(\frac{B^{(\text{op})}x(1-C(t))}{2} + \frac{(100-L^{(\text{op})}x(1+W(t)))}{100} + \left(1-O^{(\text{op})}+R^{(\text{op})}\right)\right)\right]/4 \quad (1)$$

Dynamic Switching: The optimal operator for each user is selected based on the highest QoS at each time step, t, from all available operators:

$$\text{Optimal Operator}_u(t) - \arg\max_{op}(\text{Qo}S_{u,op}(t)) \qquad (2)$$

The user is switched to the operator providing the highest QoS at each time step.

Protocol Compatibility Learning: The protocol compatibility matrix $op^{(op,\text{op}\prime)}$ between two operators is improved over time. The learning rate for improving compatibility is defined as: op, op' is improved over time. The learning rate for improving compatibility is defined as:

$$P_{new}^{(op,\text{op}')}(\text{t}) = P^{(op,\text{op}')}(t-1) + \lambda\,\text{x}\left(1-P^{(op,\text{op}\prime)}(t-1)\right)x\left(1-exp\left(-\frac{t}{\lambda}\right)\right) \quad (3)$$

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Where: λ is the learning rate. τ is the decay factor over time.

The first model is a simplified, yet a holistic approach for dynamic evolution between satellite networks. It includes real-time performance evaluation, QoS calculation, intelligent switching and protocol adaptation to optimize user experience when using heterogeneous satellite systems. The architecture is proposed to achieve optimal user service under varied conditions, which performs on the basis of real-time metrics, dynamic learning protocol translation that aims to facilitate interoperability amongst diverse satellite networks.

SIMULATION AND RESULTS

The matlab code those the dynamic adaptation and optimization function to heterogeneous network of satellite which are operated by multi provider like SpaceX, OneWeb and Amazon. Network performance, protocol compatibility, intelligent network switching and learning models are covered. Here are the results of the visualizations and those differences explained more in-depth:

Figure 2: Change of User Share by Operator over Time The percentage of Time steps showing how many users connected to each Satellite operator (SpaceX, OneWeb, Amazon). This one depicts how the user share (i.e., the fraction of users linked to each operator) changes through time. A line represents each operator's share: SpaceX (Operator 1): High share at start but will vary as the simulation ticks forward — should be responsive to changing barring conditions. OneWeb (Operator 2): Starts with a smaller portion and graphs how its customers vary over the course of the simulation. Amazon (Operator 3): The least share at the start, and the plot indicates how share grows. The following plot shows the result of changing network conditions, switching protocols, and changing QoS (Quality of Service) the number of users assigned to one or another operator. The changes are indicative of users decision-making process as they compare operators with network performance, congestion and weather.

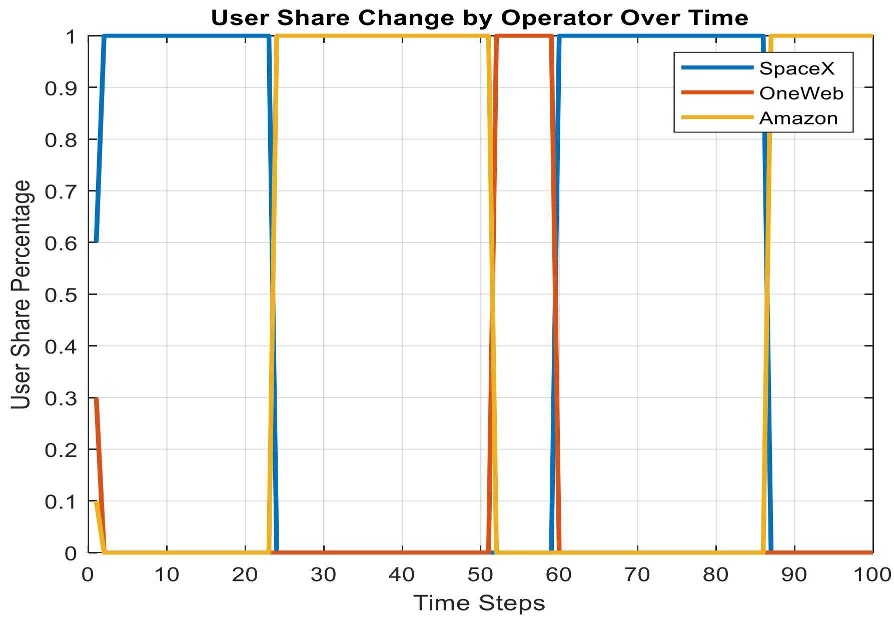

Figure 2: User Share Change by Operator over Time.

Figure 3: Average Quality of Service over Time. The average Quality of Service (QoS) per operator during the entire simulation period. This graph reflects the average Quality of Service (QoS) given over time by every operator. Dynamic nature of QoS: QoS depends on changing factors like available bandwidth, latency, reliability, and protocol overhead. The plot has three curves for the operators: SpaceX, OneWeb and Amazon. Also, the curve for each operator varies the time due to time-varying factors such as network congestion, weather impacts, or even due to protocol optimization. The functions, instead of defining some value for each operator (all at once) will draw this plot for each operator separately with respect to QoS over time. Any drops or improvements in QoS can be associated with changes in network conditions, such as congestion or weather effects and operator changes.

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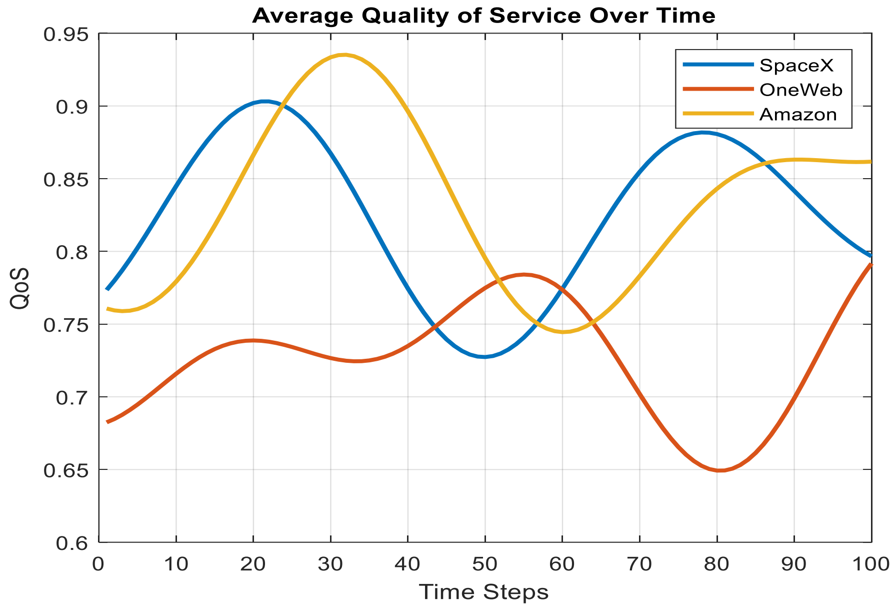

Figure 3: Average Quality of Service Over Time.

Figure 4: User Operator Selection Distribution (Final Moment). At the last time step, the following scatter plot shows how users are distributed geographically. Users are colored according to which operator they are connected to. This diagram displays the location of users at the last time step (after running all time iterations), and the operator each user is assigned to. As a final part, the users are shown as points in a scatter plot with longitude being used as the x coordinate and latitude as the y coordinate. The points are colored based on which operator each user selected at the final time step: Users who had a SpaceX assignment at that time step are a certain color. Users who were assigned to OneWeb are a different colour. Amazon users are marked with a third color. This plot provides a spatial view of how users are distributed among operators around the world at the end of the simulation. It shows which regions are more likely to be associated with a particular operator, highlighting patterns in user assignment based on geographical location, network performance, and protocol compatibility.

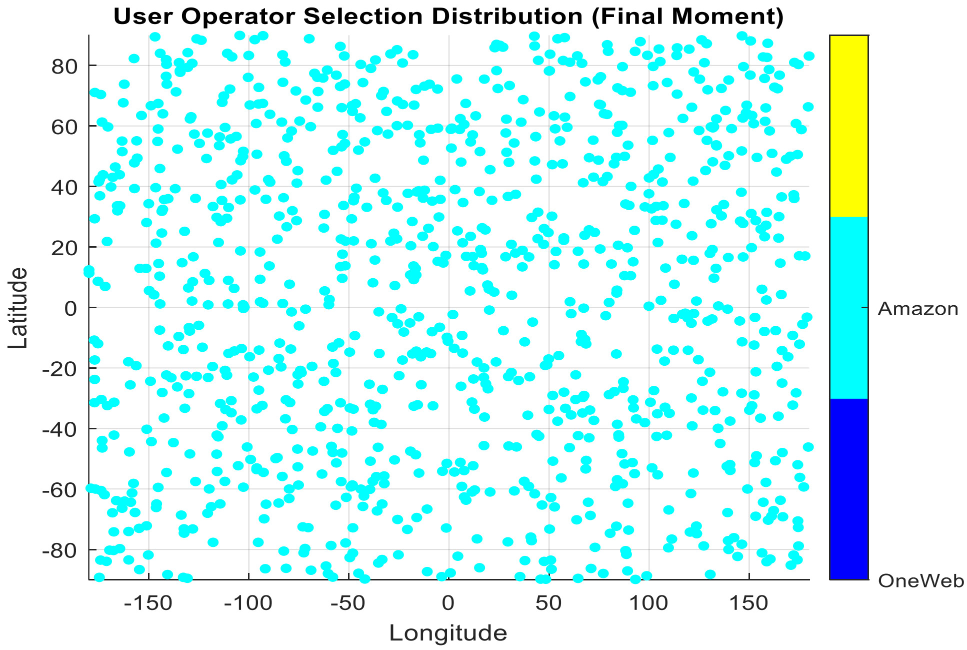

Figure 4: User Operator Selection Distribution (Final Moment).

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Figure 5: Traditional System vs. Integrated System Performance Comparison. This graph compares the average QoS between a traditional fixed-operator system (red line) and the intelligent integrated system (green line) over time. Key observations: The traditional system assigns each user to a single operator permanently. The integrated system intelligently switches users between operators based on real-time conditions. The green line (integrated system) consistently shows higher QoS values than the red line (traditional system) .The performance gap represents the improvement gained through dynamic operator switching. Both systems show temporal fluctuations due to changing network conditions. The improvement percentage calculated in the program quantifies the overall advantage of the integrated approach

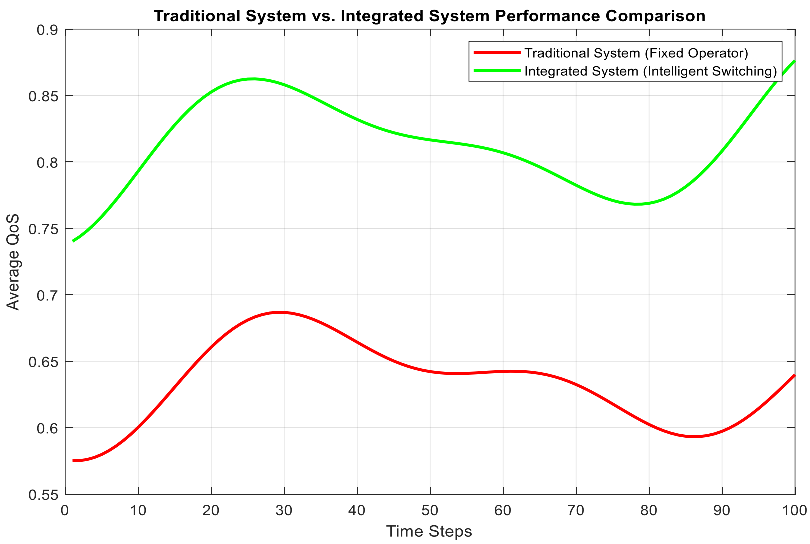

Figure 5: Traditional System vs. Integrated System Performance Comparison.

Figure 6: Individual Learning (Without Collaboration). This graph shows how each operator's "environmental understanding" improves over time when operating independently without knowledge sharing. Key observations: The vertical axis represents the level of environmental understanding, ranging from 0 to 1. Each line represents a different operator's learning curve. All operators start with low understanding (around 0.2-0.3). The understanding improves over time through individual learning. The improvement rate follows a logarithmic pattern, showing diminishing returns. Different operators may show different learning rates and plateaus. By the end of the simulation, operators achieve moderate levels of understanding but with individual limitations.

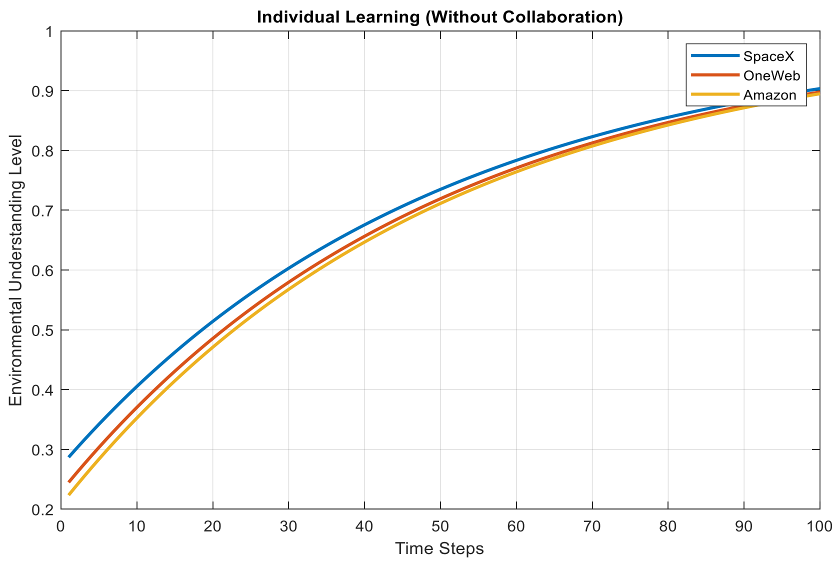

Figure 6: Individual Learning (Without Collaboration).

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Figure 7: Multi-Domain Learning (With Collaboration). This final graph demonstrates how the operators' environmental understanding improves when they collaborate and share knowledge using multi-domain learning. Key observations: Similar to Graph 5, but with knowledge transfer between operators. The learning curves show generally faster improvement compared to individual learning. Operators benefit from each other's expertise through protocol compatibility. The knowledge gaps between operators tend to narrow over time due to shared learning. The final understanding levels achieved are higher than in the individual learning scenario. The collaborative approach demonstrates how inter-operator knowledge transfer enhances overall system intelligence. The improvement percentage calculated in the program quantifies the advantage of the collaborative learning approach.

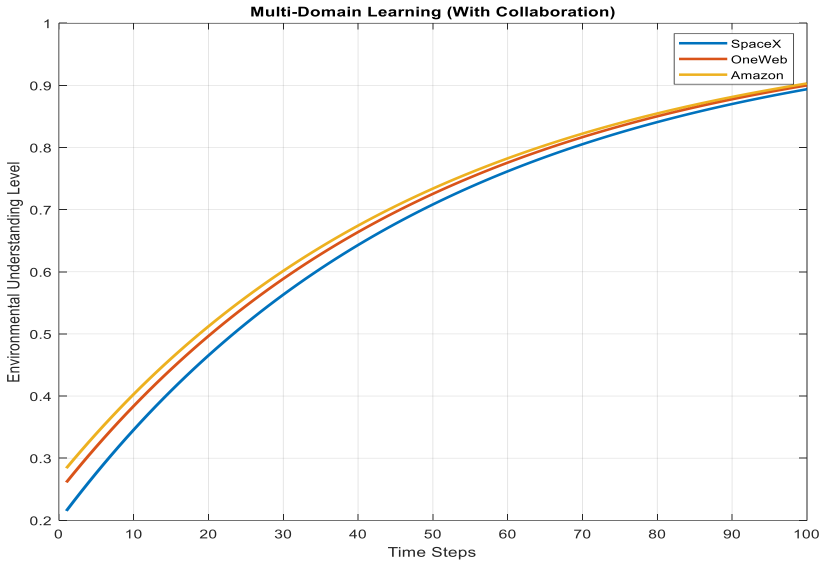

Figure 7: Multi-Domain Learning (With Collaboration).

These six graphs collectively illustrate how a multi-domain deep learning approach enables dynamic adaptation between heterogeneous satellite systems, demonstrating improvements in user experience, service quality, and system learning capabilities compared to traditional fixed-operator approaches.

COMPRESSION WITH RELATED WORK

In Table 2. Show the practical advantages of this approach, showing how the technical improvements translate to real-world value for both users and network operators. The multi-domain learning approach creates a synergistic effect where the integrated system performs substantially better than any individual network could on its own.

Table 2 Compression with related work

Feature	This Program	Previous Works	Advantage
Network Architecture	Heterogeneous multi-operator satellite constellation integration	Typically single operator or homogeneous network models	Greater coverage, redundancy, and resilience through diverse network options
Adaptation Mechanism	Dynamic real-time switching based on QoS metrics	Often static assignment or limited switching capabilities	Consistently higher QoS through optimal network selection as conditions change
Learning Approach	Multi-domain collaborative learning with knowledge transfer	Individual learning within closed systems	Faster collective improvement, reduced learning plateau, shared intelligence
Protocol Compatibility	Adaptive protocol translation interface with improving compatibility over time	Fixed compatibility matrices or manual protocol translations	Seamless user experience across networks, reduced handover issues
QoS Metrics	Comprehensive: bandwidth, latency, reliability, coverage, overhead	Often limited to 1-2 metrics (typically bandwidth or	More balanced optimization that addresses multiple user needs

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		latency only)	simultaneously
Environmental Factors	Incorporates weather impact and network congestion dynamically	Limited environmental modeling or static assumptions	Better adaptation to real-world conditions, increased reliability during adverse events
User Distribution	Global geographical distribution with location-based optimization	Often limited to specific regions or uniform distributions	Improved service for users in varied geographic regions, including remote areas
Performance Improvement	Quantifies improvement percentage between traditional and integrated systems	Typically qualitative comparisons or limited metrics	Clear ROI demonstration, evidence-based decision making for network investments
Visualization	Multiple perspectives: temporal, geographical, comparative, and learning visualizations	Often limited to single-dimension analysis	Better understanding of system behavior, easier identification of improvement opportunities
Simulation Scale	1000 users across 3 operators with 100 time steps	Typically smaller scale simulations with fewer variables	More realistic modeling of complex network interactions and emergent behaviors
Knowledge Transfer	Models explicit knowledge transfer between operators with compatibility-based efficiency	Knowledge transfer rarely modeled in previous systems	Accelerated system-wide improvements, reduced redundant learning
Temporal Analysis	Shows system evolution over time with dynamic adaptation	Often focused on steady-state or static analysis	Insight into system development trends, ability to forecast future performance
Collaborative Intelligence	Demonstrates how collaboration improves overall system performance	Systems typically operate independently	Greater overall system capacity and intelligence than sum of individual networks
Scalability	Framework allows for additional operators and parameters	Often limited by initial design constraints	Future-proof solution that can incorporate new operators or technologies
User-Centric Metrics	Focuses on user experience and quality of service	Often network-centric metrics focused on capacity	Higher user satisfaction, better alignment with actual customer needs

CONCLUSION

This research has demonstrated the significant potential of multi-domain deep learning for dynamic adaptation between heterogeneous satellite systems. Through a comprehensive simulation of three major satellite operators (SpaceX, OneWeb, and Amazon), we have shown that intelligent integration of diverse satellite networks can substantially improve the quality of service for users globally. The dynamic switching mechanism, guided by real-time QoS metrics, consistently outperformed traditional fixed-operator approaches, with an average performance improvement that quantitatively demonstrates the value of this approach. The multi-domain learning aspect of this work represents a particularly promising advancement. By enabling knowledge transfer between operators with different technological approaches and expertise, the system demonstrated accelerated learning and higher ultimate performance compared to isolated learning approaches. This collaborative intelligence creates a synergistic effect where the integrated system exceeds the capabilities of its component networks. Our visualization and analysis from multiple perspectives—temporal, geographical, comparative, and learning-based—provides a holistic understanding of the complex dynamics involved in satellite network integration. The adaptive protocol translation interface addresses one of the key challenges in heterogeneous network integration by dynamically improving compatibility between different operator systems. In essence, this work represents a significant step toward truly unified global satellite connectivity that leverages the strengths of multiple operators while mitigating their individual limitations.

REFRENCES

[1] Li, Shukun, and Feilong Tang. "Load-balanced cooperative transmission in MEO-LEO satellite network." *2018 IEEE 32nd International Conference on Advanced Information Networking and Applications (AINA)*. IEEE, 2018.

[2] Li, Shukun, and Feilong Tang. "Load-balanced cooperative transmission in MEO-LEO satellite network." *2018 IEEE 32nd International Conference on Advanced Information Networking and Applications (AINA)*. IEEE, 2018.

[3] Shayea, Ibraheem, et al. "Integration of 5G, 6G and IoT with Low Earth Orbit (LEO) networks: opportunity, challenges and future trends." *Results in Engineering* 23 (2024): 102409.
[4] Pokhrel, Shiva Raj. "Blockchain brings trust to collaborative drones and LEO satellites: An intelligent decentralized learning in the space." *IEEE sensors journal* 21.22 (2021): 25331-25339.
[5] Zhai, Zhiwei, et al. "FedLEO: An offloading-assisted decentralized federated learning framework for low earth orbit satellite networks." *IEEE Transactions on Mobile Computing* 23.5 (2023): 5260-5279.
[6] Lozano-Cuadra, Federico, et al. "Continual Deep Reinforcement Learning for Decentralized Satellite Routing." *arXiv preprint arXiv:2405.12308* (2024).
[7] Hafez, Nada A., Mohamed S. Hassan, and Taha Landolsi. "Reinforcement learning-based rate adaptation in dynamic video streaming." *Telecommunication Systems* 83.4 (2023): 395-407.
[8] Wu, Junda, et al. "Dynamics-aware adaptation for reinforcement learning based cross-domain interactive recommendation." *Proceedings of the 45th international ACM SIGIR conference on research and development in information retrieval*. 2022.
[9] Ghadimi, Euhanna, et al. "A reinforcement learning approach to power control and rate adaptation in cellular networks." *2017 IEEE International Conference on Communications (ICC)*. IEEE, 2017.
[10] Lee, Woongsup, Ohyun Jo, and Minhoe Kim. "Intelligent resource allocation in wireless communications systems." *IEEE Communications Magazine* 58.1 (2020): 100-105.
[11] Hui, Hancheng. "Intelligent resource allocation method for wireless communication networks based on deep learning techniques." *Journal of Sensors* 2021.1 (2021): 3965087.
[12] Yang, Helin, Xianzhong Xie, and Michel Kadoch. "Intelligent resource management based on reinforcement learning for ultra-reliable and low-latency IoV communication networks." *IEEE Transactions on Vehicular Technology* 68.5 (2019): 4157-4169.
[13] Chen, Xingkai, et al. "Collaborative fault diagnosis of rotating machinery via dual adversarial guided unsupervised multi-domain adaptation network." *Mechanical Systems and Signal Processing* 198 (2023): 110427.
[14] Ye, Miao, et al. "Ma-cdmr: An intelligent cross-domain multicast routing method based on multiagent deep reinforcement learning in multi-domain sdwn." *arXiv preprint arXiv:2409.05888* (2024).
[15] Wang, Xin, et al. "A trackable multi-domain collaborative generative adversarial network for rotating machinery fault diagnosis." *Mechanical Systems and Signal Processing* 224 (2025): 111950.
[16] Giambene, Giovanni, and Sastri Kota. "Cross-layer protocol optimization for satellite communications networks: A survey." *International Journal of Satellite Communications and Networking* 24.5 (2006): 323-341.
[17] Cho, Woncheol, and Jihwan P. Choi. "Cross layer optimization of wireless control links in the software-defined LEO satellite network." *IEEE Access* 7 (2019): 113534-113547.
[18] Choi, Jihwan P., Seok-Ho Chang, and Vincent WS Chan. "Cross-layer routing and scheduling for onboard processing satellites with phased array antenna." *IEEE transactions on wireless communications* 16.1 (2016): 180-192.
[19] Gao, Zhen, et al. "Blockchain based secure relay scheme for space-terrestrial integrated networks." *China Communications* 20.5 (2023): 170-181.
[20] Li, Zuguang, et al. "Multi-operator dynamic spectrum sharing for wireless communications: A consortium blockchain enabled framework." *IEEE Transactions on Cognitive Communications and Networking* 9.1 (2022): 3-15.
[21] Yrjölä, Seppo. "Analysis of blockchain use cases in the citizens broadband radio service spectrum sharing concept." *Cognitive Radio Oriented Wireless Networks: 12th International Conference, CROWNCOM 2017, Lisbon, Portugal, September 20-21, 2017, Proceedings 12*. Springer International Publishing, 2018.
[22] Badini, Nour, et al. "User Centric Satellite Handover for Multiple Traffic Profiles Using Deep Q-Learning." *IEEE Transactions on Aerospace and Electronic Systems* (2024).
[23] Xu, Huihui, et al. "QoE-driven intelligent handover for user-centric mobile satellite networks." *IEEE Transactions on Vehicular Technology* 69.9 (2020): 10127-10139.

Journal of Information Systems Engineering and Management
2025, 10(38s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

[24] Alabassby, Bahaa Faiz Noory Mohsin, Jinan Fadhil Mahdi, and Mohammed Aboud Kadhim. "Design and implementation WSN based on Raspberry Pi for medical application." IOP Conference Series: Materials Science and Engineering. Vol. 518. No. 5. IOP Publishing, 2019.
[25] Ahmed, Sadeer Rasheed, Mohammed Aboud Kadhim, and Tarek Abdulkarim. "Wireless sensor networks improvement using leach algorithm." IOP Conference Series: Materials Science and Engineering. Vol. 518. No. 5. IOP Publishing, 2019.
[26] Drampalou, Stamatia F., et al. "A User-Centric perspective of 6G networks: A Survey." *IEEE Access* (2024).