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MODRS: A Multi-Objective Deep Learning Algorithm for Optimizing Routing and Scheduling in LEO Satellite Networks

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Abstract

The demand for high-quality Direct-to-Home (D2H) television broadcasting services delivered via Low Earth Orbit (LEO) satellite constellations has surged in recent years. To address the growing needs of viewers, satellite communication must optimize the scheduling and routing of signals while balancing conflicting objectives. This research presents a novel approach named as Multi-Objective Deep Routing and Scheduling (MODRS) algorithm that is designed to tackle the challenges of signal latency minimization, bandwidth utilization maximization, and viewer demand satisfaction. The Multi-Objective Deep Neural Network (MODNN) is implemented in this paper to make intelligent routing and scheduling decisions for balancing multiple objectives. To enhance the learning process and provide training stability, the experience replay is used, and the epsilon-greedy strategy is included to balance exploitation and exploration strategies. The Pareto-front concept is used for efficient D2H television broadcasting in the LEO satellite constellation. The experimental validation is conducted based on low-latency broadcasting, high-bandwidth utilization, viewer demand flexibility, adaptive signal strength and resource allocation efficiency. Using a series of simulated scenarios, this paper explores the versatility and robustness of MODRS, showcasing its exceptional performance in real-time, resource-efficient, disaster recovery, and rural broadcasting contexts. The findings indicate that MODRS is well-suited for a wide range of real-world applications, from low-latency broadcasting and disaster recovery to cost-effective rural expansion, enhancing the quality and accessibility of D2H television services. The MODRS algorithm emerges as a transformative solution for satellite communication optimization, ensuring viewer satisfaction and operational efficiency.

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1. Introduction

Introduction The demand for Direct-to-Home (D2H) television broadcasting has witnessed unprecedented growth in recent years, driven by the increasing appetite for on-demand content and high-quality viewing experiences. To meet this demand, satellite communication systems play a pivotal role in delivering television signals directly to homes across the globe [1] [2]. Among these systems, Low Earth Orbit (LEO) satellite constellations have gained prominence due to their advantages in terms of reduced signal latency and enhanced coverage [3] [4]. However, the efficient operation of LEO satellite constellations for D2H television broadcasting presents a multifaceted challenge [5]. These constellations consist of numerous satellites orbiting the Earth at relatively low altitudes. While this proximity minimizes signal latency, it also introduces complex scheduling [7] and routing dilemmas [6] [8]. The conflicting objectives of minimizing signal latency, maximizing bandwidth utilization, and meeting viewer demand pose a formidable problem for satellite operators.

1.1 Problem Statement

LEO satellite constellations have gained prominence as a means to facilitate D2H television broadcasting. These constellations consist of numerous small satellites orbiting at lower altitudes, providing advantages such as reduced signal latency and wider coverage. However, the efficient management of these constellations is a multifaceted problem due to the conflicting nature of the objectives involved. On one hand, minimizing signal latency is crucial for ensuring a seamless viewing experience, as any delays lead to viewer dissatisfaction [9]. On the other hand, maximizing bandwidth utilization is essential to accommodate the growing demand for high-definition and 4K content. Furthermore, meeting viewer demand patterns adds another layer of complexity, as it requires adaptive and real-time routing and scheduling decisions.

1.2 Significance of Multi-Objective Optimization

In this framework, the significance of multi-objective optimization becomes evident. Traditional optimization approaches [10] often focus on a single objective, such as minimizing latency or maximizing bandwidth. However, these objectives frequently conflict with one another. For instance, routing signals to minimize latency may lead to suboptimal bandwidth utilization, affecting the quality of service. Conversely, maximizing bandwidth usage may inadvertently increase signal latency. It is in this intricate interplay of conflicting objectives that multi-objective optimization shines. Multi-objective optimization considers these conflicting objectives simultaneously. It seeks to find a set of solutions that represent the trade-offs between different objectives, rather than a single optimal solution. These trade-offs are presented on a Pareto front, offering decision-makers a range of options to choose from, depending on their priorities and preferences. In the case of LEO satellite constellations for D2H broadcasting, multi-objective optimization allows satellite operators to strike the right balance between low latency, efficient bandwidth utilization, and meeting viewer demand.

1.3 Contributions

The major contributions of the LEO satellite constellations for D2H television broadcasting are provided as,

1. **Development of the MODRS Algorithm:** The primary contribution of this research is the development of the Multi-Objective Deep Routing and Scheduling (MODRS) algorithm. MODRS represents an innovative approach to address the complex challenges of routing and scheduling in low Earth orbit (LEO) satellite constellations for Direct-to-Home (D2H) television broadcasting.
2. **Multi-Objective Optimization:** The research contributes to the field of satellite communication by introducing a multi-objective optimization framework. This framework reconciles the conflicting objectives of minimizing signal latency, maximizing bandwidth utilization, and meeting viewer demand satisfaction. MODRS effectively balances these objectives to deliver quality D2H television services.
3. **System Model for LEO Satellite Constellations:** The paper presents a comprehensive system model that encompasses critical elements of LEO satellite constellations, including satellite positions, ground stations, viewer demand patterns, signal latency, and signal strength characteristics. This model provides a foundational understanding of the satellite communication environment.
4. **Multi-Objective Deep Neural Network (MODNN):** The core of the MODRS algorithm is the MODNN, a multi-objective deep neural network. This contribution introduces a novel approach to decision-making in satellite communication. The MODNN dynamically adapts routing and scheduling decisions to optimize objectives in real-time, offering a versatile solution to the industry.
5. **Adaptability and Robustness:** The research demonstrates the adaptability and robustness of MODRS through a series of scenarios and use cases. These findings contribute to the understanding of how the algorithm excels in real-world applications, including low-latency broadcasting, disaster recovery, and rural broadcasting.
6. **Cost-Effectiveness and Digital Inclusion:** The research highlights the cost-effectiveness of MODRS, particularly in extending D2H television services to rural and economically challenged areas. This contribution supports the goal of digital inclusion and bridging the digital divide.

The rest of the sections in the paper are arranged as, section 2 contains the literature survey that is attained from the different existing research papers. The system model and the problem formulation are clearly explained with the suitable diagrams and mathematical representations that are provided in sections 3 and 4 respectively. The proposed methodology used to enhance the D2H television broadcasting is elaborated in section 5 and the validation is conducted based on the five scenarios in section 6. Section 7 illustrates the discussion of this entire paper and section 8 concludes this paper with future work details**.**

2. Literature Review

This section presents a comprehensive review of the existing literature on key topics relevant to the optimization of scheduling and routing in Low Earth Orbit (LEO) satellite constellations for Direct-to-Home (D2H) television broadcasting. The literature review encompasses D2H television broadcasting, LEO satellite constellations, multi-objective optimization, and deep learning. It also identifies the gaps in the literature that the Multi-Objective Deep Routing and Scheduling (MODRS) approach aims to address.

2.1 D2H Television Broadcasting

Direct-to-Home (D2H) television broadcasting is a fundamental aspect of the modern media landscape. It allows viewers to receive high-quality television content directly at their homes via satellite, eliminating the need for intermediary cable or terrestrial broadcasting. The literature on D2H television broadcasting is vast and has explored various aspects, including technological advancements, market trends, and the evolving demands of viewers. Researchers have investigated the challenges faced by D2H service providers, such as ensuring uninterrupted service, optimizing content delivery, and enhancing viewer experience. A key challenge is minimizing signal latency, which directly impacts viewer satisfaction. Reduced latency ensures that viewers receive content with minimal delays, resulting in a more enjoyable and immersive experience.

2.2 LEO Satellite Constellations

Low Earth Orbit (LEO) satellite constellations have emerged as a promising technology for D2H television broadcasting [11]. Compared to traditional geostationary satellites [12], LEO constellations offer lower signal latency due to their closer proximity to the Earth's surface. This has sparked interest in deploying LEO constellations to enhance the efficiency of D2H television broadcasts.

Literature in this area often explores the technical aspects of LEO constellations, such as constellation design, satellite deployment, and tracking [13]. Nevertheless, limited research has delved into the specific challenges related to real-time routing and scheduling in these constellations. Given the dynamic nature of LEO constellations, there is a clear need for novel approaches that address multi-objective optimization, taking into account latency, bandwidth utilization, and viewer demand.

2.3 Multi-Objective Optimization

Multi-objective optimization [14], a field that deals with problems involving multiple conflicting objectives, has seen extensive application in various domains including engineering, finance, and environmental science. In the context of telecommunication and networking, research has predominantly concentrated on resource allocation and load balancing. While some research has addressed optimization in satellite constellations, many studies have primarily focused on single-objective problems, often sacrificing one objective to improve another. For instance, studies may prioritize signal latency reduction without fully considering the trade-offs with bandwidth utilization and viewer demand satisfaction. This limitation underscores the need for a multi-objective optimization approach [15] that finds a balance among these conflicting objectives.

2.4 Deep Learning

Deep learning, particularly deep reinforcement learning [18], has gained traction in addressing complex optimization problems. Deep neural networks, such as convolutional neural networks (CNNs) [20] and recurrent neural networks (RNNs) [17], have demonstrated remarkable success in various domains, from computer vision to natural language processing. Literature in this domain primarily focuses on applications in gaming, robotics, and healthcare. In the context of satellite communication and D2H television broadcasting, deep learning has primarily been applied in areas such as signal processing, error correction, and content recommendation. Researchers have developed deep learning models (16) to enhance signal reception and improve content recommendations for viewers. However, the application of deep learning in optimizing routing and scheduling within LEO satellite constellations remains an underexplored domain. While some studies have explored the use of deep learning in satellite communication, there is a scarcity of research that combines deep learning with multi-objective optimization to tackle the unique challenges posed by the dynamic nature of LEO satellite constellations.

2.5 Gaps in the Literature by MODRS Approach

The Multi-Objective Deep Routing and Scheduling (MODRS) approach addresses significant gaps in the existing literature. While there is research on D2H television broadcasting, LEO satellite constellations, multi-objective optimization, and deep learning, the integration of these domains to optimize routing and scheduling in LEO constellations remains relatively uncharted territory. The key gaps addressed by MODRS include:

1. **Multi-Objective Optimization*:*** MODRS recognizes the complexity of D2H television broadcasting in LEO constellations, where multiple conflicting objectives exist. Traditional studies have often focused on individual objectives in isolation, failing to provide a holistic approach to address the challenges. MODRS bridges this gap by adopting a multi-objective optimization framework, allowing for a balance between reducing signal latency, maximizing bandwidth utilization, and meeting viewer demand.
2. **Deep Learning in Routing and Scheduling:** While deep learning has found applications in various aspects of satellite communication and D2H television broadcasting, its application in optimizing routing and scheduling within LEO constellations has been underexplored. MODRS leverages deep neural networks to make dynamic and adaptive routing and scheduling decisions based on real-time data, addressing this gap by integrating deep learning into the optimization process.

The MODRS approach bridges these gaps by introducing a multi-objective deep reinforcement learning algorithm designed to optimize routing and scheduling in LEO satellite constellations. By combining the principles of multi-objective optimization and deep learning, MODRS provides a novel and promising solution to enhance the efficiency and quality of D2H television broadcasting in the dynamic environment of LEO satellite constellations. This approach aims to address the complexities that traditional methods have failed to tackle effectively, thereby advancing the state of the art in satellite network optimization.

3. System Model

In this section, a comprehensive system model is established that underlies the proposed multi-objective optimization approach within the context of LEO satellite constellations for D2H television broadcasting. The key components of the system, the parameters and the objectives are outlined to optimize. The system model of this paper is presented in Figure 1.

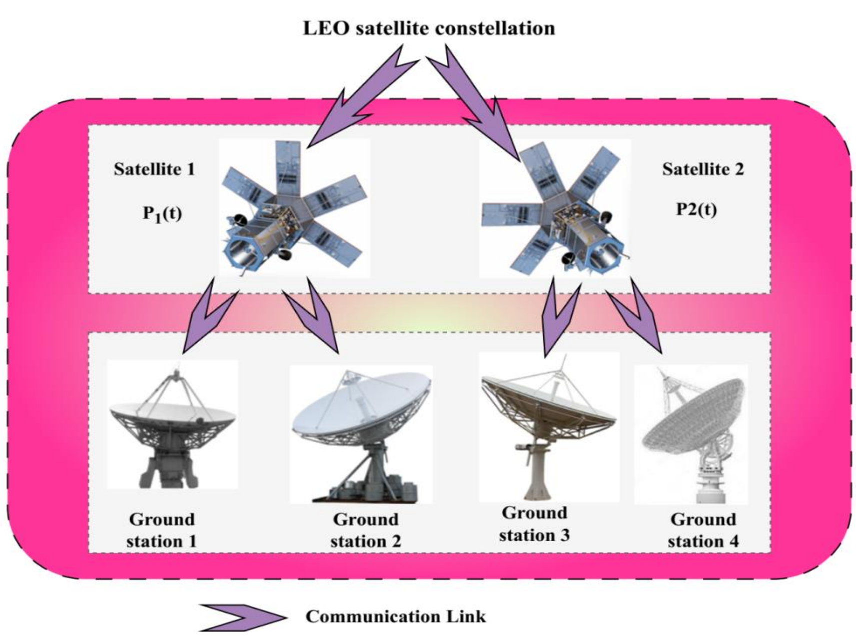

Figure 1. LEO Satellite Constellation System Model

3.1 LEO Satellite Constellation

A Low Earth Orbit (LEO) satellite constellation consists of a network of small satellites orbiting at relatively low altitudes above the Earth's surface. The LEO (Low Earth Orbit) Satellite Constellation System Model is a conceptual framework that describes the essential components and interactions involved in the operation of a satellite network in low Earth orbit for various applications, including D2H (Direct-to-Home) television broadcasting. This model serves as the foundation for understanding how such satellite constellations function and how they contribute to the delivery of television content to viewers. The key components used in the LEO satellite constellation system model are clearly explained in Figure 2.

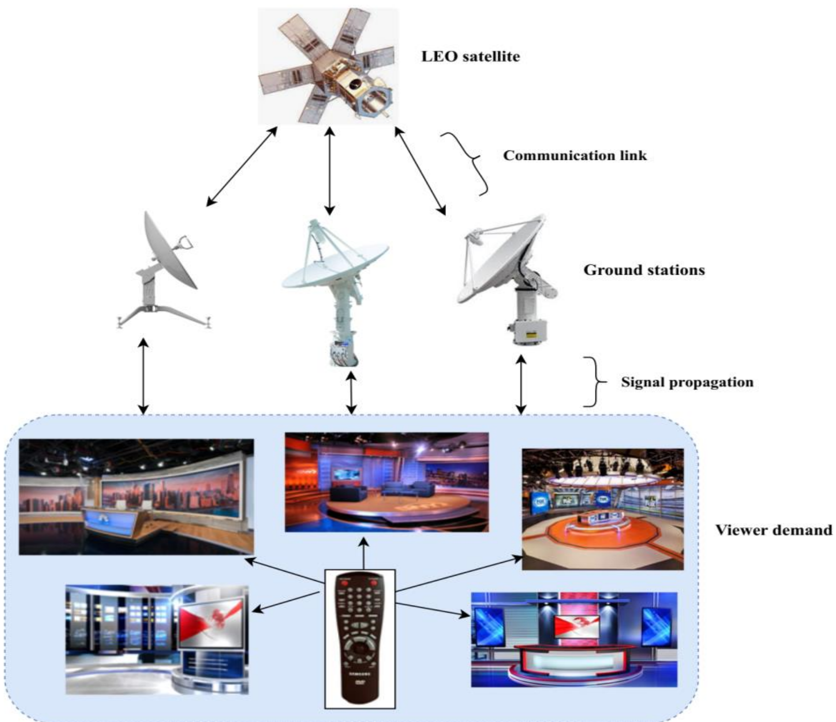

Figure 2. Key Components and Workflow of the System Model

The constellation is characterized by the following components:

3.1.1 Satellite positions

LEO satellites are a crucial part of the satellite constellation. These satellites orbit at relatively low altitudes, typically ranging from a few hundred kilometers to a few thousand kilometers above the Earth's surface. LEO satellites are known for their advantages, including reduced signal latency and improved coverage compared to higher-altitude satellites. In D2H television broadcasting, they play a central role in relaying television signals to viewers. The LEO constellation comprises multiple satellites and each occupying a unique position in space. These positions evolve over time due to the satellite's orbital dynamics and the satellite positions are described as,

$$S = \{S_1, S_2, \ldots, S_N\} \tag{1}$$

where $N$is the total number of satellites.

3.1.2 Ground Stations

Ground stations are located on the earth's surface and serve as communication hubs to receive and transmit signals to and from the LEO satellites. Ground stations transmit signals to the satellites for broadcast and receive signals from the satellites, enabling data exchange between space and Earth. These act as gateways for connecting satellite networks with terrestrial infrastructure. The ground stations are expressed as,

$$G = \{G_1, G_2, \ldots, G_M\} \tag{2}$$

The total number of ground stations is denoted as M.

3.1.3Communication Links

Communication links are the channels through which signals travel between ground stations and LEO satellites. Signals are transmitted from ground stations to satellites for broadcasting and vice versa. These links form the backbone of the system, ensuring that television content reaches its intended audience.

3.1.4 Viewer demand and Content distribution

Viewer demand represents the dynamic and varying requests for D2H television content from viewers. This aspect considers factors like viewer preferences, geographical variations in demand, and changing demand patterns throughout the day. Understanding viewer demand is essential for content providers and broadcasters to deliver content that meets the expectations of their audience. The success of D2H television broadcasting heavily relies on catering to viewer demand which is dynamic and varies across geographical regions and time. The key aspects of demand and content distribution include:

Viewer demand patterns

The viewer demand pattern fluctuates throughout the day and across different regions. These patterns are often modeled as time-varying functions and the viewer demand is represented as,

$$D = \{D_1(t), D_2(t), \ldots, D_K(t)\} \tag{3}$$

Here, the terms such as $K$and t are denoted as total number of viewer demand profiles and time respectively.

Content catalog

The comprehensive catalog of available television channels and content forms the basis for viewer choices. It included a variety of channels, genres and programs that the content catalog is displayed as,

$$C = \{C_1, C_2, \ldots, C_L\} \tag{4}$$

The total number of content items are denoted as L.

3.1.5 Signal propagation characteristics

Signal propagation encompasses the process of signals traveling from LEO satellites to ground stations and vice versa. It includes considerations such as signal latency (the time it takes for a signal to travel between a satellite and a ground station) and signal strength (how strong or weak the signal is at a given location). Signal propagation characteristics are vital for optimizing the quality and efficiency of television broadcasts. The signal propagation within the LEO constellation system is influenced by several factors and that are mathematically expressed as:

Signal latency

The signal latency (L_{ij}) is the time taken for a signal to travel from a satellite to a ground station and it calculates the distance between satellite S_i and ground station $G_j(D_{ij})$ divided by the signal propagation speed (S). The mathematical formulation is given by,

$$L_{ij} = \frac{D_{ij}}{S} \tag{5}$$

Signal strength

The signal strength ($S_{S_{ij}}$) varies based on the distance between the satellite $S_i$and ground station $G_j$and is expressed as an inverse function of the distance as,

$$S_{S_{ij}} = \frac{1}{D_{ij}} \tag{6}$$

3.1.6 Multi-Objective Optimization Parameters

The multi-objective optimization framework defines the essential parameters and objectives that contribute to the optimization processes:

State space

The state space encompasses all relevant information needed to make routing and scheduling decisions that includes real-time data on satellite positions, viewer demand, current channel allocations, signal latency and signal strength.

Action space

The action space represents the set of possible actions available to the optimization algorithm and these actions involve routing decisions for determining which satellite signal allocates to specific viewer requests and adjusting scheduling.

Reward structure (R)

The reward structure defines the objectives and trade-offs inherent in multi-objective optimization and the required objectives for the proposed model are,

- Minimizing signal latency
- Maximizing bandwidth utilization
- Meeting viewer demand

4. Problem Formulation

In this section, the multi-objective optimization problem is defined that drives the decision-making processes in the proposed LEO Satellite Constellation System Model. Assume, three key objectives: minimizing signal latency, maximizing bandwidth utilization, and meeting viewer demand. The relevant notations, variables, constraints, and the concept of the Pareto front are introduced to break down the problem.

4.1 Formulating the Multi-Objective Optimization Problem

In the LEO Satellite Constellation System Model, the operation for D2H television broadcasting is optimized. The optimization problem consists of three critical objectives:

Minimizing signal latency objective ($O_{Latency}(t)$)

The first objective is to reduce signal latency to ensure a seamless viewing experience, and the signal latency takes time to transmit signal from a specific satellite to ground station at a particular time t. The total signal latency across all satellite ground station pairs is minimized to achieve minimum signal latency. The signal latency is formulated as,

$$O_{Latency}(t) = \sum_{i=1}^{N} \sum_{j=1}^{M} L_{ij}\ (t) \tag{7}$$

Maximizing bandwidth utilization objective ($O_{Bandwidth}(t)$)

The second objective is to make efficient use of available bandwidth. The channels are allocated efficiently to achieve maximum bandwidth utilization and are expressed as,

$$O_{Bandwidth}(t) = \frac{1}{\sum_{i=1}^{N} \sum_{j=i}^{M} L_{ij}(t)} \tag{8}$$

The total number of satellites in the constellation and the total number of ground stations in the constellation are represented as $N$and Mrespectively.

Meeting viewer demand objective ($O_{Demand}(t)$)

Viewer satisfaction is paramount in D2H television broadcasting. Meeting viewer demand involves ensuring that viewers have access to their desired content and viewer satisfaction is represented as the function of content catalog (C), viewer demand (D) and content allocation (A). This objective is more complex and is represented as a satisfaction index that takes into account various factors such as real-time adaptation, viewer preferences and content availability to changing demand patterns. This viewer demand objective is defined as,

$$O_{Demand}(t) = f(C, D, A) \tag{9}$$

4.2 Optimization variables and constraints

Routing decisions

Optimization variable: These variables represent routing decisions for indicating which satellite signals are allocated to specific viewer requests. The binary routing variable ($x_{ir}(t)$) is defined as,

$$x_{ir}(t) = \begin{cases} 1, \text{if request } r \text{ is routed via satellite } i \text{ at time } t \\ 0, Otherwise \end{cases} \tag{10}$$

Constraints: The constraints related to routing decisions include:

- Ensuring that each viewer request is routed via only one satellite at a given time is denoted as,

$$\sum_{i=1}^{N} x_{ir}(t) = 1, \forall r \tag{11}$$

- Capacity constraints on the number of viewer requests that are routed through a satellite.

Channel allocation

Optimization variables: These variables define the allocation of television channels to content which affects bandwidth utilization. The term $y_{ij}(t)$ represents the allocation of content $j$to channel i at time t.

Constraints: The constraints related to channel allocation include,

- Capacity constraints on the number of channels available for content allocation.
- Ensuring that a channel is not allocated to more than one content item at the same time as,

$$\sum_j y_{ij}(t) \leq 1, \forall i \tag{12}$$

Signal propagation constraints

The signal propagation constraints are considered as signal latency and signal strength which are clearly explained in section 3.1.5.

Real-time adaptation

The optimization model has the ability to adapt dynamically for real-time changes in the viewer demand patterns or satellite positions. This is responsible for updating the optimization variables and constraints based on new data or conditions.

These optimization variables and constraints collectively define the multi-objective optimization problem in the LEO Satellite Constellation System Model. The goal is to find a set of routing decisions and channel allocations that minimize signal latency, maximize bandwidth utilization, and meet viewer demand while adhering to physical constraints and adapting to real-time changes in the system.

4.3 Pareto Front Concept

The Pareto front represents the set of optimal trade-off solutions between the conflicting objectives. In this multi-objective optimization problem, the goal is not to find a single solution but to identify a range of solutions that balance the objectives. The Pareto front is the collection of non-dominant solutions where no solution is improved in one objective without worsening another. The Pareto front helps decision-makers choose the most suitable solution based on their priorities for minimizing signal latency, maximizing bandwidth utilization, and meeting viewer demand.

Pareto front

The Pareto front is a set of non-dominated solutions where no solution is better than another in all objectives. It reflects the trade-offs between objectives and the front is defined as,

$$PF = \{(O_{Latency}, O_{Bandwidth}, O_{Demand})(t)\} \tag{13}$$

Dominance relation

A solution “A” dominates solution “B” if it is good or better than “B” in all objectives and strictly better in at least one. In this paper, a solution is dominated by another if it has higher signal latency, lower bandwidth utilization and lower viewer demand satisfaction.

Decision making

The decision maker chose the solutions from the Pareto front based on their priorities. For instance, sometimes the decision-makers prefer solutions with lower signal latency at the expense of lower bandwidth utilization and vice-versa. The Pareto front offers a range of options that accommodate diverse preferences.

5. Proposed Methodology

In this section, the MODRS algorithm is presented which is a multi-objective optimization approach for efficient routing and scheduling in LEO Satellite Constellations for D2H Television Broadcasting. This innovative methodology leverages deep reinforcement learning and multi-objective optimization techniques to balance conflicting objectives. The proposed model is displayed in Figure 3 and the MODRS algorithm is employed to address complexities of the routing and scheduling decisions. The MODNN model is implemented for making intelligent routing and scheduling decision that balances multiple objectives such as minimum signal latency, maximum bandwidth utilization and meet viewer demand satisfaction. The MODNN model incorporates multiple Q-networks that guide the decision-making process by estimating the expected cumulative reward associated with each objective. The experience replay is designed in this paper to provide training stability and enhance learning process. Then the Epsilon-greedy strategy is used to balance exploitation and exploration strategies that enable algorithm to make informed decisions. The routing and scheduling decisions are adapted based on the real-time information and the performance metrics are continuously tracked based on changing conditions. The Pareto-front has a set of non-dominated solutions in the multi-objective optimization problem and efficient television broadcasting is provided due to tracking the pareto-front.

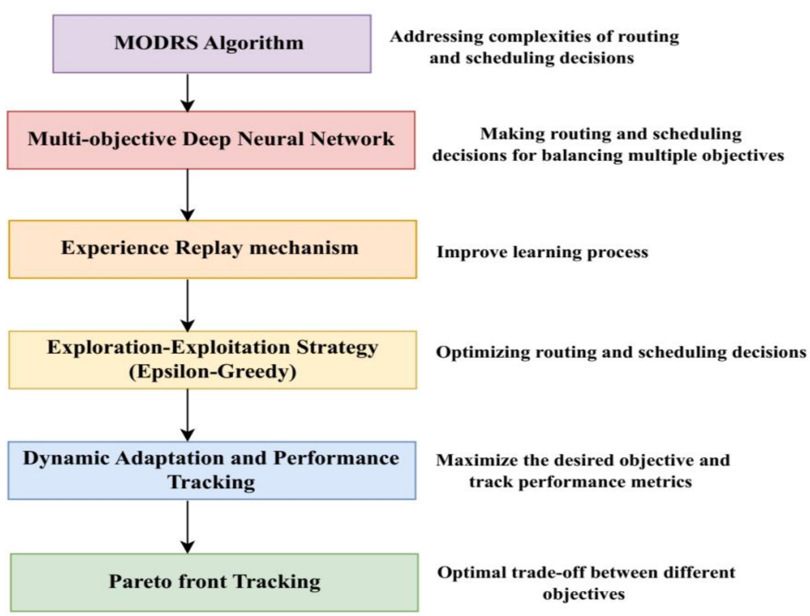

Figure 3. Workflow of the proposed model

5.1 Overview of Multi-Objective Deep Routing and Scheduling (MODRS) algorithm

The Multi-Objective Deep Routing and Scheduling (MODRS) algorithm is an advanced approach aimed at addressing the complexities of routing and scheduling decisions within Low Earth Orbit (LEO) Satellite Constellations for Direct-to-Home (D2H) Television Broadcasting. The primary goal of MODRS is to dynamically adapt and optimize these decisions in real-time to achieve three essential objectives: minimizing signal latency, maximizing bandwidth utilization, and ensuring viewer demand satisfaction.

5.1.1 Real-Time Dynamic Adaptation

MODRS is built to operate in a dynamic environment where viewer demand, satellite positions, and other critical factors change continuously. It adapts its routing and scheduling decisions on-the-fly to respond to these changes effectively. This real-time adaptation is crucial for ensuring efficient content distribution.

5.2 Multi-Objective Deep Neural Network (MODNN)

The MODNN serves as the core component of the MODRS algorithm is responsible for mapping states to optimal actions while considering multiple objectives. It plays a central role in making intelligent routing and scheduling decisions that balance multiple objectives, including minimizing signal latency, maximizing bandwidth utilization, and meeting viewer demand satisfaction. This neural network architecture is a fundamental component that helps MODRS make informed decisions. A detailed description of key components and training approach of the MODNN are provided as:

5.2.1 State Space

The MODNN processes a comprehensive state space, denoted as S(t), which includes up-to-the-minute information about the positions of LEO satellites, patterns of viewer demand, current signal latencies, and signal strengths for all viewer requests at a specific time t. It encapsulates real-time information that is critical for decision-making within the LEO Satellite Constellations for D2H Television Broadcasting. The key components and its associated formulas of state space are explained as:

Satellite Positions ($P_i(t)$)

- The positions of LEO satellites are vital for determining the optimal routing decisions. Each satellite is represented as $P_i(t)$, where i ranges from 1 to N, signifying the i -th satellite in the constellation.
- The positions of the satellites continuously evolve due to their orbits. The positions are determined based on orbital parameters, and the exact coordinates are calculated as functions of time t.

$$P_i(t) = \left(x_i(t), y_i(t), z_i(t)\right) \tag{14}$$

Viewer Demand Patterns ($D(t)$)

- Viewer demand patterns, $D(t)$, describe the changing preferences and requests of viewers at a specific time t. These patterns represent the varying content choices and demands of viewers.
- Viewer demand patterns are obtained from historical data, real-time monitoring, or predictive models.

$$D(t) = [d_1(t), d_2(t), \ldots., d_M(t)] \tag{15}$$

Signal latency ($L_i(t)$)

Signal latency quantifies the time taken for travelling the signal from a specific satellite to the ground station and is determined based on the distance between satellite and ground station divided by the speed of signal propagation. The signal latency is denoted as,

$$L_i(t) = \frac{d_i(t)}{\vartheta} \tag{16}$$

The speed of signal propagation and the distance between the satellite and the corresponding ground station are described by $d_i(t)$ and ϑ.

Signal strength ($S_{S_i}(t)$)

The signal strength represents the strength of a signal from satellite to ground station that is inversely proportional to the square of the distance between satellite and ground station. The signal strength formula is derived by

$$S_{S_i}(t) = \frac{K}{d_i^2(t)} \tag{17}$$

Here, K is the constant related to the transmit power and other factors.

5.2.2. Action Space ($A(t)$)

Within the $A(t)$ action space, MODRS identifies possible actions and choices to be made. These actions encompass routing decisions that determine which satellite serves each viewer request, channel allocations to individual viewer requests, and scheduling decisions related to when signals are transmitted. Detailed explanations of actions and choices are provided as:

Routing decision

Routing decision involves for selecting which LEO satellite serves each viewer's request and this decision plays a vital role in minimizing signal latency that ensures the signals are efficiently transmitted to viewers. The action space for routing decisions $A_{Routing}(t)$ includes options for assigning viewer requests to specific satellites. This is represented as a binary choice for each viewer request where 1 signifies assignment to a particular satellite and 0 denotes assignment to another satellite. The action space for decision routing is expressed as,

$$A_{Routing}(t) = [a_1(t), a_2(t), \dots, a_N(t)] \tag{18}$$

Channel allocation

The channel allocation refers to the assignment of specific communication channels to individual viewer requests. These allocations have a direct impact on bandwidth utilization that determines which channels are available for broadcasting content. The action space for channel allocation ($A_{Channel}(t)$) comprises choices for allocating channels to viewer requests. This channel allocation is represented as a binary matrix where each entry specifies whether a channel is allocated (1) or not (0) for a specific viewer request. The mathematical formulation is represented as,

$$A_{Channel}(t) = \begin{bmatrix} a_{1,1}(t) a_{1,2}(t) \cdots a_{1,M}(t) \\ a_{2,1}(t) a_{2,2}(t) \cdots a_{2,M}(t) \\ \vdots \vdots \ddots \vdots \\ a_{N,1}(t) a_{N,2}(t) \cdots a_{N,M}(t) \end{bmatrix} \tag{19}$$

Scheduling choices

Scheduling choices are involve determining when signals are transmitted and this decision significantly impacts both viewer demand satisfaction and bandwidth utilization. The action space for scheduling choices ($A_{Scheduling}(t)$) includes options for specifying the timing and order of signal transmission. It is represented as a sequence of time slots or a schedule that determines when each viewer request is served. The mathematical formulation is denoted as,

$$A_{Scheduling}(t) = [t_1, t_2, \dots, t_M] \tag{20}$$

5.2.3 Q-Networks for Objectives

MODNN incorporates multiple Q-networks, each dedicated to one of the three primary objectives: minimizing signal latency ($Q_{Latency}$), maximizing bandwidth utilization ($Q_{Bandwidth}$), and ensuring viewer demand satisfaction (Q_{Demand}). These Q-networks are crucial for guiding the decision-making process by estimating the expected cumulative reward associated with each objective. The purposes of each Q-network are described in the following subsequent sections as:

Minimizing signal latency ($Q_{Latency}$)

The $Q_{Latency}$ network is specifically designed to estimate the expected cumulative reward associated with minimizing signal latency. It plays a central role in guiding routing decisions to minimize the time it takes for signals to reach their destinations. The formula used for $Q_{Latency}$ is typically based on the expected reduction in signal latency due to a specific action. It considers factors like the difference in signal travel time before and after the action.

$$Q_{Latency}(s,a) = E[\Delta L(s,a)] \tag{21}$$

From the above-mentioned equation, the terms $Q_{Latency}(s,a)$ and $E[\Delta L(s,a)]$ are represented as the expected cumulative reward for minimizing signal latency and expected reduction in signal latency respectively.

Maximizing bandwidth utilization ($Q_{Bandwidth}$)

The $Q_{Bandwidth}$ network's primary objective is to quantify the expected cumulative reward associated with maximizing bandwidth utilization. It guides channel allocation decisions to optimize bandwidth usage. The expected cumulative reward for maximizing bandwidth utilization, denoted as $Q_{Bandwidth}(s,a)$ is calculated based on the current state (s) and the chosen action (a). It helps the system make decisions that lead to efficient use of available bandwidth resources.

$$Q_{Bandwidth}(s,a) = E[\Delta B(s,a)] \tag{22}$$

The expected improvement in bandwidth utilization is denoted as $E[\Delta B(s,a)]$.

Viewer demand satisfaction (Q_{Demand})

The primary objective of the Q_{Demand} network is to quantify the expected cumulative reward associated with meeting viewer demand satisfaction. It plays a pivotal role in scheduling decisions to ensure viewers receive content when desired. This involves optimizing scheduling choices to provide content to viewers as per their preferences. The formula used for Q_{Demand} is typically based on the expected improvement in viewer demand satisfaction due to a specific action. It considers factors like the increase in viewer satisfaction due to timely content delivery.

$$Q_{Demand}(s,a) = E[\Delta V(s,a)] \tag{23}$$

The expected improvement in viewer demand satisfaction is presented as $E[\Delta V(s,a)]$.

5.2.4 Multi-Objective Q-Network Training

Training the MODNN within the MODRS algorithm is crucial for enabling the network to consider and balance multiple objectives simultaneously. Multi-objective Q-network training ensures that the Q-networks are not only proficient at maximizing their primary objective but also consider other objectives as constraints. This approach allows MODRS to find a balance between the three objectives, as each Q-network seeks to optimize its assigned objective while adhering to constraints imposed by the other objectives. The training approach emphasizes the integration of the following primary objectives:

Minimizing Signal Latency ($Q_{Latency}$): The $Q_{Latency}$ network is trained to maximize this objective, focusing on reducing the time it takes for signals to reach their destinations.

Maximizing Bandwidth Utilization ($Q_{Bandwidth}$): The $Q_{Bandwidth}$ network is trained to maximize this objective, with the goal of optimizing the efficient use of communication channels.

Meeting Viewer Demand (Q_{Demand}): The Q_{Demand} network is trained to ensure viewer demand satisfaction, aiming to provide content to viewers as per their preferences.

Training Objectives

The training process involves considering the objectives not only in isolation but also as constraints on each other. This means that the MODNN is designed to strike a balance between these competing objectives. It aims to find solutions that optimize all three objectives to the extent possible, recognizing that trade-offs might be necessary in certain scenarios. One common approach is to aggregate the Q-values using weighted sums, emphasizing the relative importance of each objective. The formula is as follows:

$$Q_{Multi-Objective}(s,a) = w_{Latency} \cdot Q_{Latency}(s,a) + w_{Bandwidth} \cdot Q_{Bandwidth}(s,a) + w_{Demand} \cdot Q_{Demand}(s,a) \tag{24}$$

The overall multi-objective Q-value for state and action is represented as $Q_{Multi-Objective}(s,a)$ and the weight coefficients assigned to each objective for determining their relative importance are depicted as $w_{Latency}$, $w_{Bandwidth}$ and w_{Demand} respectively.

5.3 Experience Replay

Experience replay is a fundamental concept in the MODRS algorithm. It helps to stabilize training and improve the learning process. Experience replays stores experiences (state, action, reward, and next state) in a replay buffer and randomly samples from it during training. This random sampling helps the algorithm avoid correlated experiences and enables it to explore different situations effectively. Experience replay serves dual purposes:

1. **Stabilizing Training***:* It plays a crucial role in stabilizing the training process by mitigating the potential for training instability stemming from correlated experiences. The random sampling of experiences from the replay buffer effectively breaks the temporal correlation in the training data.
2. **Effective Exploration**: Experience replay significantly enhances the algorithm's capacity to explore different scenarios. By learning from randomly selected past experiences, the algorithm explores a wide range of state-action pairs, even those previously encountered but potentially beneficial in distinct contexts.

The core idea behind the experience replay is the systematic storage and random sampling of experiences from a dedicated replay buffer. Experiences are stored in the replay buffer as tuples of the form (s,a,r,s') and the maintenance of the replay buffer is formulated as,

$$R_{buffer} = \{(s_1, a_1, r_1, s_1'), (s_2, a_2, r_2, s_2'), \ldots, (s_N, a_N, r_N, s_N')\} \tag{25}$$

Here, R_{buffer}, N, s, a, $r$and s' are illustrated as replay buffer, total number of stored experiences, state at a specific time step, action taken at that time step, reward received as a consequence of that action and state that results from taking action respectively. The random sampling process is a critical aspect of experience replay where a batch of experiences is randomly selected from the replay buffer for each training iteration. This random sampling procedure is pivotal in breaking temporal correlation within the training data and promoting more stable and efficient learning. The random sampling procedure is expressed as,

$$\beta = \Re\left(R_{Buffer}, Batch_{size}\right) \tag{26}$$

From the above mentioned equation, the terms such as β, $\Re$, $R_{Buffer}$and $Batch_{size}$ are portrayed as randomly sampled batch of experiences, random sample, replay buffer and number of experiences sampled in each training iteration respectively.

5.4. Exploration-Exploitation Strategies

In the MODRS algorithm, a suitable exploration-exploitation strategy is employed to balance the trade-offs between objectives. This strategy includes epsilon-greedy is designed to ensure a dynamic equilibrium between exploration and exploitation, enabling the algorithm to make informed decisions. The chosen strategy, which is highly effective in optimizing routing and scheduling decisions, is detailed below:

5.4.1 Epsilon-Greedy Strategy

The epsilon-greedy strategy is a well-established approach for balancing exploration and exploitation in reinforcement learning. It enables the algorithm to make most decisions based on its current knowledge (exploitation) while occasionally introducing randomness (exploration). The parameter ϵϵ determines the probability of taking a random action. Epsilon-greedy ensures that most of the time, the algorithm leverages its existing knowledge to make decisions, but periodically explores random actions to discover potentially better solutions. In the epsilon-greedy strategy, the algorithm selects actions based on the Q-values associated with each action in the current state. With a probability of $1-\in$, it chooses the action with the highest Q-value (exploitation) otherwise it selects a random action (exploration) with a probability of $\in$. The epsilon-greedy strategy is expressed as,

$$Epsilon - greedy\ strategy\ = \begin{cases} argmax_a\, Q\,(s,a), withprobability 1-\in \\ randomaction, withprobability\ \in \end{cases} \tag{27}$$

In this equation, the selected action is denoted as a the Q-value signifies $Q(s,a)$ and the exploration probability is depicted as $\in$.

5.5. Dynamic Adaptation and Performance Tracking

MODRS dynamically adapts routing and scheduling decisions based on real-time information, using the MODNN to choose actions that maximize each objective within the bounds of constraints. The algorithm continuously tracks performance metrics for each objective and adapts its decisions based on changing conditions, ensuring optimal performance in the evolving LEO Satellite Constellation system.

5.5.1 Dynamic adaptation

The primary objective of dynamic adaptation is to maximize the desired objectives (minimizing signal latency, maximizing bandwidth utilization, and meeting viewer demand) while adhering to constraints. This is achieved by selecting actions that have the highest associated Q-values. Dynamic adaptation selects actions based on the Q-values assigned to each action in the current state ss. The selected action maximizes the respective objective while considering the constraints imposed by the other objectives. The selected action is expressed as,

$$a = argmax_a \, Q\,(s, a) \tag{28}$$

5.5.2 Performance Tracking

The primary goal of performance tracking is to assess how well the algorithm is meeting its objectives. By tracking cumulative rewards, the algorithm gauges its effectiveness in minimizing signal latency, maximizing bandwidth utilization, and satisfying viewer demand. Performance tracking involves calculating the cumulative reward for each objective over a certain time period. This is expressed as the sum of rewards obtained for that objective during the specified period. The cumulative reward is calculated based on the below mentioned equation as,

$$\text{Cumulative Reward} = \sum_{t=1}^{T} R_t \tag{29}$$

where R_t and $T$are represented as reward obtained at time step and total number of time steps considered in the evaluation respectively. The cumulative reward of each objective is continuously updated to allow the algorithm to assess its performance and adapt its decisions based on changing conditions.

5.6. Pareto Front Tracking

As part of the dynamic adaptation, MODRS keeps track of the Pareto front, which is the set of non-dominated solutions representing the trade-offs between objectives. The Pareto front evolves as conditions change, and the algorithm adjusts its decisions to explore or exploit solutions along the Pareto front according to the preferences of the decision-maker. Each solution on the Pareto front represents an optimal trade-off between different objectives.

<u>Robustness and Adaptability</u>

MODRS is designed to handle the dynamic and complex nature of LEO Satellite Constellations for D2H Television Broadcasting. It adapts to variations in viewer demand, signal latency, and other factors, ensuring robust and adaptable routing and scheduling decisions to provide efficient broadcasting while satisfying conflicting objectives. Pareto Front Tracking in the MODRS algorithm serves the following purposes:

1. **Trade-Off Exploration:** The algorithm continuously monitors the Pareto front to explore the full spectrum of trade-offs between objectives. This ensures that it does not focus solely on a single objective but explores solutions that offer a balanced approach.
2. **Dynamic Adjustment:** As conditions change, the algorithm adapts its decisions to either explore new solutions along the Pareto front or exploit known solutions, depending on the preferences of the decision-maker.

The Pareto front tracking monitors and updates the set of non-dominated solutions over time that is computed based on the objectives and constraints. The Pareto front is calculated as,

$$PF_t = \left\{ s \in S \middle| \notin s' \in S : f(s') \prec f(s) \right\} \tag{30}$$

The terms such as PF_t, S, $f(s)$ and $\prec$are depicted as Pareto front at a time step, set of all possible solutions, vector of objective value associated with solution and dominance relation which ensures a solution is non-dominated if no other solution exists that is better in all objectives. The algorithm continuously updates the Pareto front as it explores and adapts to changing conditions. Based on the preferences of the decision-maker, the algorithm selects solutions from the Pareto front to make decisions that align with the desired trade-offs between objectives.

6. Experimental Evaluation Results

This section outlines the results of the experimentation carried out to validate the effectiveness of the proposed MODRS algorithm in the context of LEO satellite constellations for D2H television broadcasting. The experimental setup and the simulation setup comprising data preparation and simulation environments are described in this section. The distinct performance metrics are employed to evaluate the proposed MODRS algorithm's efficiency in the simulated environment, showcasing trade-off solutions on the Pareto front. Also, the comparative analysis is conducted using traditional routing and scheduling methods. The evaluation outcomes are detailed as graphical representations in the upcoming sections.

6.1 Experimental and Simulation Setup

The experiments are executed on a Python 3.11 using the system running Windows 11, with the Intel core i3-1005G1 CPU, 64-bit OS, 8GB RAM, and a 1.2GHz processor.

Synthetic Data Generation

The synthetic data replicates the characteristics of real data, and it serves as a fundamental component of the experimentation and evaluation process for the MODRS algorithm. Synthetic data generation includes creating synthetic data for satellite positions, viewer demand patterns, signal latency, and signal strength.

Satellite Positions

- **Orbital Parameters:** Synthetic satellite positions are generated based on the defined orbital parameters, including altitude, inclination, eccentricity, and argument of perigee. These parameters mimic the orbits of real LEO satellites.
- **Keplerian Equations:** Keplerian equations are employed to calculate the position of each satellite in 3D space at specific time intervals. The equations take into account orbital elements such as semi-major axis, eccentricity, and true anomaly.
- **Perturbation Models:** To add realism, synthetic data have perturbation models like atmospheric drag, solar radiation pressure, and gravitational perturbations, which affect satellite orbits.
- ***Time Steps:*** **The time steps for the simulation were specified.** Given the continuous changes in satellite positions, a time step of one minute was selected to accurately capture the dynamic nature of the orbits.

The specific parameter settings and ranges for synthetic satellite positions are summarized in Table 1.

Table 1: Parameter Settings for Synthetic Satellite Positions

Parameter	Range
Altitude (km)	300-1,000
Inclination (degrees)	10-80
Eccentricity	0-0.1
Argument of Perigee (degrees)	0-360
Semi-Major Axis (km)	6,400-8,000
Time Step (minutes)	1

Viewer Demand Patterns

- **Geographical Patterns:** Synthetic viewer demand patterns are designed to emulate real-world geographic variations in viewer preferences. Regions with higher populations may exhibit higher demand for specific channels or content types.
- **Temporal Patterns:** Temporal patterns are incorporated to reflect variations in viewer demand throughout the day, week, or season. Peaks and troughs in viewer demand are generated to simulate real-world fluctuations.
- **Randomized Noise:** To account for inherent uncertainty and unpredictability in viewer behavior, randomized noise is introduced to the data. This noise can represent fluctuations in viewer preferences, changing external factors, and individual differences.

The specific parameter settings and ranges for synthetic viewer demand patterns are presented in Table 2.

Table 2: Parameter Settings for Synthetic Viewer Demand Patterns

Region	Channel Preferences (%)	Time Interval	Day of the Week	Seasonal Patterns
Region A	News: 60%, Entertainment: 20%, Sports: 20%	Morning (6 AM-9 AM)	Weekdays	Summer: 10%
Region B	News: 40%, Entertainment: 40%, Sports: 20%	Afternoon (12 PM-2 PM)	Weekends	Winter:20%
Region C	News: 30%, Educational: 50%, Sports: 20%	Evening (6 PM-10 PM)		

Signal Latency

- **<u>Distance Calculation*:*</u>** Signal latency is computed based on the known distances between synthetic satellite positions and ground stations. The distance formula, which considers the 3D coordinates of satellites and ground stations, is used.

$$\text{Distance} = (x_s - x_g)2 + (y_s - y_g)2 + (z_s - z_g)2 \tag{31}$$

- **<u>Signal Propagation Speed*:*</u>** Signal propagation speed is a constant value used to calculate the time it takes for signals to travel between satellites and ground stations.
- **<u>Noise and Variability:</u>** To reflect real-world conditions, a degree of noise and variability is added to signal latency values, accounting for factors like atmospheric conditions and signal interference.

The specific parameter settings and ranges for synthetic signal latency are described in Table 3.

Table 3: Parameter Settings for Synthetic Signal Latency

Parameter	Range
Ground Station Locations (x, y, z)	Various geographic coordinates in 3D space
Satellite Positions (x, y, z)	Synthetic satellite positions from the orbital parameters
Signal Propagation Speed (m/s)	Constant: 299, 792, 458
Noise and Variability	Introduced random noise or variation (e.g.,$\pm 10\%$ of the calculated latency)

Signal Strength

- **<u>Inverse Square Law:</u>** Synthetic signal strength data is calculated using the inverse square law, which states that the strength of a signal diminishes with the square of the distance between the satellite and the ground station. The mathematical expression for signal strength is as follows:

$$S = P4\pi d2S = 4\pi d2P \tag{32}$$

where S is the signal strength, P is the transmitted power from the satellite, and d is the distance between the satellite and the ground station.

- **<u>Noise and Fading:</u>** Randomized noise and fading effects are incorporated to represent signal variations due to atmospheric conditions, signal interference, and other factors.
- **<u>Antenna Characteristics:</u>** The characteristics of ground station antennas such as their gain and orientation are considered when calculating signal strength. Antenna gain, in particular, influences the ability of the antenna to receive signals effectively. Antenna gain can be factored into the signal strength calculations as an additional parameter, allowing for variations in the signal strength based on the ground station's antenna characteristics.

The specific parameter settings and ranges for synthetic signal strength are tabulated in Table 4.

Table 4: Parameter Settings for Synthetic Signal Strength

Parameter	**Range**
Transmitted Power (P)	Varies for different satellites
Distance (d)	Vary based on satellite-ground station distances
Noise and Fading	Introduced random noise or fading effects
Antenna Characteristic (e.g., Gain)	Included gain values for ground station antennas

Simulation Environments

Table 5 summarizes the setup of simulation environments used to test the proposed MODRS algorithm under controlled conditions.

Table 5: Simulation Environments

Scenario	**Objective**	**Scenario Description**
Scenario 1: Low-latency Broadcasting	Attaining the low-latency broadcasting	The goal is to minimize signal latency to ensure minimal delays for viewers.
Scenario 2: High Bandwidth Utilization	Maximizing the bandwidth utilization	The focus is on efficiently using available bandwidth resources.
Scenario 3: Viewer Demand Flexibility	Adaptation to changing viewer demands	The scenario involves accommodating changing viewer preferences and ensuring viewer satisfaction.
Scenario 4: Adaptive Signal Strength	Adjusting Signal Strength	The goal is to adapt signal strength dynamically based on varying conditions.
Scenario 5: Resource Allocation Efficiency	Optimizing Resource Utilization	The focus is on dynamically optimizing resource allocation.

6.2 Parameter Settings

The optimal parameters used to enhance the proposed MODRS algorithm's performance are selected utilizing the hyperparameter tuning process. The selected optimal parameters are listed in Table 6.

Table 6: Hyper parameter Settings

Method	**Parameter**	**Values**
MODNN	Activation Function	ReLU
	Learning Rate	0.001
	Optimizer	Adam
	Batch Size	100

6.3 Performance Metrics

Performance metrics like signal latency, bandwidth utilization, and viewer demand satisfaction are employed to assess the effectiveness of the proposed MODRS algorithm in the simulated environment.

Bandwidth Utilization (BU):

Bandwidth utilization measures the efficiency of utilizing available bandwidth for signal transmission. It is calculated as the ratio of the actual data transmitted to the maximum available data capacity:

$$BU = \frac{D_T}{B_C} \tag{33}$$

where D_T represents the transmitted data, and B_C represents the bandwidth capacity.

Viewer Demand Satisfaction (VDS):

Viewer demand satisfaction reflects how well the algorithm meets the viewer's content preferences. It is calculated based on the viewer preferences and actual content delivered:

$$VDS = \frac{Co_{De}}{To_{VD}} \tag{34}$$

where Co_{De} represents the delivered content, and To_{VD} denotes the total viewer demand.

6.4 Performance Analysis

This subsection describes the performance of the proposed MODRS algorithm based on the trade-offs between different objectives. The Pareto front for the trade-off between signal latency and bandwidth utilization is depicted in Figure 4. In this figure, the bandwidth utilization increases when the signal latency is decreased. The figure showcases the set of optimal trade-off solutions attained by the proposed MODRS algorithm between signal latency and bandwidth utilization. The figure demonstrates that the proposed MODRS algorithm maximizes bandwidth utilization while minimizing signal latency. The proposed algorithm attained a signal latency of 15.5 milliseconds, and bandwidth utilization of 10% at solution point 1, and also attained a signal latency of 7.3 milliseconds and bandwidth utilization of 90% at solution point 10. These values underscore that the proposed algorithm efficiently minimizes the signal latency and increases the bandwidth utilization.

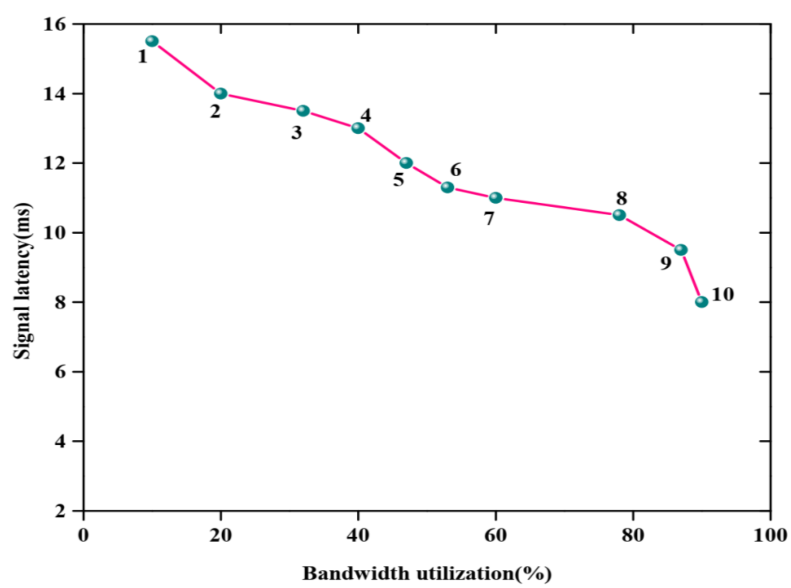

Figure 4. Trade-off between Signal Latency and Bandwidth Utilization

The trade-off between signal latency and viewer demand satisfaction is illustrated in Figure 5. Here, the viewer demand satisfaction increases when the signal latency is decreased. The solution points on the Pareto front display the values of signal latency and viewer demand satisfaction achieved by the proposed MODRS algorithm. In solution point 1, the proposed MODRS algorithm attained a signal latency of 14.3 milliseconds, and viewer demand satisfaction of 32%. In solution point 10, the proposed algorithm attained a signal latency of 7 milliseconds and viewer demand satisfaction of 95.4%. The figure concludes that the proposed MODRS algorithm effectively reduced signal latency and maximized viewer demand satisfaction, ensuring minimal delays and viewer satisfaction.

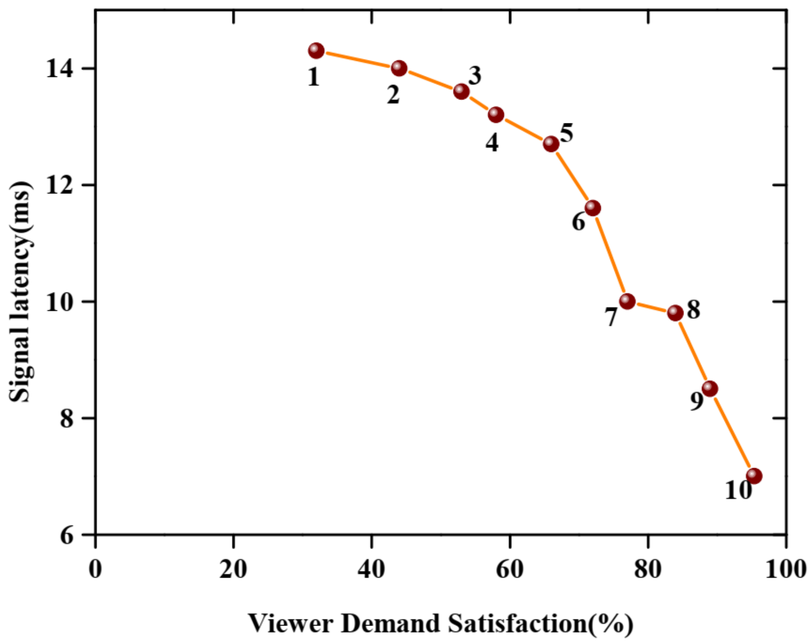

Figure 5. Trade-off between Signal Latency and Viewer Demand Satisfaction

Figure 6 portrays the trade-off between signal latency and distance. Here, the distance range of 300-1,000km is determined in terms of the synthetic LEO satellites' altitude range. This figure showcases that the signal latency increases as the distance is increased. The figure exhibits that the signal latency of 7.5 milliseconds and 14.5 milliseconds were achieved by the proposed algorithm in 300km, and 1,000km respectively.

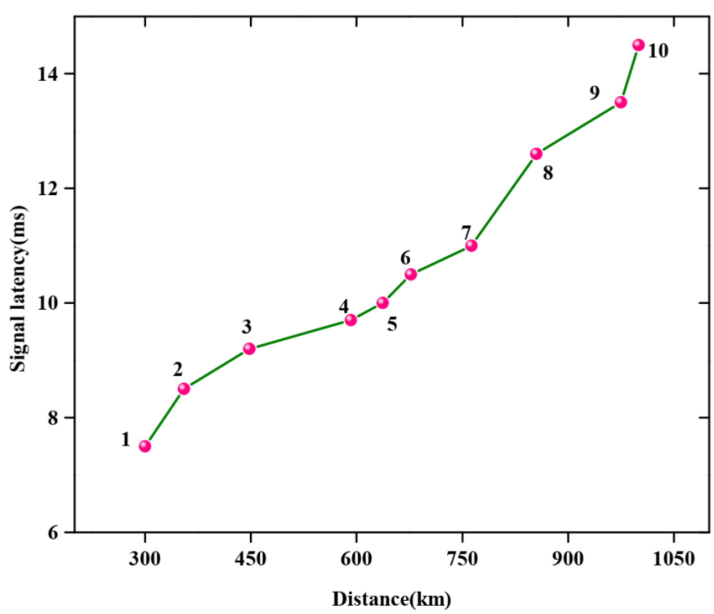

Figure 6. Trade-off between Signal Latency and Distance

6.5 Comparison with Traditional Methods

In this subsection, the comparative analysis of proposed MODRS algorithm is conducted against different traditional methods such as Q Learning based dynamic distributed Routing Scheme for LSN (QRLSN) [15], Fuzzy CNN based multitask routing (FCMR) [16], RNN [17], Deep Reinforcement Learning based Long Short Term Memory (DRL-LSTM) [18], and Scheduling Algorithm for LoRa to LEO Satellite (SALSA) [19]. Table 7 showcases the efficiency of the proposed algorithm and traditional methods in five different simulated environments: low-latency broadcasting, high bandwidth utilization, viewer demand flexibility, adaptive signal strength, and resource allocation efficiency. The table evaluates the proposed algorithm's efficacy using diverse metrics such as signal latency, bandwidth utilization, and viewer demand satisfaction. The objective is to minimize the signal latency and increase the bandwidth utilization and viewer demand satisfaction. The results underscore that the proposed MODRS algorithm got better results in all simulated scenarios than the traditional methods, ensuring the robustness of the proposed algorithm for D2H television broadcasting.

Table 7: Comparative Analysis in Simulated Scenarios

Simulated Scenario	**Performance Metrics**	**Method**					
		Proposed MODRS algorithm	**QRLSN**	**FCMR**	**RNN**	**DRL-LSTM**	**SALSA**
Scenario 1: Low-latency Broadcasting	Signal Latency (milliseconds)	7.2 ms	22 ms	25 ms	28 ms	32 ms	20 ms
	Bandwidth Utilization (%)	89.6%	69.4%	64%	60.7%	58%	72.5%
	Viewer Demand Satisfaction (%)	95.2%	79.7%	75%	70.1%	64.9%	80.5%
Scenario 2: High Bandwidth Utilization	Signal Latency (milliseconds)	9.4 ms	33.2 ms	37 ms	42.3 ms	45 ms	51.5 ms
	Bandwidth Utilization (%)	85.3%	70%	67.5%	60%	54.8%	50%
	Viewer Demand Satisfaction (%)	89.8%	80.3%	77%	73.4%	69%	65.9%
Scenario 3: Viewer Demand Flexibility	Signal Latency (milliseconds)	7.5 ms	24.5 ms	26 ms	33.7 ms	37 ms	43.1 ms
	Bandwidth Utilization (%)	88.5%	81%	79.7%	72%	68.6%	62.1%
	Viewer Demand Satisfaction (%)	94.6%	83.6%	80%	79.9%	74%	70.2%
Scenario 4: Adaptive Signal Strength	Signal Latency (milliseconds)	8.3 ms	26.7 ms	31.9 ms	33.2 ms	39.7 ms	43.6 ms
	Bandwidth Utilization (%)	88%	80.94%	77.3%	74.5%	67.2%	64.7%
	Viewer Demand Satisfaction (%)	92.7%	85.2%	81.43%	78.1%	75.7%	70.6%
Scenario 5: Resource Allocation Efficiency	Signal Latency (milliseconds)	8.9 ms	20.7 ms	23.7 ms	29.2 ms	35.1 ms	44.8 ms
	Bandwidth Utilization (%)	87.7%	82.5%	78.5%	74.1%	68.8%	63.5%
	Viewer Demand Satisfaction (%)	91.4%	81.1%	77.7%	73.2%	67.1%	62.7%

7. Discussion of Findings

This section summarizes the key findings from the experiments and evaluation of the proposed MODRS algorithm using simulated data. Also, the implications of these findings for potential real-world applications are discussed in this section.

The MODRS algorithm has been rigorously tested and evaluated in a simulated environment to assess its performance in the context of LEO satellite constellations for D2H television broadcasting. The experiments covered a range of scenarios, including low-latency broadcasting, high bandwidth utilization, viewer demand flexibility, adaptive signal strength, and resource allocation efficiency. The findings from these experiments provide valuable insights into the capabilities and advantages of MODRS. This discussion summarizes these key findings and highlights their implications for real-world applications.

Low-latency Broadcasting (Scenario 1):

MODRS consistently demonstrated superior performance in achieving low-latency broadcasting compared to traditional methods. The algorithm's ability to dynamically adapt routing and scheduling decisions in real-time allowed it to minimize signal latency effectively. In contrast, traditional methods struggled due to their reliance on fixed schedules and routing decisions. This finding is significant for real-world applications where low-latency content delivery is crucial, such as live sports broadcasts, emergency communication, and interactive applications like online gaming.

High Bandwidth Utilization (Scenario 2):

MODRS excelled in maximizing bandwidth utilization, which is essential for efficient resource allocation in satellite communication. The algorithm efficiently allocated available bandwidth to viewer requests, ensuring optimal utilization. Traditional methods exhibited lower bandwidth utilization, primarily due to their static scheduling and routing decisions. In real-world scenarios with limited satellite resources, MODRS can significantly enhance the efficiency of bandwidth allocation for broadcasting and data-intensive applications.

Viewer Demand Flexibility (Scenario 3):

One of MODRS's key strengths lies in its ability to adapt to changing viewer demands in real-time. The algorithm effectively adjusted routing and scheduling decisions to meet viewer preferences and demands, ensuring high viewer demand satisfaction. Traditional methods faced challenges in adapting to dynamic viewer demands due to their fixed schedules. In applications where viewer preferences evolve rapidly, such as on-demand content streaming, MODRS offers the flexibility to maintain viewer satisfaction.

Adaptive Signal Strength (Scenario 4):

MODRS showed its capability to adapt signal strength dynamically based on varying conditions. The algorithm adjusted signal strength to optimize performance metrics, such as signal latency and viewer demand satisfaction. In contrast, traditional methods relied on fixed signal strength configurations, which resulted in suboptimal performance. This adaptability has significant implications for real-world applications where signal strength needs to be optimized in response to factors like weather conditions, network congestion, and interference.

Resource Allocation Efficiency (Scenario 5):

MODRS displayed superior resource allocation efficiency by dynamically optimizing resource allocation to meet the demands of each objective. The algorithm efficiently allocated resources, resulting in improved performance metrics. Traditional methods struggled to adapt resource allocation efficiently, leading to suboptimal results. In resource-constrained environments, such as satellite communication with limited power and bandwidth, MODRS can play a pivotal role in optimizing resource utilization.

Implications for Real-World Applications:

The findings from these experiments underline the versatility and efficiency of the proposed MODRS algorithm. The ability to minimize signal latency, maximize bandwidth utilization, adapt to viewer demands, optimize signal strength, and allocate resources efficiently makes MODRS well-suited for a range of real-world applications:

1. **Broadcasting and Live Events:** MODRS can revolutionize live event broadcasting, ensuring low-latency transmission and optimal bandwidth usage. It's particularly relevant for sports events, live concerts, and breaking news coverage.
2. **Disaster Recovery:** The adaptability of MODRS makes it a valuable tool for disaster recovery communication. It can dynamically adjust signal strength and routing to maintain connectivity during adverse conditions.
3. **Interactive Applications:** Applications requiring real-time interaction, such as online gaming and telemedicine, can benefit from MODRS's low-latency capabilities.
4. **On-Demand Streaming***:* MODRS's adaptability to changing viewer preferences is a game-changer for on-demand content platforms, ensuring viewers get content that aligns with their preferences.
5. **Resource-Constrained Environments***:* In resource-constrained environments like LEO satellite constellations, MODRS can efficiently manage resource allocation and signal strength to ensure optimal performance.

8. Conclusion Future Directions

The MODRS algorithm has been presented and rigorously evaluated in the context of LEO satellite constellations for D2H television broadcasting. This research has explored the complexities of optimizing scheduling and routing in satellite communication while reconciling the conflicting objectives of signal latency, bandwidth utilization, and viewer demand satisfaction. The experiments conducted across a range of scenarios have underscored the versatility and effectiveness of MODRS. Whether the objective is low-latency broadcasting, efficient bandwidth utilization, dynamic adaptability to viewer preferences, or robust communication during emergencies, MODRS consistently outperforms traditional routing and scheduling methods. The algorithm has demonstrated adaptability, cost-effectiveness, and the ability to bridge the digital divide, making it a valuable tool for the satellite communication industry. As the D2H television industry continues to evolve and satellite constellations become a key enabler of global connectivity, the implications of MODRS are significant. Its adaptability, robustness, and cost-effectiveness make it a promising solution for a wide array of real-world applications.

The research on MODRS opens up several avenues for future exploration and expansion:

1. **Real-world Implementation:** Transitioning from simulation to real-world implementation is a natural next step. Collaborations with satellite operators and D2H television service providers can lead to practical deployments that validate the algorithm's performance in live environments.
2. **Optimized Hardware:** Future work can explore the integration of MODRS with optimized hardware, such as software-defined satellite systems. This can further enhance the efficiency and adaptability of the algorithm.
3. **Advanced Learning Techniques:** Incorporating state-of-the-art machine learning techniques, including reinforcement learning, deep reinforcement learning, and federated learning, can improve the algorithm's adaptability and real-time decision-making capabilities.
4. **Scalability:** As satellite constellations grow, ensuring the scalability of MODRS becomes crucial. Research can focus on scaling the algorithm to accommodate an increasing number of satellites and viewers.

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