Learning-Based Beam Placement for Rain Attenuation in Multi-Beam Satellite Communication Systems

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***Abstract*—Satellite communication has been recognized as an effective means to complement the limitations of terrestrial networks by providing wide-area coverage. In particular, multi-beam satellite systems can simultaneously serve multiple regions by dividing the coverage area into numerous narrow beams, thereby improving spectrum efficiency and overall capacity. However, rain attenuation is a critical issue that causes signal degradation and reduces data transmission rates. This paper proposes a DQN-based beam placement optimization scheme to maintain communication performance in regions affected by rain attenuation. The proposed scheme improves data transmission rates by increasing transmit power in rain-attenuated regions and reduces interference by covering those regions with the minimum number of beams. Simulation results obtained through Monte Carlo evaluations demonstrate that the proposed method effectively mitigates performance degradation caused by rain attenuation and significantly enhances overall spectral efficiency.**

***Index Terms*—Multi-beam Satellite Communication; Rain Attenuation Mitigation; Deep Q-Network (DQN)**

I. Introduction

Satellite communication can overcome the limitations of conventional terrestrial networks by providing wide-area service coverage. In particular, Low Earth Orbit (LEO) satellite systems offer low propagation delay and high data transmission rates, making them a critical communication solution in remote regions and during disaster scenarios [1]. To further enhance the overall efficiency of such systems, multi-beam satellite systems have been actively considered.

A multi-beam satellite system enables a single satellite to generate multiple narrow beams that simultaneously serve different geographical areas and user groups [2]–[4]. This approach plays a key role in improving spectrum efficiency and increasing overall system capacity. By leveraging multi-beam operations, limited frequency resources can be utilized more effectively, thereby supporting large-scale connectivity and accommodating the growing demand for high-throughput satellite networks.

Meanwhile, in satellite communication systems, rain attenuation is a significant environmental factor that can lead to reduced data transmission rates and even service interruptions [5]. Effective mitigation and management strategies for rain attenuation are therefore essential to improving the overall performance of satellite systems.

In this paper, we propose a method that improves data transmission performance by increasing the transmit power in regions affected by rain attenuation and optimizes beam placement to cover such regions with the minimum number of beams. The proposed method is based on a Deep Q-Network (DQN) framework, aiming to reduce interference and maximize data transmission efficiency. As a result, it effectively mitigates performance degradation caused by rain attenuation.

II. Proposed Method for Rain-Attenuation-Aware Beam Management

We consider consider a downlink data transmission scenario in a LEO satellite system employing a multi-beam configuration. The LEO satellite is located at the point $(0, 0, r_E + H)$ in a Cartesian coordinate system, where the center of the Earth is the origin. Here, r_E and H denote the Earth's radius and the altitude of the satellite, respectively. The satellite generates K distinct beams, and each beam, indexed by $k \in K = \{1, 2, \ldots, K\}$, covers a specific region. On the UV-plane, the beam spacing is represented by D, which can be determined by the following equation:

$$D = \sqrt{3}\sin\left(\frac{\theta_{3\mathrm{dB}}}{2}\right). \tag{1}$$

$\theta_{3\mathrm{dB}}$ denotes the $3\,\mathrm{dB}$ beamwidth radiated by the satellite. It is assumed that the satellite beams are arranged in a hexagonal lattice. The boresight direction of each beam can be represented on the UV-plane, and the beam center on this plane is defined as (u_k, v_k). The spherical coordinates are transformed into UV-plane coordinates through the following equations:

$$u = \sin(\theta)\cos(\omega), \quad v = \sin(\theta)\sin(\omega),$$

where θ and ω represent the elevation angle and the azimuth angle, respectively. Accordingly, a point (x, y, z) on the Earth's surface in the Cartesian coordinate system can be expressed as

$$(x, y, z) = (0, 0, r_E + H) + d\big(\sin\theta\cos\omega,\, \sin\theta\sin\omega,\, \cos\theta\big),$$

where d is defined as follows:

$$d = -r_E \sin\alpha + \sqrt{r_E^2 \sin^2\alpha + 2r_E H + H^2},$$

where

$$\alpha = \cos^{-1}\big((r_E + H)\sin\theta / r_E\big).$$

Assuming that all beams share the same frequency band, the signal-to-interference-plus-noise ratio (SINR) at position (u, v) on the UV-plane for the k-th beam can be expressed as follows [6]:

$$\gamma(u, v) = \frac{p_k g_k(u, v)}{\sigma^2 + \sum_{l \neq k} p_l g_l(u, v)},$$

where p_k denotes the transmit power allocated to the k-th beam, $g_k(u, v)$ represents its channel gain, and σ^2 denotes the noise power. If a beam is not activated, its transmit power is assumed to be zero. Based on this, the achievable data rate for a user located at (u, v) on the UV-plane can be calculated as

$$R(u, v) = \log_2\big(1 + \gamma(u, v)\big).$$

The main objective of the proposed method is to increase the transmit power of beams that support regions affected by rain attenuation, thereby improving the data rate within the area of interest. Let $\mathcal{R}$ denote the region where rain attenuation occurs within the coverage area. The region $\mathcal{R}$ must be supported by the minimum number of beams. Assuming that each beam can be represented as a circle with radius D on the UV-plane, the problem can be reduced to covering $\mathcal{R}$ with the minimum number of such circles.

Let the K multi-beams be defined as $\{\mathcal{B}_1, \mathcal{B}_2, \ldots, \mathcal{B}_K\}$, where

$$\mathcal{B}_k = \{(u, v) \in \mathbb{R}^2 : (u - u_k)^2 + (v - v_k)^2 \leq D^2\}.$$

Here, $z_k \in \{0, 1\}$ is a binary variable indicating whether beam $\mathcal{B}_k$ is selected ($z_k = 1$) or not ($z_k = 0$). Based on this, the above problem can be formulated as

$$\min_{(u_k, v_k),\, \forall k} \sum_{k=1}^{K} z_k \quad \text{s.t.} \quad \mathcal{C} \supseteq \mathcal{R},$$

where $\mathcal{C}$ is defined as

$$\mathcal{C} = \bigcup_{\substack{k \in \{1,2,\ldots,K\} \\ z_k = 1}} \mathcal{B}_k.$$

In general, the above problem is NP-hard. Therefore, this paper addresses the problem by employing a Deep Q-Network (DQN)-based approach.

We model the above optimization problem as a Markov decision process and solve it using a DQN-based approach. In this formulation, the environment state is defined by the current configuration of all beams, including the center coordinates and the activation indicators of each beam, i.e., $S = \{(u_k, v_k, z_k) \mid k = 1, 2, \ldots, K\}$. At every decision step, the agent takes an action that modifies the configuration of a particular beam, such as adjusting its center position or toggling its activation. The reward function is designed to minimize the total number of active beams while simultaneously encouraging a higher coverage ratio over the rain-attenuated region. Specifically, the reward is expressed as

$$r = -\left(\sum_{k=1}^{K} z_k\right) + \lambda\rho,$$

where the coverage ratio ρ is given by

$$\rho = \frac{|\mathcal{C} \cap \mathcal{R}|}{|\mathcal{R}|},$$

and $\lambda \in \mathbb{R}^+$ is a positive weighting parameter that balances the two objectives in the reward function. Through repeated interactions with the environment, the DQN agent learns a beam management policy that activates only the necessary beams and arranges them to maximize the coverage of $\mathcal{R}$ while minimizing $\sum z_k$.

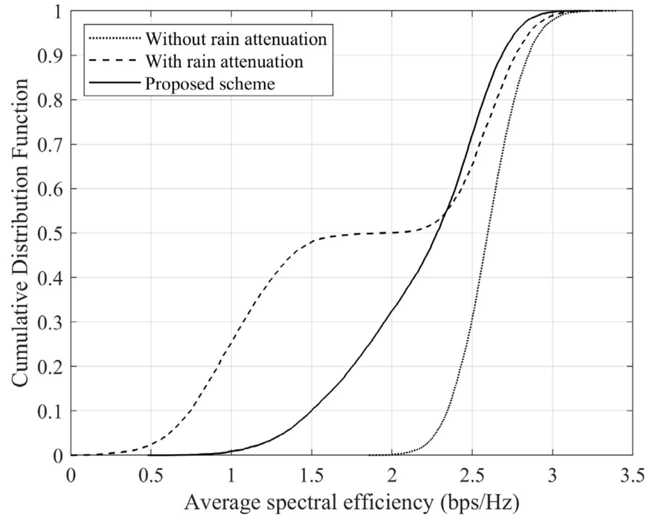

Fig. 1. Cumulative Distribution Function of Average Spectral Efficiency under Different Environments and with the Proposed Scheme.

III. Simulation Results

The DQN agent was trained in an offline simulation environment, where the satellite scenario parameters were configured based on the values reported in [6]. In each training episode, one rain-attenuated region was applied, chosen at random from a set of 20 predefined regions with different locations and sizes. Over the course of 50,000 episodes, the agent was exposed to these various rain patterns and learned a policy that generalizes across these representative scenarios. During training, the agent updated its policy using an ϵ-greedy exploration strategy and experience replay. After training, the learned policy was evaluated through 10,000 Monte Carlo trials to ensure statistical reliability.

Figure 1 illustrates the resulting average spectral efficiency of a low Earth orbit satellite system operating at an altitude of 600 km. The comparison includes a baseline without rain attenuation, a scenario with rain attenuation but without the proposed scheme, and a scenario where the proposed DQN-based method is applied. As shown in the figure, rain attenuation causes a notable reduction in the average spectral efficiency for terminals located in affected regions, whereas the proposed method mitigates this degradation by increasing transmit power in those regions and minimizing interference, leading to a substantial improvement in overall spectral efficiency.

IV. Conclusion

This paper proposed a DQN-based beam placement optimization scheme to enhance multicast communication in regions affected by rain attenuation. The scheme learns a policy that increases transmit power in rain-attenuated areas while covering them with the minimum number of beams, thereby minimizing interference. Simulation results show that the proposed approach significantly improves average spectral efficiency and effectively mitigates performance degradation caused by rain attenuation.

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References

[1] O. Kodheli *et al.*, "Satellite Communications in the New Space Era: A Survey and Future Challenges," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 1, pp. 70–109, 2021.
[2] K.-X. Li *et al.*, "Downlink Transmit Design for Massive MIMO LEO Satellite Communications," *IEEE Transactions on Communications*, vol. 70, no. 2, pp. 1014–1028, Feb. 2022.
[3] Z. Lin *et al.*, "Dynamic Beam Pattern and Bandwidth Allocation Based on Multi-Agent Deep Reinforcement Learning for Beam Hopping Satellite Systems," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 4, pp. 3917–3930, Apr. 2022.
[4] Y. Chen *et al.*, "Low-Complexity Dynamic Beam Placement Optimization Methods for LEO Satellite Multicast Communications," *IEEE Wireless Communications Letters*, doi: 10.1109/LWC.2025.3578837, 2025.
[5] Y. Wang *et al.*, "Effect of Rain Attenuation on the Availability of LEO Satellite Communication System," in *Proceedings of the 2023 5th International Conference on Electronics and Communication, Network and Computer Technology (ECNCT)*, Guangzhou, China, 2023.
[6] H.-H. Choi *et al.*, "Joint Optimization of Beam Placement and Transmit Power for Multibeam LEO Satellite Communication Systems," *IEEE Internet of Things Journal*, vol. 11, no. 8, pp. 14804–14813, Apr. 2024.