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Joint Optimization Algorithm for Adaptive Filtering and Dynamic Resource Allocation in 5G NTN Low Earth Orbit Satellite Communications

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ABSTRACT

With the deep integration of 5G and Non-Terrestrial Networks (NTN), Low Earth Orbit (LEO) satellites have emerged as key enablers for constructing integrated space-air-ground communication networks due to their wide coverage and flexible deployment. However, the high-speed movement of LEO satellites results in rapidly time-varying channels and multipath fading, causing significant signal degradation from noise and interference. Meanwhile, the surge in access devices demands urgent dynamic allocation of resources such as spectrum and power. Existing studies show that traditional fixed-parameter filtering algorithms struggle to track time-varying channels, static resource allocation schemes fail to fully exploit channel state information, and single-resource optimization neglects the coupling between multiple resources. Some joint optimization approaches suffer from poor dynamic adaptability and high computational complexity. To address these challenges, this paper proposes a joint optimization method for adaptive filtering and dynamic resource allocation tailored for 5G NTN LEO satellite communications. First, an improved adaptive filtering algorithm with dynamic parameter adjustment is designed to optimize filtering parameters in real time based on channel state estimation, enhancing signal interference resilience. Then, leveraging precise channel state information, a dynamic resource allocation algorithm considering service demands and resource constraints is developed to achieve cross-layer collaborative allocation of spectrum and power resources. A joint optimization framework aligned with the LEO satellite communication scenario is constructed, where the synergy between signal processing and resource allocation effectively improves system communication reliability and resource utilization efficiency. This provides theoretical and technical support for the practical deployment of 5G NTN LEO satellite systems.

1. INTRODUCTION

In the context of the vigorous development of global digitalization, the fifth-generation mobile communication technology 5G [1-3] is deeply integrated with NTN [4, 5]. LEO satellites [6, 7], with their wide coverage, low latency potential, and flexible network deployment capability, have become a key component in constructing integrated space-air-ground communication networks. The 5G NTN LEO satellite system [8-11] can effectively address issues such as insufficient coverage in remote areas and poor reliability in emergency communication scenarios in traditional terrestrial networks by incorporating satellites into the communication network architecture, providing a new solution for seamless global communication. However, the high-speed movement of LEO satellites leads to rapidly time-varying channel characteristics and multipath fading, and the signal transmission process is easily affected by noise, co-channel interference, and other factors, which seriously restrict signal quality and system performance. At the same time, with the sharp increase of access devices [12, 13], the limited spectrum and power resources face challenges of efficient allocation. Traditional fixed resource allocation methods cannot adapt to dynamically changing service demands and channel conditions, and efficient signal processing and resource allocation technologies urgently need to be studied.

Research on the key issues of signal processing and resource allocation in 5G NTN LEO satellite systems has important theoretical significance and practical application value. Through the joint optimization study of adaptive filtering and dynamic resource allocation for LEO satellite signals, the inherent mechanisms of signal transmission and resource utilization in integrated space-air-ground communication networks can be deeply revealed, enriching and expanding the application of wireless communication theory in complex dynamic environments. Efficient adaptive filtering algorithms can significantly improve the received signal quality, reduce bit error rate, and ensure communication reliability; reasonable dynamic resource allocation strategies can realize fine-grained management of resources such as spectrum and power, improve resource utilization, and meet the diverse requirements of different service types for transmission rate, latency, and other performance indicators, thus promoting the wide application of 5G NTN LEO satellite systems in IoT, aviation communication, maritime communication, and other fields, and assisting the construction of seamless global coverage communication networks.

Currently, research on LEO satellite signal processing and resource allocation has achieved certain results, but many problems still need to be solved. In terms of signal filtering, traditional fixed-parameter filtering algorithms [14, 15] are difficult to track the rapid channel changes caused by the high-speed movement of LEO satellites in real time, and the filtering performance significantly deteriorates under strongly time-varying channel environments. In the field of resource allocation, most existing studies consider signal processing and resource allocation separately. For example, the static resource allocation strategies proposed in studies [16, 17] do not fully utilize the channel state information obtained during signal processing, resulting in decision-making for resource allocation that lacks specificity and effectiveness. In addition, some studies optimize only a single resource and ignore the coupling relationship among multiple resources, making it difficult to achieve overall system performance optimization. The joint optimization algorithms proposed in studies [18, 19] consider the combination of signal processing and resource allocation, but lack adaptability to satellite mobility and user service demand changes in dynamic scenarios. Furthermore, the complexity of the algorithms is relatively high, making practical deployment difficult.

This paper focuses on the key technical challenges of 5G NTN LEO satellite systems and conducts joint optimization research on adaptive filtering and dynamic resource allocation. The main content includes two parts: On one hand, addressing the time-varying channel characteristics in LEO satellite signal transmission, an improved 5G NTN LEO satellite adaptive filtering algorithm based on dynamic parameter adjustment is proposed. This algorithm adaptively adjusts filtering parameters by real-time estimation of channel state information, effectively suppressing noise and interference and improving the received signal quality. On the other hand, combined with the accurate channel state obtained from the improved filtering algorithm, a dynamic resource allocation algorithm for 5G NTN LEO satellites is designed, considering service demands and resource constraints, to achieve dynamic allocation of spectrum, power, and other resources among different users and services, improving resource utilization efficiency.

The research value of this paper lies in the first joint optimization of adaptive filtering and dynamic resource allocation, fully considering the interaction between the two, and constructing a joint optimization framework more consistent with the actual scenario of LEO satellite communications. By improving the adaptive filtering algorithm to enhance channel estimation accuracy, more reliable basis is provided for resource allocation; with the dynamic resource allocation algorithm optimizing resource configuration, the signal transmission environment is further improved, forming a synergistic optimization effect between the two. The research results can effectively improve the communication performance and resource utilization efficiency of 5G NTN LEO satellite systems, providing important theoretical support and technical solutions for the practical deployment and application of LEO satellite communication systems, and have important practical significance for promoting the development of integrated space-air-ground communication networks.

2. DESIGN OF IMPROVED ADAPTIVE FILTERING ALGORITHM FOR 5G NTN LEO SATELLITE SIGNALS

The proposed improved adaptive filtering algorithm for 5G NTN LEO satellite signals is divided into the following three parts:

(1) To address the problem of time-varying channel noise and interference caused by high-speed movement in 5G NTN LEO satellite signals, the algorithm first performs Ensemble Empirical Mode Decomposition (EEMD) on the original signal, decomposing the nonlinear and non-stationary signal into multiple Intrinsic Mode Function (IMF) components and a residual term distributed from high frequency to low frequency. By calculating the zero-crossing rate of each order IMF component and the ratio of zero-crossing rates with adjacent higher-order components, and using the significant difference in frequency characteristics between high-frequency noise and low-frequency noise in LEO satellite signals, dynamic identification is performed on the positions where the zero-crossing rate of IMF components changes abruptly. Specifically, components with high zero-crossing rate and abrupt ratio change are determined to contain high-frequency noise, while components with low zero-crossing rate and smooth changes are classified as low-frequency noise influenced regions, thus achieving adaptive differentiation of different noise-type components and providing a basis for subsequent layered filtering.

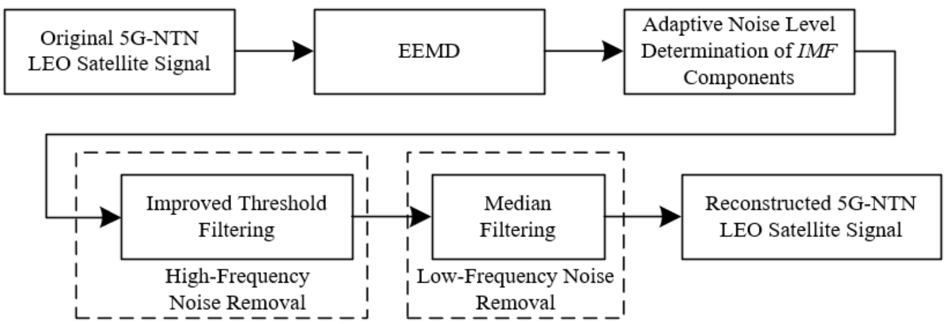


Figure 1. Design of the improved adaptive filtering algorithm flow for 5G NTN LEO satellite signals

(2) In the filtering stage of IMF components dominated by high-frequency noise, the algorithm uses a fixed threshold method to determine the initial threshold for each order component, and proposes an improved threshold function by combining the advantages of traditional soft and hard threshold functions. This function introduces adjustable parameters to balance the precise reconstruction characteristic of the hard threshold function and the smooth continuity of the

soft threshold function, avoiding the discontinuous abrupt change at the threshold point in the hard threshold and the constant bias problem in the soft threshold. Especially considering the characteristics of high-frequency noise energy concentration and complex time-varying patterns in LEO satellite signals, it can more accurately retain effective signal components and suppress noise. By comparative analysis with commonly used threshold functions in the literature, the proposed improved algorithm performs better in signal-to-noise ratio improvement and signal distortion control. In specific implementation, the improved function is applied progressively to IMF components judged to be dominated by high-frequency noise, filtering out burst noise while retaining high-frequency features of the signal, enhancing the signal's anti-interference ability in time-varying channels.

(3) For IMF components and residual terms influenced by low-frequency noise, the algorithm adopts a median filtering baseline correction method. First, the median filtering window width is adaptively determined according to the frequency range of low-frequency noise. Edge extension techniques at both ends are used to avoid signal distortion caused by edge effects, ensuring effective suppression of slowly time-varying noise. Median filtering can smooth baseline drift while preserving the signal contour, especially suitable for low-frequency phase deviation and power fluctuation issues caused by satellite trajectory changes in LEO satellite signals. After targeted filtering of high- and low-frequency noise components, all processed IMF components and residual terms are superimposed to reconstruct the 5G NTN LEO satellite signal with different noise types removed. This process, through a layered processing strategy, realizes differentiated suppression of high- and low-frequency noise in LEO satellite signals, significantly improving the received signal quality while maintaining time-varying features, providing more reliable channel state inputs for subsequent dynamic resource allocation.

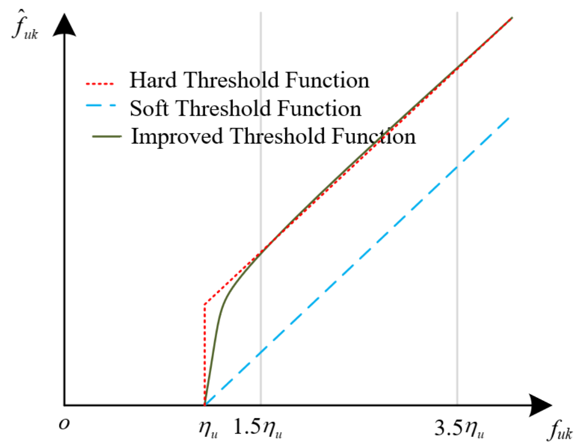


Figure 2. Comparison of threshold functions before and after improvement

Figure 1 shows the flow design of the improved adaptive filtering algorithm for 5G NTN LEO satellite signals. In 5G NTN LEO satellite signal processing, the inherent defects of traditional hard and soft threshold functions cannot meet the complex time-varying characteristics requirements of LEO satellite signals. Due to the satellite's high-speed movement and multipath propagation, LEO satellite signals present strong non-stationarity and a wide noise frequency span. Their high-frequency IMF components contain both high-frequency signal components carrying key information, such as rapidly changing phase modulation features, and high-frequency noise, such as random interference caused by multipath fading. The discontinuity of the hard threshold function at the threshold point causes oscillations in the filtered signal near the threshold. For LEO satellite communication relying on precise phase and amplitude information, this may introduce demodulation errors. The soft threshold function's fixed amplitude offset at the threshold guarantees continuity but causes amplitude distortion, especially in high-frequency components where signal energy concentrates near the threshold. This distortion accumulates and affects signal reconstruction accuracy.

Assuming the amplitude of the k-th data point of the u-th order IMF is denoted by f_{uk}, and the amplitude of that point after filtering is $\hat{f}_{uk}$. The formula of the hard threshold function is:

$$\hat{f}_{uk} = \begin{cases} f_{uk}, |f_{uk}| \geq \eta_u \\ 0, |f_{uk}| < \eta_u \end{cases} \tag{1}$$

The formula of the soft threshold function is:

$$\hat{f}_{uk} = \begin{cases} SGN(f_{uk})(|f_{uk}| - \eta_u), |f_{uk}| \geq \eta_u \\ 0, |f_{uk}| < \eta_u \end{cases} \tag{2}$$

For the adaptive filtering goal of LEO satellite signals, it is required to remove high-frequency noise while maximizing the retention of effective time-frequency features of the signal. Therefore, the threshold function needs to be improved to balance continuity and amplitude accuracy. Specifically, considering the complex time-varying characteristic of intertwined high-frequency noise and effective signals in 5G NTN LEO satellite signals, the improved threshold function design adopts an implementation idea that integrates the advantages of soft and hard thresholds to balance signal continuity and amplitude accuracy. Figure 2 shows the comparison of threshold functions before and after improvement. The specific formula is as follows:

$$\hat{f}_{uk} = \begin{cases} SGN(f_{uk})\left(\left(f_{uk}^2 - \left(\eta_u / \exp(f_{uk} - \eta_u)\right)^2\right)^{1/2}\right), \\ |f_{uk}| \geq \eta_u \\ 0, |f_{uk}| < \eta_u \end{cases} \tag{3}$$

When $f_{uk} \to \pm\infty$, there is:

$$\underset{f_{uk} \to \pm\infty}{LIM} \hat{f}_{uk} = \underset{f_{uk} \to \pm\infty}{LIM} \sqrt{f_{uk}^2 - \eta_u / \infty} = f_{uk} \tag{4}$$

When $f_{uk} \to \eta_u$, there is:

$$\underset{f_{uk} \to \eta_u}{LIM} \hat{f}_{uk} = \underset{|f_{uk}| \to \eta_u}{LIM} \sqrt{f_{uk}^2 - \eta_u^2 / r^0} = 0 \tag{5}$$

Considering that after EEMD decomposition of LEO satellite signals, the amplitude distribution of effective signals and high-frequency noise in high-frequency IMF components shows continuity differences, the improved threshold function constructs a piecewise continuous and adaptively adjustable function form: when the amplitude is less than the threshold, it borrows the continuous characteristic of the soft threshold function to avoid reconstruction oscillations caused by the discontinuity point of the hard threshold; when the amplitude exceeds the threshold, a nonlinear adjustment factor is introduced so that the filtered amplitude gradually approaches the true value with increasing original amplitude, eliminating the constant bias problem of the soft threshold. Specifically, through the function design of the above formula, the filtered IMF component amplitude maintains continuity at the threshold point, avoiding oscillations caused by hard threshold discontinuity, and gradually reduces the fixed offset of the soft threshold as amplitude moves away from the threshold, ensuring the key information carried in phase and amplitude of the high-frequency signal is completely preserved.

3. DYNAMIC RESOURCE ALLOCATION FOR 5G NTN LEO SATELLITES

3.1 System model

Figure 3 shows the schematic diagram of the 5G NTN LEO satellite communication system model. The 5G NTN LEO satellite model constructed in this paper is based on multi-beam coverage and Orthogonal Frequency Division Multiplexing (OFDM) as the core architecture, aiming to provide a foundational framework for dynamic resource allocation. The LEO satellite achieves wide-area coverage by generating Y directional beams, collectively denoted as $Y=\{y \mid y=1,2,\ldots,Y\}$. The user set $I=\{i \mid i=1,2,\ldots,I\}$ contains I users randomly distributed within the coverage area of each beam. The number of users accessing beam y in time slot s is I^y_s, satisfying $\Sigma^Y_{y=1} I^y_s=I$. Under the OFDM mode, users within the same beam communicate without interference via orthogonal subcarriers, while co-channel interference arises among different beams due to shared spectrum resources, which is the key problem to be solved in dynamic resource allocation. The model assumes that each beam is allocated V orthogonal subcarriers, and each subcarrier in time slot s can be assigned to only one user to avoid intra-beam interference, focusing on inter-beam interference coordination and resource optimization.

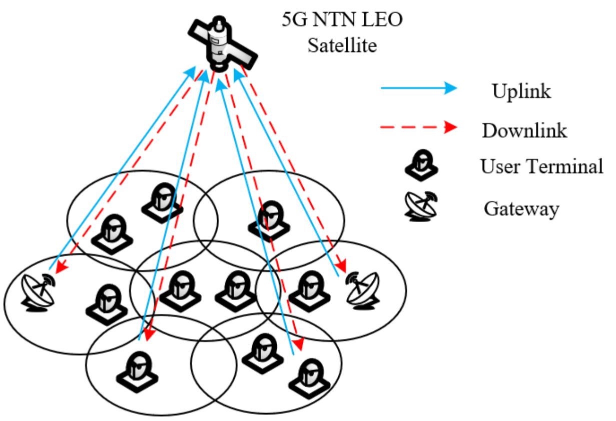


Figure 3. 5G NTN LEO satellite communication system model

The satellite information control center collects link state parameters in real time to provide data support for dynamic resource allocation. Among these, transmission power PPP is an adjustable resource, initialized when a beam is activated and dynamically adjusted according to user demand. The free-space loss model is used to characterize channel fading, combined with the time-varying channel characteristics caused by the high-speed movement of the satellite, providing channel gain references for subcarrier allocation and power control. The model defines the available resources for each beam in time slot s as the set of V subcarriers $V=\{v|v=1,2,\ldots,V\}$. The resource allocation strategy must satisfy the single-user single-subcarrier constraint, while optimizing cross-beam power allocation to suppress co-channel interference. By incorporating user access, subcarrier allocation, and power control into a unified framework, the model aims to balance coverage performance and Spectral Efficiency (SE) through dynamic resource allocation, reducing system complexity and improving communication reliability in multi-beam scenarios, thus providing a structured state space and action space input for deep reinforcement learning algorithms.

In the dynamic resource allocation model based on time slot division, the channel characteristics of the satellite remain stable within each time slot. The signal transmission quality of a user connected to a specific beam subcarrier is determined by the channel gain parameter reflecting spatial propagation loss, which is directly related to dynamic factors such as the real-time distance and relative position between the satellite and the user. The transmission power on subcarriers of each beam is regarded as an adjustable resource: the transmission power of the beam determines the effective signal strength received by the target user, while the transmission power of other beams on the same subcarrier causes inter-beam interference due to spectrum sharing. Specifically, assuming the propagation loss in vacuum is denoted by M, the beam gain between user i and beam y is denoted by $H_{y,i}$, and the channel gain of user i connecting to subcarrier v in beam y at time slot s is:

$$g^v_{y,i} = H_{y,i} / M \tag{6}$$

Assuming the 3dB beamwidth angle is ϕ_{3fY}, the maximum gain of the receiving antenna is H_{MAX}, the angle between the beam center and user terminal is $\phi_{y,i}$, and the first kind first- and third-order Bessel functions are K_1 and K_3. The expression for $H_{y,i}$ is:

$$H_{y,i}(\varphi) = H_{MAX}\left(\frac{K_1\left(i\left(\varphi_{y,i}\right)\right)}{2i\left(\varphi_{y,i}\right)} + \frac{36K_3\left(i\left(\varphi_{y,i}\right)\right)}{2i\left(\varphi_{y,i}\right)^3}\right) \tag{7}$$

Assuming the propagation distance is f, and the wavelength is η, the expression for M is:

$$M = 4\pi f / \eta^2 \tag{8}$$

Let the transmission power of the v-th subcarrier in the y-th beam at time slot s be denoted as $O^{(y,v)}_s$. Similarly, the transmission power of user i in the v-th subcarrier of beam y' at time slot s is $O^{(y',v)}_s$. The non-interference signal power of subcarrier v in beam y is calculated as:

$$R^{y,v}_s = O^{(y,v)}_s H_{y,i} / M = g^v_{y,i} O^{(y,v)}_s \tag{9}$$

When multiple beams use the same subcarrier simultaneously, the signal energy from non-target beams couples through spatial propagation to the target user's receiver, forming aggregated interference. Its intensity is related to the transmission power of interfering beams and corresponding channel gains. This co-channel interference is the core challenge of multi-beam systems in LEO satellites, directly affecting signal reception quality and resource allocation efficiency. The interference signal power from subcarrier v in other beams excluding beam y is calculated by:

$$U_s^{(y,v)} = \sum_{y' \neq y} O_s^{(y',v)} H_{y',v} / M = \sum_{y' \neq y} g_{y',v}^{v} O_s^{(y',v)} \tag{10}$$

The Signal-to-Interference-plus-Noise Ratio (SINR) is a key metric measuring the impact of interference on user signal reception, defined as the ratio of effective signal power to the sum of interference signal power and background noise power. Increasing transmission power in the beam can enhance target signal strength but simultaneously increases interference to users in other beams; conversely, reducing power can lower interference but may degrade the signal quality in the beam. The dynamic balance between these two is the core contradiction in resource allocation strategy design. Assuming the variance of additive white Gaussian noise is β, the binary variable indicating whether terminal device i is connected to beam y at time slot s is $\lambda^{(y,i)}_s$, and the SINR of user i on subcarrier v in beam y at time slot s is $\varepsilon^{(y,v,i)}_s$, its expression is:

$$\varepsilon_s^{(y,v,i)} = \frac{\lambda_s^{(y,v)} g_{y,i}^{(v)} O_s^{(y,v)}}{\sum_{y' \neq y} g_{y,i}^{(v)} O_s^{(y,v)} + \beta^2} \tag{11}$$

The expression for $\lambda^{(y,i)}_s$ is:

$$\lambda_s^{(y,i)} = \left[0,1\right] \tag{12}$$

$$E_s^{y,v} = \frac{Y}{V} \log_2 \left(1 + \sum_{i=1}^{I} \varepsilon_s^{(y,v,i)} \right) \tag{13}$$

The overall system throughput quantifies the effect of resource allocation and is defined as the sum of transmission rates of all activated users on allocated subcarriers. Since each subcarrier can be allocated to only one user in a single time slot (subcarrier exclusivity constraint), throughput optimization requires dynamically adjusting transmission power of subcarriers in each beam and user allocation strategies, maximizing SE while suppressing inter-beam interference. This process requires deep reinforcement learning algorithms to perceive signal strength, interference levels, and user access status of each beam in real time, making intelligent decisions to optimally balance interference and transmission efficiency, ultimately improving the overall performance of LEO satellite communication systems. The overall system throughput is:

$$E_s = \sum_{v=1}^{V} \sum_{y=1}^{Y} E_s^{y,v} \tag{14}$$

In 5G NTN LEO satellite dynamic resource allocation, system performance needs to consider both SE and EE as core indicators. SE is defined as the overall data transmission rate of the system, reflecting the utilization density of spectrum resources; EE is the ratio of system throughput to power consumption, measuring the effective data transmission capability per unit energy consumption. There is a significant contradiction between these two in practical optimization: simply increasing SE can raise data rates but causes power consumption to surge, reducing EE; conversely, excessively pursuing EE may cause signal quality degradation or resource idleness, leading to SE loss. This conflicting trade-off makes single-metric optimization unable to meet the dual needs of green energy saving and efficient transmission in LEO satellite communications. A compromise strategy is needed to coordinate the relationship between them, achieving overall system performance improvement under limited spectrum and power resource constraints. Assuming the satellite system's transmission power consumption is denoted as O_x, constant circuit power consumption as O_z, and total power consumption as $O_{SUM}=O_x+O_z$, the EE in time slot s is:

$$\lambda_{RR}^{(s)} = \frac{E}{O_{SUM}} \tag{15}$$

The SE of the system is:

$$\lambda_{TR}^{(s)} = E_s \tag{16}$$

By weighting EE and SE with weighting factors α and Y/O_{SUM} respectively to unify the dimensions of the two terms, there is:

$$\lambda(s) = \eta_{RR}^{(s)} + \alpha \frac{Y}{O_{SUM}} \lambda_{TR}^{(s)} \tag{17}$$

To address the above multi-objective optimization problem, this paper uses the weighted sum of SE and EE as the unified optimization objective. By introducing weighting parameters to balance their priorities, the original problem is transformed into a single-objective optimization problem. Specifically, under the dynamic resource allocation framework based on time slot division, decision variables include the transmission power of subcarriers in each beam and the allocation relationship between users and subcarriers. Constraints cover subcarrier exclusivity, power limits, and time-varying channel stability. Since SE and EE have different units and cannot be directly added with physical meaning, a dimensionless weighting coefficient constructs the weighted objective function, enabling the algorithm to optimize transmission rate and power consumption efficiency simultaneously when dynamically adjusting resource allocation strategies. Assuming the satellite's maximum transmission power is O_{MAX}, and the minimum transmission power per subcarrier is O_{MIN}, the optimization problem can be expressed as:

$$\begin{cases} ARGMAX\, \lambda(s) \\ s.t. O_s^{(y,v)} \geq O_{MIN}; \forall v, y \\ \sum_{v,y} O_s^{(y,v)} \leq O_{MAX}; \forall v, y \end{cases} \tag{18}$$

3.2 Algorithm description

Figure 4 shows the proposed dynamic resource allocation framework for 5G NTN LEO satellites in this paper. To address the multi-objective optimization conflict between SE and EE in 5G NTN LEO satellite systems, the dynamic resource allocation problem is modeled as a Markov Decision Process (MDP), and intelligent policy optimization is realized by Deep Reinforcement Learning (DRL). Under the MDP framework, the environment is defined as the real-time operating scenario of the satellite communication system, including key parameters such as the dynamic distribution of user access to beams, the transmission power state of each beam, time-varying channel gain, and inter-beam co-channel interference levels. The state space is designed as $t^{y,v}=\{P^y,O^y_s\}$, where P^y represents the number of users accessing each beam in time slot s, intuitively reflecting the traffic load; O^y_s is the discretized beam power level, which reduces algorithm complexity while maintaining power adjustment precision by dividing the continuous power range into a finite number of fine levels. This adapts to the limited computing capability of LEO satellite payloads and provides feasible state input for real-time decision making. The defined discretization rule is:

$$\left(O_{MAX}-O_{\sigma}\right)\leq\sum_{v=0}^{V}O_{s}^{y,v}<\left(O_{MAX}-O_{\sigma+1}\right),O_{s}^{y}=\sigma \tag{19}$$

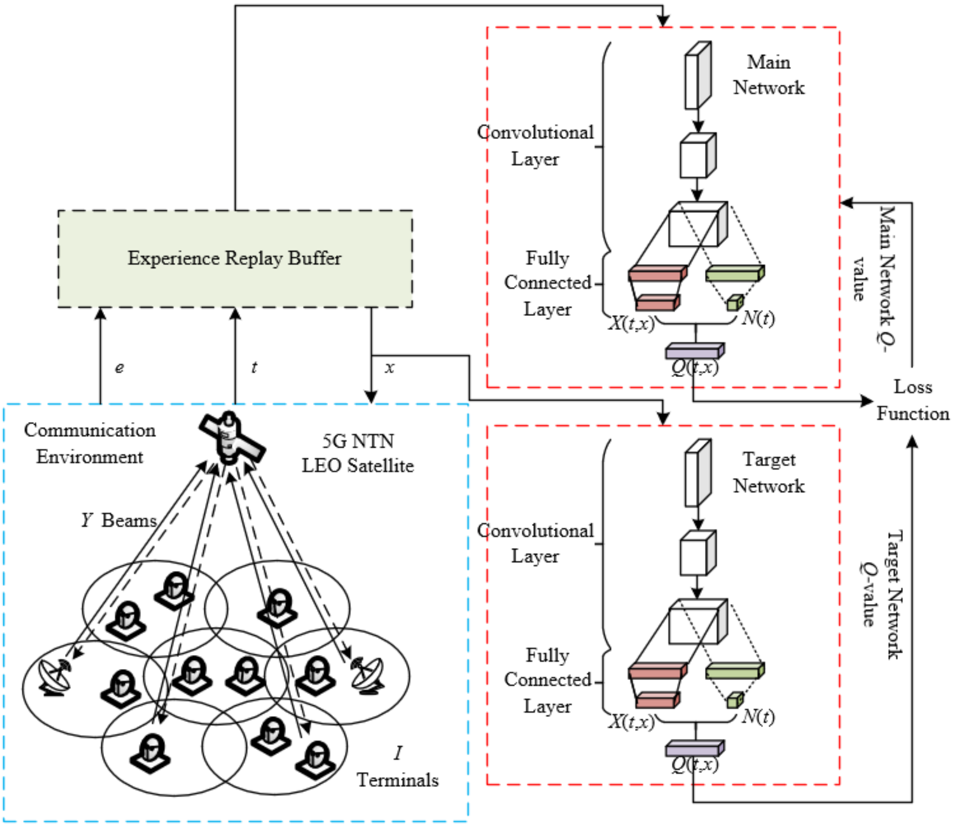


Figure 4. 5G NTN LEO satellite dynamic resource allocation framework

The action space is constructed as $X=\{x_1,x_2,\ldots,x_{3V}|x_y=(v_y,\Delta O^{y,v}_s)\}$, where each action corresponds to a power adjustment operation on a specific subcarrier in a beam, including three choices: "increase," "decrease," and "no change." The power adjustment amount $\Delta O^{y,v}_s$ is strongly correlated with the capacity change of the subcarrier's served user: when user capacity increases, power is increased to guarantee signal quality $\Delta O^{y,v}_s=+|\Delta O^{y,v}_s|$; when capacity decreases, power is reduced to save energy $\Delta O^{y,v}_s=-|\Delta O^{y,v}_s|$; when capacity is stable, power remains unchanged $\Delta O^{y,v}_s=0$. This design deeply couples subcarrier resource allocation with power control, enabling the algorithm to dynamically adjust resource allocation based on real-time service demands, achieving collaborative optimization of SE and EE while suppressing inter-beam co-channel interference, thus avoiding the response lag of traditional static strategies to traffic fluctuations.

The reward function is designed with the weighted sum of SE and EE as the core objective. Through dimensionless weighting coefficients balancing their priorities, the multi-objective optimization problem is converted into a single-objective optimization problem. Considering the physical unit differences between SE and EE, their direct summation lacks comparability; therefore, a weighted comprehensive reward signal is constructed to provide real-time feedback on the overall benefit of resource allocation strategies: positive rewards are given when the policy increases system throughput within a reasonable power consumption range, and negative rewards are given when pursuing a single metric excessively causes performance imbalance. This design encourages the agent to explore the Pareto optimal solutions between SE and EE in a dynamic environment, satisfying the high-rate communication requirements of 5G NTN while meeting the stringent green energy-saving constraints of LEO satellites, thus forming an adaptive regulation mechanism balancing efficiency and power consumption.

The core algorithm proposed in this paper improves training stability through the collaborative architecture of a main network and a target network. The main network is responsible for generating real-time power adjustment strategies based on the current state, directly affecting satellite resource allocation; the target network estimates the target Q-values, reducing the variance fluctuations of the value function during training and enhancing the robustness of the algorithm under time-varying channels. The Q-function is decomposed into a state-value function $N(t;\ \phi,\ \alpha)$ and an advantage function $X(t,\ x;\ \phi,\ \beta)$, where the former evaluates the overall value of the current state, and the latter quantifies the contribution of each action to the state value. Assuming the convolutional layer parameters of the network are denoted by ϕ, and the fully connected layer parameters of the two branches are denoted by β and α, the specific expression of the Q-function is:

$$W\left(t,x;\varphi,\beta,\alpha\right)=N\left(t,x;\varphi,\beta\right)+X\left(t,x;\varphi,\beta\right) \tag{20}$$

To avoid parameter non-uniqueness issues, the sum of the advantage function outputs is forced to be zero, ensuring precise evaluation of action benefits by the model. Therefore, the Q-function can be represented as:

$$\begin{aligned}&W\left(t,x;\varphi,\beta,\alpha\right)=N\left(t;\varphi,\alpha\right)\\&+\left(X\left(t,x;\varphi,\beta\right)-AMX\left(t,x';\varphi,\beta,\right)\right)\end{aligned} \tag{21}$$

During training, an ε-*greedy* strategy balances "exploration-exploitation": initially accumulating experience through random exploration, and later focusing on efficient policies to improve convergence speed; the experience replay buffer stores tuples of state, action, reward, and next state, reducing data correlation through batch learning. Network parameters are updated using the Adam optimization algorithm, and the target network is synchronized at fixed intervals, forming a stable end-to-end optimization closed loop.

4. EXPERIMENTAL RESULTS AND ANALYSIS

Figure 5 compares the performance of the proposed algorithm with traditional filtering methods such as LMS, KF, EMD, and MWF by the relationship between BMSE and signal-to-noise ratio (SNR). A smaller BMSE indicates smaller error between the filtered signal and the original signal, thus better filtering performance. As shown in the figure, across the entire SNR range, the BMSE values of the proposed algorithm are lower than those of other comparison algorithms. When SNR = 1 dB, the BMSE of the proposed algorithm is about 0.07, while MWF is about 0.08, and LMS is higher; when SNR = 10 dB, the BMSE of the proposed algorithm approaches 0.03, significantly lower than LMS, KF, and other algorithms. With increasing SNR, the BMSE decreasing trend of the proposed algorithm is more obvious, and it always maintains the lowest error level. At SNR = 5 dB, the BMSE of the proposed algorithm is about 12% lower than the second-best MWF; at SNR = 8 dB, it is about 15% lower than LMS. These data indicate that the proposed algorithm has stronger noise and interference suppression capability for LEO satellite time-varying channels over a wide SNR range, and the filtering accuracy is significantly better than traditional methods. The experimental results fully verify the effectiveness of the proposed adaptive filtering improvement algorithm for 5G NTN LEO satellite signals. The algorithm adaptively adjusts filtering parameters by real-time estimation of channel state information, accurately matching the time-varying characteristics of LEO satellite channels. Compared to traditional filtering algorithms with fixed parameters, it has stronger robustness in non-stationary channel environments, effectively reducing noise residual and signal distortion. In different SNR scenarios, the proposed algorithm shows the best filtering performance. The high-precision filtering results provide more accurate CSI input for the dynamic resource allocation algorithm, enabling resource allocation strategies to be optimized based on real channel states, thereby improving the weighted sum performance of SE and EE.

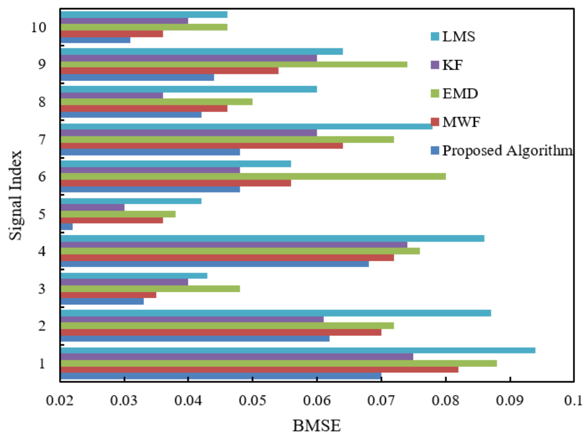


Figure 5. Comparison of filtering performance of different filtering methods

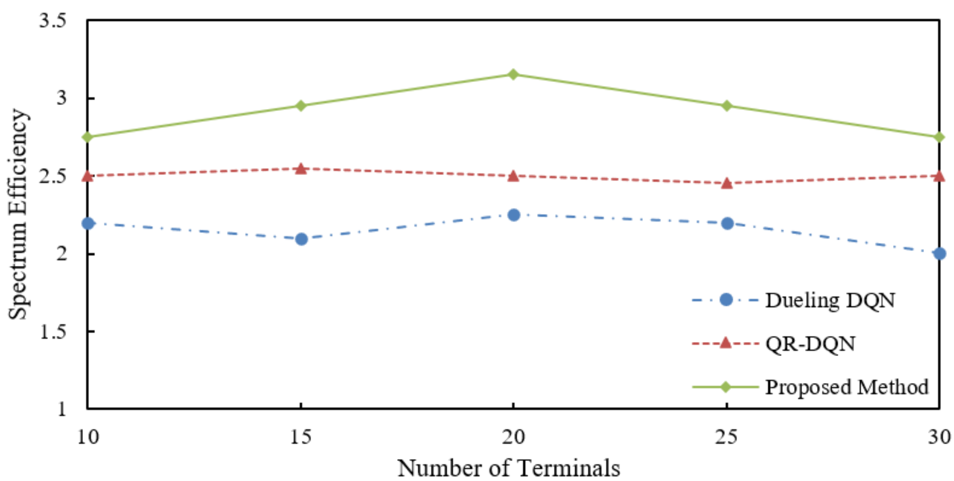


Figure 6. SE under different number of terminals in 5G NTN LEO satellite communication system

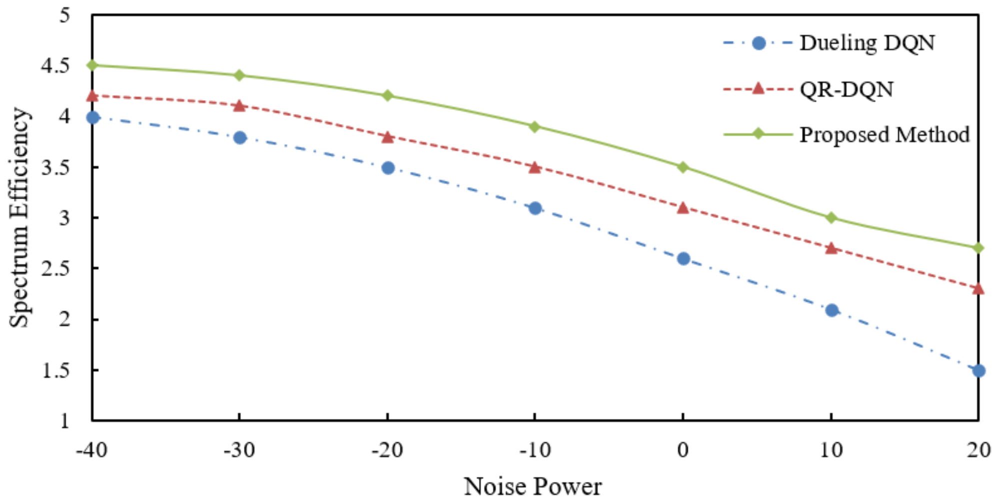


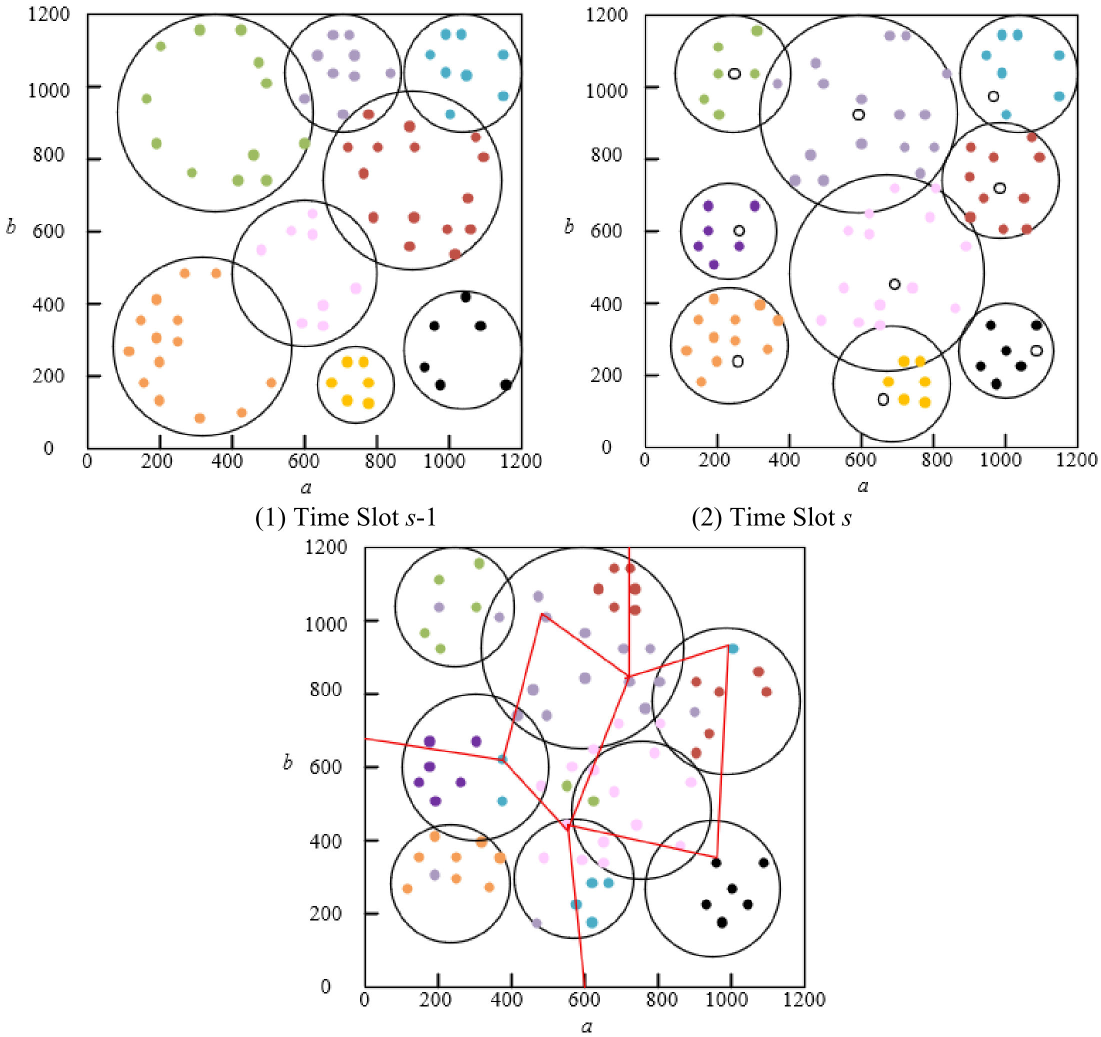
Figure 7. SE under different noise powers in 5G NTN LEO satellite communication system

Figure 6 compares the SE of different algorithms in the 5G NTN LEO satellite system with the number of terminals as the variable. SE is the core indicator measuring resource utilization capability; higher values indicate faster transmission rates per unit bandwidth. Data show: When the number of terminals is between 10 and 20, the SE of the proposed method shows an upward trend and always leads DuelingDQN and QR-DQN. At 20 terminals, the SE of the proposed method reaches 3.2, an increase of about 39% over DuelingDQN (2.3) and about 28% over QR-DQN (2.5), demonstrating its efficient scheduling capability under medium load. When the number of terminals is between 20 and 30, although the proposed method slightly decreases, it still maintains the highest value. Among comparison algorithms, DuelingDQN decreases to 2.0, QR-DQN decreases to 2.4 (4% decrease), while the proposed method decreases only 12.5%, and its absolute performance remains leading, reflecting robustness under high load scenarios. The experimental results fully verify the effectiveness of the proposed dynamic resource allocation algorithm for 5G NTN LEO satellites. The algorithm deeply integrates accurate channel states obtained from adaptive filtering, allowing resource allocation strategies to dynamically adjust based on real channel conditions. For example, with cleaner filtered signals, the algorithm can accurately judge terminal communication demands, avoiding resource waste caused by channel estimation errors in traditional algorithms. This joint optimization of "filtering-resource allocation" maintains leading SE amid terminal load changes, proving the effectiveness of the collaborative mechanism. Compared to the comparison algorithms, the proposed method has more comprehensive state space modeling and finer action space design, enhancing adaptability to the dynamic LEO satellite environment.

Figure 7 compares the SE of different algorithms in the 5G NTN LEO satellite system with noise power as the variable. SE is the core indicator measuring resource utilization capability; higher values indicate faster transmission rates per unit bandwidth. Data show that at noise power of -40 dB, the SE of the proposed method is about 4.5, slightly higher than QR-DQN and DuelingDQN, initially demonstrating performance advantages. As noise power increases, SE of all three algorithms decreases, but the decrease in the proposed method is the smallest. At noise power 20 dB, the SE of the proposed method is about 2.8, 87% higher than DuelingDQN and 27% higher than QR-DQN; at noise power 0 dB, the proposed method is 40% higher than DuelingDQN and 17% higher than QR-DQN. This indicates that the proposed algorithm's ability to maintain SE under high noise environments is significantly better than comparison algorithms, with outstanding anti-noise interference performance. The experimental results fully verify the effectiveness of the proposed dynamic resource allocation algorithm for 5G NTN LEO satellites. The algorithm deeply integrates accurate channel states obtained from adaptive filtering, enabling resource allocation strategies to dynamically adapt to noise environments. Under high noise, the cleaner filtered channel information allows the algorithm to precisely identify effective communication demands of terminals, avoiding resource waste and thus maintaining high SE. Comparison algorithms, lacking full utilization of filtered channel information, show increased blind resource allocation under noise enhancement, causing sharp drops in SE; the proposed method only decreases by 38%, highlighting the interference resistance benefits of joint optimization.

Figure 8 visually presents the spatiotemporal optimization process of dynamic resource allocation by the subcarrier set partitioning illustrations at different time slots. At time slot s-1, subcarriers are partitioned into multiple independent regions according to service distribution, reflecting the coverage of initial resource allocation; in time slot s, some regions shrink or reorganize, reflecting resource adaptive adjustment under changing service demands; in time slot s+1, subcarrier sets form dynamic scheduling paths connected by red lines, showing the algorithm's real-time response capability to time-varying channels and services. As can be seen, subcarrier regions continue to be optimized across time slots; for example, the yellow subcarrier group is an independent small region at s-1 but is integrated into the central resource pool at s+1, indicating the algorithm can flexibly merge or split resources according to service priority and channel state, avoiding resource waste caused by fixed allocation. Black circles closely enclose service distributions with no resource overlap or service blind spots, reflecting the algorithm's refined management of resources such as spectrum and power. The high-priority services connected by red lines in time slot s+1 obtain centralized resource scheduling, improving key service transmission efficiency. The algorithm dynamically adjusts subcarrier allocation on the time slot dimension based on real-time channel state provided by adaptive filtering. The fast fading of channels caused by LEO satellite high-speed movement is quickly adapted through "time slot-level" resource scheduling, avoiding performance degradation of traditional static algorithms.

Figure 9 compares the provided capacity and communication demand of three algorithms by beam number. Provided capacity reflects the business traffic supported after resource allocation by the algorithm, and communication demand represents actual business load. Data show that for each beam, the proposed method's provided capacity is always higher than or equal to communication demand, and significantly better than DuelingDQN and QR-DQN. For example, in beam 7, the proposed method provides about 1050 capacity, highly matching the demand and achieving resource supply-demand balance; DuelingDQN provides only 950, QR-DQN about 1020, showing clear advantages in resource utilization precision for the proposed method. As beam business complexity increases, the provided capacity of the proposed method always leads and best fits the demand. Taking beam 5 as an example, demand is about 800, the proposed method provides about 850, while DuelingDQN only 750, QR-DQN about 820, further verifying the proposed algorithm's adaptability to dynamic business demands. The algorithm deeply integrates real-time channel state obtained from adaptive filtering, enabling resource allocation strategies to dynamically respond to business traffic changes. By dynamically adjusting subcarrier allocation, power spectral density, and beam resource scheduling, the proposed method achieves high matching between provided capacity and demand in each beam. In multi-beam scenarios of LEO satellites, business demand differences among beams are significant. The proposed algorithm realizes dynamic cross-beam resource flow through global strategy optimization of deep reinforcement learning, improving overall system resource utilization. In the figure, red bars of beams 1–7 closely fit the blue bars, proving the algorithm can balance resources among multiple beams, avoid local resource idleness or shortage, and enhance system adaptability to complex business loads.



(1) Time Slot s-1　(2) Time Slot s

(3) Time Slot s+1

Figure 8. Illustration of subcarrier set partitioning results at different time slots

Figure 10 compares the system utility of three algorithms with satellite transmit power as the variable. System utility comprehensively measures the weighted sum of SE and EE, with higher values indicating better balance of resource utilization and energy consumption. As power increases, the system utility of the proposed method is always higher than comparison algorithms. At power 160, the proposed method's utility reaches 50, 25% higher than QR-DQN and 233% higher than DuelingDQN (15); at power 130, the proposed method already surpasses zero utility, while QR-DQN just reaches zero, and DuelingDQN is still -10, proving its high efficiency even in low power scenarios, and more obvious advantages in high power. The utility growth slope of the proposed method is significantly higher than comparison algorithms, indicating better conversion of power resources into system utility. For example, as power increases from 110 to 160, the utility of the proposed method increases by 70, QR-DQN increases by 60, and DuelingDQN only increases by 40, reflecting refined utilization of power resources and avoiding power waste in traditional algorithms. The algorithm integrates accurate channel states from adaptive filtering and dynamically optimizes power allocation strategy. At low power, with cleaner CSI after filtering, power is prioritized for high-value services to improve utility output per unit power; at high power, multi-beam channel states are utilized to realize optimal scheduling of power among spectrum and users, maximizing utility. This "precise power delivery" mechanism solves the problem of disconnection between power and performance in traditional algorithms.

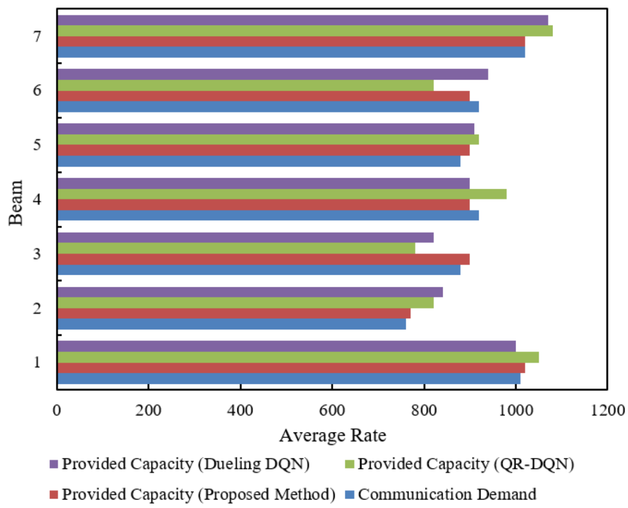


Figure 9. Comparison of communication demand and provided capacity of each beam under different methods

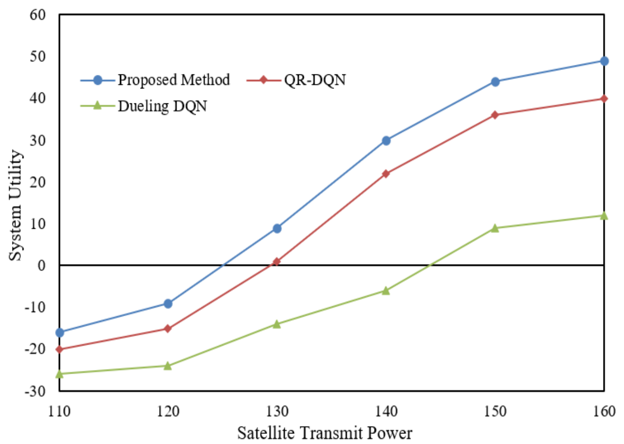


Figure 10. Relationship between system utility and satellite transmit power under different methods

In summary, the proposed dynamic resource allocation algorithm significantly improves the utility of 5G NTN LEO satellite systems through efficient conversion of power resources, collaborative multi-objective optimization, and adaptation to dynamic environments. The experimental data in Figure 10 intuitively demonstrate its performance advantages across the full power range, especially its utility growth ability under high power, providing key technical support for green energy saving and efficient transmission of LEO satellite communications, effectively solving the contradiction between "power limitation and performance demand," with important engineering value.

5. CONCLUSIONS

This paper addressed key technical challenges of 5G NTN LEO satellite systems by conducting joint optimization research on adaptive signal filtering and dynamic resource allocation, constructing a closed-loop system of "channel awareness-resource optimization." At the signal processing level, the proposed dynamic parameter adjustment filtering algorithm effectively suppressed noise and interference by real-time estimation of channel state, providing high-precision channel input for resource allocation. At the resource management level, the deep reinforcement learning resource allocation algorithm, which integrated filtered channel information, realized dynamic scheduling of spectrum and power, balancing SE and EE. Under dynamic scenarios such as terminal load, noise power, and transmit power, the system utility significantly outperformed comparison algorithms, resolving conflicts of single-metric optimization and improving resource utilization efficiency. Experimental data show that the joint optimization mechanism enables the system to accurately match resources with services under time-varying channels and multiple service loads, enhancing the performance stability and adaptability of the space-air-ground integrated network.

In terms of research value, this paper innovatively deeply coordinates signal processing and resource management, breaking through the contradiction of "time-varying channels-resource limitations-diverse services," providing key technical support for 5G NTN deployment, and promoting the space-air-ground integrated network toward green, efficient, and intelligent adaptation with important engineering application value. However, limitations exist such as high computational complexity, adaptability to extreme channel scenarios yet to be verified, and insufficient consideration of multi-satellite cooperation. Future research may focus on lightweight models to reduce computational overhead, enhance robustness in extreme scenarios, expand distributed multi-agent reinforcement learning frameworks for satellite-ground cooperation, achieve global intelligent resource scheduling, further improve algorithm practicality and universality, and lay a more solid foundation for next-generation space-air-ground integrated network resource management. Through continuous optimization, it is expected to solve core bottlenecks of LEO satellite communications, promoting technological upgrades and widespread application of integrated space-air-ground networks.

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