Intelligent Approaches to Managing Communication Channels in Hybrid Terrestrial-Satellite Networks with LEO Segment

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Abstract. The integration of terrestrial 5G/6G networks with Low Earth Orbit (LEO) satellite systems is creating a class of hybrid Satellite–Terrestrial Integrated Networks/Non-Terrestrial Networks (STIN/NTN) for which channel management in the face of highly dynamic topologies and traffic heterogeneity is becoming a key challenge. This paper examines intelligent approaches to radio resource allocation in such networks based on deep reinforcement learning (DRL) and multi-agent algorithms. A conceptual architecture for a channel management system in a hybrid network with a LEO segment is proposed, including a centralized Software-Defined Networking/Artificial Intelligence (SDN/AI) coordinator and distributed DRL agents at the satellite and ground base station levels. To analytically interpret the gains from intelligent management, an aggregated M/M/c/c teletraffic model is introduced, using the concept of an "equivalent number of channels," which allows for linking DRL resource allocation with classical assessments of blocking probability and throughput. The obtained numerical results show that increasing the effective system capacity by 20% due to intelligent inter-segment load redistribution leads to a 30–40% reduction in blocking and a 10–18% increase in throughput in the high-load region, which is consistent with the results of detailed DRL studies for LEO networks presented in the modern literature.

Keywords: *blocking probability; channel management; deep learning; Erlang B; LEO networks; M/M/c/c; NTN; multi-agent DRL; radio resource management; spectral efficiency; SDN coordinator.*

1 Introduction

The integration of non-geostationary satellite systems (primarily LEO constellations) with terrestrial 5G/6G networks is considered a key area of development for the global communications infrastructure and the NTN/SAGIN (Space–Air–Ground Integrated Networks) concept [1-3]. As shown in a number of reviews on integrated satellite-terrestrial networks and radio resource management, the main bottleneck of such systems is the management of radio

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resources and communication channels in conditions of highly dynamic and heterogeneous networks [1, 2, 4, 5].

In parallel, the application of artificial intelligence methods in satellite communications is developing: from autonomous payload management and onboard processing to intelligent radio resource planning and handover optimization in mega-constellations. The studies [6, 7] have systematically demonstrated how artificial intelligence methods are applied in satellite and non-territorial networks: from autonomous payload management and onboard processing to radio resource planning. A separate layer of research is devoted to the application of DRL and multi-agent algorithms for routing, beam-hopping, and bandwidth/power allocation in LEO constellations and integrated networks [8-11].

Numerical and simulation experiments for multi-beam LEO systems and integrated NOMA (Non-Orthogonal Multiple Access) networks have shown that DRL approaches to channel and power allocation provide a 25–40% reduction in blocking probability and a 5–15% increase in spectral/energy efficiency compared to heuristic and classical optimization methods [8, 9, 12-14].

However, most existing works either focus on the purely satellite LEO segment (beam management, inter-satellite links, handover in mega-constellations), or consider integrated networks at the level of high-level resource management, without offering detailed models for managing communication channels in a hybrid 'ground–LEO' architecture.

The scientific problem is to create such methods of communication channel management that:

1. take into account both ground and LEO segments;
2. are scalable to a large number of users and satellites;
3. work in conditions of incomplete and dynamically changing information;
4. provide the required QoS/QoE, reliability and energy efficiency indicators.

1.1 Main Contributions

The main contributions of this work can be summarized as follows:

1. A conceptual architecture for intelligent communication channel management in hybrid terrestrial–satellite networks with a LEO segment is proposed. The architecture combines a centralized SDN/AI controller with distributed DRL agents operating in both terrestrial and satellite segments.

2. A unified formulation of the channel management problem is developed that jointly considers terrestrial and LEO resources within a single constrained optimization framework with QoS and energy efficiency criteria.
3. An aggregated analytical teletraffic model based on the M/M/c/c scheme is introduced using the concept of equivalent channels, which enables a quantitative evaluation of blocking probability and throughput in hybrid networks.
4. A hierarchical control approach is proposed where high-level inter-segment resource coordination is performed by an SDN/AI controller, while local resource allocation decisions are learned by DRL agents.
5. Numerical results demonstrate that intelligent load redistribution between terrestrial and satellite segments can significantly reduce blocking probability and improve throughput under high traffic loads.

2 Materials and Methods

For clarity, all variables and parameters used in the mathematical formulation are defined at their first occurrence in the manuscript. The same notation is used consistently throughout the paper. In particular, the symbols *T, EE, B*, and *D* respectively denote throughput, energy efficiency, blocking probability, and delay, while the coefficients α_i and β_i represent weighting parameters used in the optimization objective and reward function.

2.1 Hybrid Terrestrial-Satellite Network Model

A fragment of a hybrid network is considered, including (Figure1):

1. ground segment: multiple 5G/6G base stations (gNB) located in the region under study and connected to the operator's cloud/edge infrastructure, SDN/AI controller;
2. LEO segment: several low-orbit satellites that form multi-beam coverage of a given region;
3. user segment: terminals with dual or multiple radio interfaces (terrestrial, satellite, if necessary, mmWave and FSO (Free Space Optics) links).

The user segment refers to user equipment (UE) and IoT devices equipped with at least one terrestrial network radio interface and, if necessary, a satellite, mmWave and/or FSO interface [15-17].

In the considered model, LEO satellites move along predefined orbital trajectories typical for large satellite constellations. The orbital motion leads to time-varying satellite–user distances, which affects propagation losses, Doppler shifts, and channel availability. These dynamics are reflected in the time-dependent channel parameters used in the model.

User mobility in the terrestrial segment is modeled in a simplified stochastic manner typical for cellular systems, where user terminals move within the service area with moderate velocities corresponding to pedestrian and vehicular scenarios. The mobility affects the instantaneous SINR values, possible handover events between terrestrial and satellite segments, and the availability of communication channels.

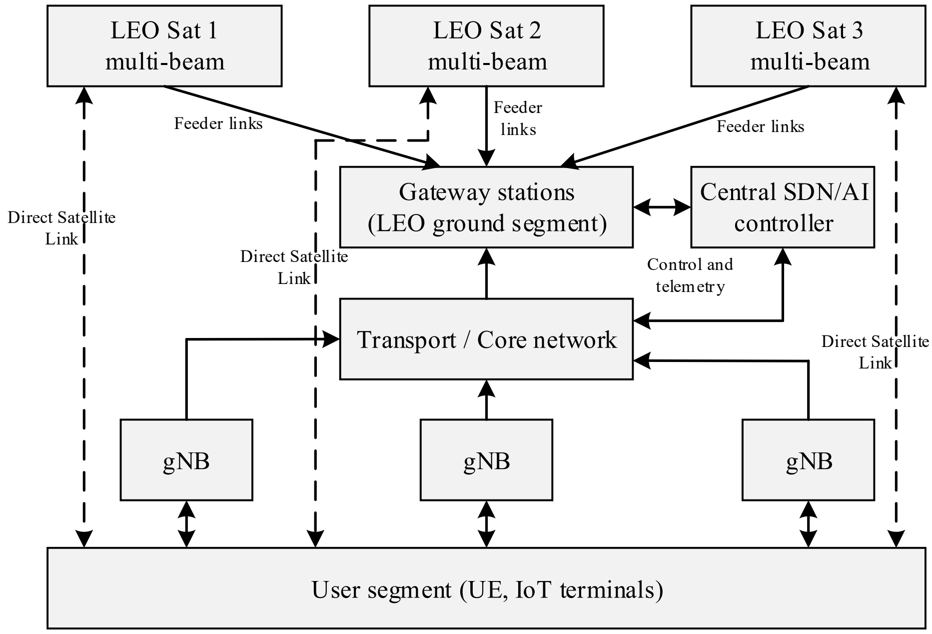

Figure 1 Hybrid network architecture.

For further analysis we assume:

Each user *u* at time *t* has access to a set of channels:

$$C_u(t) = C_u^T \cup C_u^S(t) \tag{1}$$

where $C_u^T(t)$ and $C_u^S(t)$ correspond to the terrestrial and LEO segments.

Channel $c \in C_u(t)$ is characterized by the transmit power, P_c; the bandwidth, Δf_c; the antenna gain; and the path loss.

The instantaneous channel capacity is determined by Shannon's formula [18] in Eq. (2):

$$R_c(t) = \Delta f_c \log_2\left(1 + \gamma_c(t)\right), \left[\frac{\text{bit}}{\text{s}}\right] \tag{2}$$

where $\gamma_c(t)$ is the current SINR (Signal to Interference + Noise Ratio) on a given channel.

For LEO lines, $\gamma_c(t)$ is set via the line balance in Eq. (3):

$$\gamma_c(t) = \frac{P_c^{tx} G_c^{tx} G_c^{rx}}{N_0 \Delta f_c L_c(d_c(t)) + I_c(t)} \quad (3)$$

where $L_c(d_c(t))$ are losses in free space and atmosphere (function of the satellite–terminal distance); and $I_c(t)$ is the total interchannel interference.

User traffic is heterogeneous in its requirements: for each user u and its active session, the required bitrate R_u^{req}, maximum allowable delay $D_u^{\max}$, and target blocking probability $B_u^{\max}$ are specified.

In the future, the average values of the throughput $R_c(t)$ according to Eqs. (2)-(3) will be used to calculate the equivalent number of channels q_c according to Eq. (7) and to parameterize the teletraffic model M/M/c/c.

2.2 Traffic Model and Service Classes

Let the network support several service classes $k \in K$ (eMBB, mMTC, URLLC, satellite backhaul, etc.) [19]. For each class, a Poisson flow of requests with intensity λ_k and an exponential distribution of session duration with parameter μ_k is assumed. Then in Eq. (4), the offered traffic (in erlangs) for class k is equal to:

$$A_k = \frac{\lambda_k}{\mu_k} \quad (4)$$

Total load on the hybrid system in Eq. (5):

$$A = \sum_{k \in K} A_k \quad (5)$$

For each class, requirements for service quality are set in following Eq. (6):

$$B_k \leq B_u^{\max},\ D_k \leq D_u^{\max} \quad (6)$$

where B_k is the probability of blocking requests of class k;

D_k- average delay (including channel delay and possible reconnections between segments).

This parameterization allows us to further link the analytical model with teletraffic (via the classical M/M/c/c scheme), as well as to use these same parameters in the simulation model and in setting the task for DRL agents.

2.3 Unified Resource Representation and Channel Types

Table 1 provides a comparative description of the most important types of communication channels used in a hybrid terrestrial-satellite network (terrestrial sub-6 GHz, mmWave, LEO RF, laser inter-satellite, etc.) [20].

Table 1 Main types of communication channels in hybrid terrestrial-satellite networks.

Channel type	Frequency range (typical)	Typical delay (one-way)	Doppler / dynamics	Sensitivity to weather	Advantages	Limitations/Typical Scenarios
Terrestrial cellular Sub-6 GHz	0.7–6 GHz	< 5 ms (radio interface)	Low/medium, due to user mobility	Moderate	Good coverage in cities, mature infrastructure	Limited service area, shading, congestion in hotspots
Ground mmWave	24–52 GHz	< 5 ms	High sensitivity to antenna movement and orientation	High (rain, obstacles)	Very high capacity, small cells	Short range, requires dense gNB network
Satellite LEO RF (Ku/Ka)	10–30 GHz	2–10 ms (radio + propagation)	High (satellite speed)	Medium/high (rain in Ka)	Global coverage, low latency relative to Geostationary Earth Orbit (GEO)	Limited onboard resources, complex handover, regulatory restrictions
Inter-satellite RF (ISL RF)	Ku/Ka	1–2 ms	High but predictable	Average	Reduced gateway load, flexible routing	Frequency coordination, interference in a megaconstellation
Optical feeder LEO–ground	Optics (1550 nm)	1–5 ms	High targeting accuracy	Very high (clouds, haze)	Very high throughput, narrow beam	Requires clear skies and is difficult to operate.
Inter-satellite optical channel	Optics	0.5–2 ms	Predictable (orbit)	Low (above the atmosphere)	Maximum Inter-Satellite Link (ISL) capacity, low interference	Strict requirements for targeting accuracy, cost

The summary characteristics of the channels in Table 1 allow us to move to a unified description of resources as 'equivalent channels' with a base rate of R_0 (e.g., $R_0 = 10$ Mbps). For this purpose, the average throughput of each channel type, calculated according to Eqs. (2)-(3), is used and then the integer capacity q_c is introduced.

In Eq. (7), for each physical channel c we define an integer 'capacity':

$$q_c = \left\lfloor \frac{E[R_c(t)]}{R_0} \right\rfloor \tag{7}$$

where $\mathrm{E}[R_c(\mathrm{t})]$ is the average throughput based on the results of linear balance and/or simulation. Then in Eq. (8), the total number of equivalent channels in the system is:

$$c = \sum_{c \in C} = c_T + c_S \quad (8)$$

where c_T and c_S are the contributions of the ground and satellite segments, respectively.

It is c that is used further in the aggregated teletraffic model M/M/c/c. This unified representation of resources allows, on the one hand, to maintain a connection with the physical architecture (through Eqs. (2)-(3)), and on the other hand, to obtain an analytically controlled model of service quality.

2.4 Methods of Communication Channel Management

Channel management in hybrid systems can be divided into traditional (non-intelligent) and intelligent methods. A comparison is shown in Table 2.

Table 2 Classification of communication channel management methods.

Method class	Examples	Brief description	Adaptability/ learning ability	Required data	Suitable for LEO/ hybrid networks
Static planning	Fixed frequency plans, rigid division of spectrum into segments	Channels are pre-booked, parameters do not change over time	Low	Minimum	Limited (suitable for GEO, low-mobility systems)
Heuristic algorithms	Greedy selection based on maximum SINR, threshold handover schemes	Simple local rules without global optimization	Average	Local signal quality measurements	Possible, but do not scale well with large dynamics
Optimization methods	ILP, convex optimization, Lagrangian methods	Solving optimization problems with known models and constraints	Average	Accurate models of channels and traffic	Limited by computational complexity and environmental uncertainty
Classical RL/Q-learning	Table-based learning of channel allocation policy	Reward-based policy learning; limited by state space size	Medium/high	Observations of states and rewards	Applicable, but suffers from the 'curse of dimensionality' in LEO mega-constellations
DRL (DQN, DDPG, PPO, etc.)	DRL resource distribution, DRL handover	Using neural networks to approximate value/policy functions in large spaces	High	Large arrays of telemetry, channel status, traffic	Well-suited for multi-beam LEO and hybrid networks, blocking and spectral efficiency gains are demonstrated
Multi-agent DRL	Multi-Agent DQN, centralized training – distributed execution	A set of interacting agents (satellites/beams/base stations) with coordination	High	Local and semi-global states, messaging	Preferred for mega-constellations and hybrid networks with an SDN coordinator

Recent studies on DRL-based resource management in LEO satellite networks and integrated satellite–terrestrial architectures [8–13] have demonstrated that intelligent approaches can significantly outperform traditional and heuristic methods in channel and power allocation problems, particularly under highly dynamic traffic and topology conditions.

2.5 Mathematical Formulation of the Channel Control Problem

Consider a set of users U and a set of available channels C in the terrestrial and LEO segments, and discrete time slots t = 1, 2, …. For a user $u \in U$ and a channel $c \in C$ at time t, let $x_{u,c}(t) \in \{0,1\}$ denote the binary channel assignment variable, where $x_{u,c}(t) = 1$ if user u is assigned to channel c, and $x_{u,c}(t) = 0$ otherwise. The variable $p_{u,c}(t)$ represents the transmission power allocated to the user, $\gamma_{u,c}(t)$ denotes the corresponding signal-to-interference-plus-noise ratio (SINR), and $R_{u,c}(t)$ represents the achievable data rate, which is determined according to Shannon's capacity formula.

Resource constraints and QoS can be written as in Eqs. (9) to (12):

$$\sum_{c\in C} x_{u,c}(t) \leq 1, \quad \forall u, t, \tag{9}$$

$$\sum_{u\in U} x_{u,c}(t) \leq N_c(t), \quad \forall c, t, \tag{10}$$

$$\sum_{c\in C} x_{u,c}(t) R_{u,c}(t) \geq R_u^{\mathrm{req}}, \quad \forall u, t, \tag{11}$$

$$\gamma_{u,c}(t) \geq \gamma_u^{\mathrm{th}} x_{u,c}(t), \quad \forall u, c, t, \tag{12}$$

where $N_c(t)$ is the maximum allowable number of simultaneous connections on a channel (beam), and

γ_u^{th} is the SINR threshold for the user service u.

Instantaneous total network throughput in Eq. (13):

$$T(t) = \sum_{u\in U} \sum_{c\in C} x_{u,c}(t) R_{u,c}(t). \tag{13}$$

The probability of blocking during the observation interval is defined as in Eq. (14):

$$B = \frac{N_{\mathrm{blk}}}{N_{\mathrm{tot}}} \tag{14}$$

where N_{blk} is the number of requests rejected due to lack of resources or violation of QoS thresholds, and

N_{tot} is the total number of applications.

To evaluate energy efficiency, we introduce the total power in Eq. (15):

$$P_{\mathrm{tot}}(t) = \sum_{u\in U} \sum_{c\in C} x_{u,c}(t) p_{u,c}(t) \tag{15}$$

and we will determine the energy efficiency on the interval in Eq. (16):

$$EE(t) = \frac{T(t)}{P_{\mathrm{tot}}(t)}. \tag{16}$$

Then the long-term multi-criteria quality function can be written as in Eq. (17):

$$J = \alpha_1 \bar{T} + \alpha_2 \widetilde{EE} - \alpha_3 \bar{B} - \alpha_4 \bar{D}, \tag{17}$$

where $\bar{T}, \widetilde{EE}, \bar{B}, \bar{D}$ are the indicators averaged over time and users, and

α_i are weighting coefficients.

The channel management problem is formulated as the problem of choosing a sequence of actions (channel assignments, capacities, segment) to maximize Eq. (17) under constraints Eqs. (9)- to (12).

Unlike a number of existing works [8, 10, 13, 14], where resource management was considered separately for the satellite or ground segment, the proposed formulation combines both segments into a common optimization problem with a single quality criterion and common constraints on QoS and energy efficiency.

2.6 Hierarchical Intelligent Architecture

The proposed intelligent channel management architecture implements a two-tier approach (Figure 2).

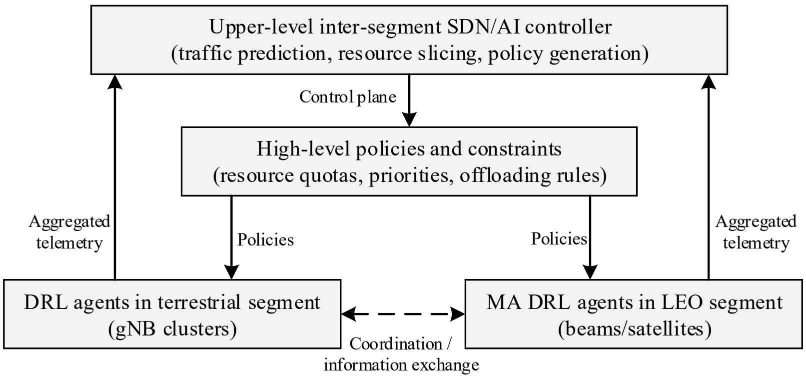

Figure 2 Hierarchical control diagram: upper level (intersegment controller) – lower level (DRL agents in segments), interconnection via control channels and telemetry.

The centralized controller (SDN/AI controller) periodically collects aggregated telemetry from gNB and LEO gateways, including resource utilization, blocking statistics, latency, and SINR metrics. Based on this data, the following processes are performed:

1. the load is predicted by service classes (for example, using Long Short-Term Memory (LSTM) models);

2. the optimal share of traffic directed to the ground and LEO segments is determined as follows in Eq. (18):

$$\eta_T(t),\;\; \eta_S(t) = 1 - \eta_T(t) \tag{18}$$

3. for each segment, resource pools (frequency, beams, power) are allocated, upper/lower boundaries are set for local DRL agent policies.

The overall workflow of the proposed DRL-based channel management approach is illustrated in Figure 3.

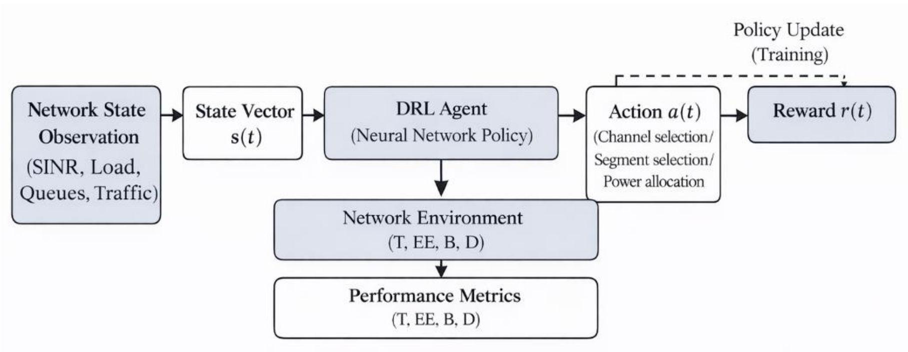

Figure 3 Workflow of the DRL-based channel management process in the hybrid terrestrial–LEO network.

The DRL agent observes the current network state (SINR, traffic load, queue lengths and service conditions), forms the state vector and selects an action corresponding to channel allocation, segment selection (terrestrial or LEO), and power configuration. The network environment then produces performance indicators such as throughput, energy efficiency, blocking probability and delay, which are used to calculate the reward signal for updating the policy during the learning process.

The resulting high-level policy is passed to the lower level as a set of restrictions and priorities for service classes.

At the lower level, local DRL agents operate:

1. in the ground segment– agents managing gNB groups;
2. in the LEO segment – a multi-agent system, where each beam/satellite is considered as a separate agent.

The state of the agent at time *t* is given by the vector in Eq. (19):

$$s_t = [L(t), G(t), Q(t), C(t)] \tag{19}$$

where L(t) is the channel loading matrix, Γ(t) is the SINR estimates, Q(t) is the queue lengths by service class, and C(t) is the class/priority features.

The action, α_t , is selected in Eq. (20):

$$a_t = \{\text{channel selection}, \text{segment selection}(\text{ground}/\text{LEO}), \text{power selection}\} \qquad (20)$$

To increase the sustainability of training, standardized indicators are introduced in Eq. (20):

$$\widetilde{T_t} = \frac{T(t)}{T_{\text{ref}}},\ \widetilde{\text{EE}}_t = \frac{EE(t)}{E_{\text{ref}}},\ \widetilde{B_t} = \frac{B(t)}{B_{\text{ref}}},\ \widetilde{D_t} = \frac{D(t)}{D_{\text{ref}}} \qquad (21)$$

where T_{ref}, EE_{ref}, B_{ref}, D_{ref} are normalizing constants selected based on typical values.

The reward function of the DRL agent is given by in Eq. (22):

$$r_t = \beta_1\widetilde{T_t} + \beta_2\widetilde{EE}_t - \beta_3\widetilde{B_t} - \beta_4\widetilde{D_t} \qquad (22)$$

where β_i are weights reflecting the relative importance of throughput, energy efficiency, blocking, and latency.

The design of the reward function reflects the multi-objective nature of the channel management problem. The positive components of the reward correspond to network throughput and energy efficiency, while the negative components penalize blocking probability and latency. This structure encourages the DRL agent to allocate resources in a way that maximizes system performance while maintaining acceptable QoS levels.

The weighting coefficients β_1–β_4 determine the relative importance of these objectives. In this work, the weights are selected based on typical priorities of hybrid terrestrial–satellite networks, where maintaining throughput and minimizing blocking probability are considered the primary objectives. The values of the coefficients are chosen to ensure balanced learning behavior and stable convergence of the DRL training process. In practical implementation, the weighting coefficients can be tuned during the training process depending on operator policies and service requirements. In this study, the coefficients were selected to prioritize throughput improvement and blocking probability reduction under high-load conditions typical for hybrid terrestrial-LEO networks.

In this framework, the DRL agent learns an optimal channel allocation policy through interaction with the network environment. At each time step, the agent observes the current system state, including channel load, SINR estimates, queue lengths, and service class priorities. Based on this state, the agent selects an action consisting of channel assignment, segment selection (terrestrial or LEO), and transmission power configuration.

The objective of the learning process is to maximize the cumulative long-term reward defined in Eq. (22), which reflects the multi-criteria optimization objective formulated in Eq. (17). During training, the DRL algorithm iteratively updates the policy parameters using observed state transitions and reward signals. As a result, the learned policy approximates the optimal solution of the constrained resource allocation problem under dynamic network conditions.

The parameters estimated during the DRL agent training process (blocking probability, delays, total power) are then compared with the analytical characteristics of the M/M/c/c model, which allows it to be used as a fast approximation for the initial assessment of the effects of intelligent control.

Thus, maximizing the total reward in Eq. (23),

$$\max_{\pi} E_{\pi}[\textstyle\sum_{t=0}^{\infty} \gamma^{t} r_{t}] \tag{23}$$

is equivalent to maximizing the quality attribute in Eq. (17) in the long-term horizon, where π is the DRL agent's policy and γ is the discount coefficient.

For the multi-agent case, a centralized learning–distributed execution paradigm is used: during training, agents have access to the extended state (joint features of several beams/satellites), while during execution they use only local observations.

2.7 Analytical Model of M/M/c/c and Connection with Physical Architecture

To obtain simple quantitative estimates, an aggregated teletraffic model of a system with failure patterns (Erlang B model) is used, which describes well the probability of blocking with a limited number of 'equivalent channels' in the system.

This model has the following assumptions:

1. The total flow of applications is modeled by a Poisson process with intensity $\lambda = \sum_k \lambda_k$.
2. The service time is exponential with parameter μ.
3. The number of equivalent channels c is determined according to Eq. (8), taking into account both the ground and LEO segments.

Suggested load in Eq. (24):

$$A = \frac{\lambda}{\mu}. \text{ [Erl]} \tag{24}$$

Blocking probability according to Erlang's B formula in Eq. (25):

$$B(A, c) = \frac{\frac{A^c}{c!}}{\sum_{k=0}^{c} \frac{A^k}{k!}}. \tag{25}$$

The average throughput (at a fixed R_0 = the speed of one equivalent channel) is calculated as:

$$T(A, c) = \big(1 - B(A, c)\big) A R_0 \tag{26}$$

To compare traditional and intelligent channel management schemes, two scenarios are considered:

1. Non-intelligent circuit: $c_{\text{non}} = 20$ equivalent channels;
2. Intelligent circuit: $c_{\text{int}} = 24$ equivalent channels (effective increase in capacity by 20% due to a more uniform load distribution between segments).

Interpretation: The transition to intelligent channel management (better inter-segment load balancing, reduced parasitic blocking under uneven load, more efficient use of LEO resources) is modeled as an increase in the effective number of channels c for the same offered load. In a practical system, this increase can be achieved through a more even load distribution by DRL agents between spokes and segments, as well as by reducing idle resources and parasitic blocking during peak load periods.

A more detailed hybrid dual-pool option is possible: the ground and LEO segments are considered as two resource pools with parameters (A_T, c_T) and (A_S, c_S), between which 'intelligent' load flow occurs. In this case, the system state is described by the pair (n_T, n_S), where $n_T \le c_T$, $n_S \le c_S$, and the stationary distribution $\pi(n_T, n_S)$ is found from the system of balance equations. The resulting blocking probability in Eq. (27):

$$B_{\text{tot}} = \sum_{(n_T, n_S) \in \partial} \pi(n_T, n_S) \tag{27}$$

where ∂ is the set of states in which a new request cannot be served in any of the segments.

In this paper, the single-pool model Eqs. (25)-(26) is used for numerical illustration.

3 Results

3.1 Comparison of Traditional and Intelligent Channel Management Systems

Summary qualitative differences between traditional and intelligent channel management systems are presented in Table 3, based on modern reviews and experimental work.

The summary results in Table 3 are consistent with quantitative estimates obtained in modern studies on DRL resource management [8, 9, 12-14]: traditional methods based on static frequency planning and local heuristics scale poorly to megaconstellations and are sensitive to incomplete data, whereas learnable policies explicitly take into account the dynamics of the LEO topology, traffic heterogeneity, and segment load correlation. This is manifested in a reduced blocking probability and improved spectral/energy efficiency in the high-load region.

Table 3 Comparison of traditional and intelligent channel management systems.

Characteristic	Traditional systems (static, heuristic, optimization)	Intelligent systems (ML/DRL, multi-agent)
Taking into account the dynamics of LEO topology	Limited, requires reconfiguration of models	Naturally taken into account through data learning
Scalability to mega-constellations	For complex tasks often unsatisfactory	Supported by neural network approximations and multi-agent schemes
Working with incomplete/noisy data	Usually requires precise models	Can learn from partial observations
Gains in blocking, spectral and energy efficiency	Basic level	blocking gain of 25–40%, spectral and energy efficiency gain of 5–15% in high-load scenarios (according to simulation studies of DRL algorithms for LEO and integrated networks [8, 9, 12–14])
Computational complexity in runtime mode	Low/medium	Medium/high, but acceptable when using MEC/cloud
Explainability of decisions	High (simple rules)	Limited, requires Explainable Artificial Intelligence (XAI)/logging

3.2 Numerical Results for the Aggregated M/M/c/c Model

For both scenarios (non-intelligent and intelligent), the dependences of the blocking probability $B(A,c)$ and the average throughput $T(A,c)$ on the load A were numerically calculated using formulas (25)-(26) for $R_0 = 10$ Mbit/s and $A \in [5, 30]$ Erl.

Figure 3 shows the dependence of the blocking probability on the load for $c_{\text{non}} = 20$ and $c_{\text{int}} = 24$. At low loads (up to $A \approx 10$), blocking is small in both cases; differences appear in the high load region:

1. at $A \approx 20$ Erl, the blocking decreases from a value of about ~0.12 to ~0.07;
2. at $A \approx 25$–30 Erl, the relative reduction reaches ≈30–40% compared to the non-intelligent scheme.

Figure 4 shows the dependence of the average throughput $T(A, c)$ on the load. In the region of unsaturated system operation, $T(A, c)$ increases almost linearly with A (this is evident from the nearly linear section in Figure 4 for $A \lesssim 15$ Erl). For the intelligent circuit (24 equivalent channels), under high loads, an additional throughput increase of approximately 10–18% is achieved due to a more efficient use of resources.

Thus, even in the aggregated M/M/c/c model, an important practical effect is formalized: an increase in the effective capacity of the system by 20% leads to a noticeable improvement in QoS under congestion, which is qualitatively consistent with the results of more detailed DRL models for multi-beam LEO networks [8, 9, 12-14].

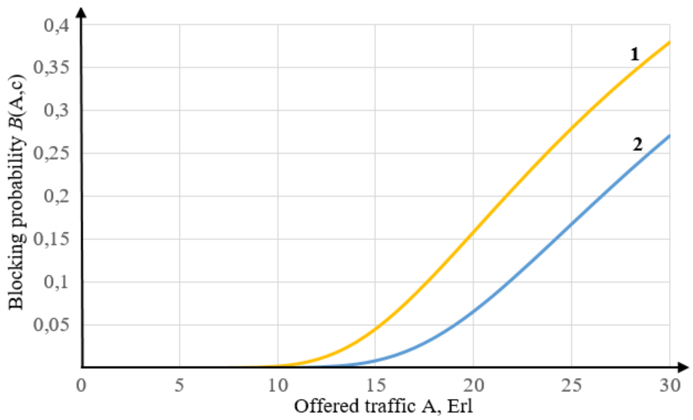

Figure 4 Dependence of blocking probability on load for non-intelligent (1) and intelligent (2) control schemes.

These results illustrate the practical advantage of intelligent channel management in hybrid terrestrial-LEO networks, where dynamic load redistribution between segments significantly reduces blocking probability under high traffic conditions.

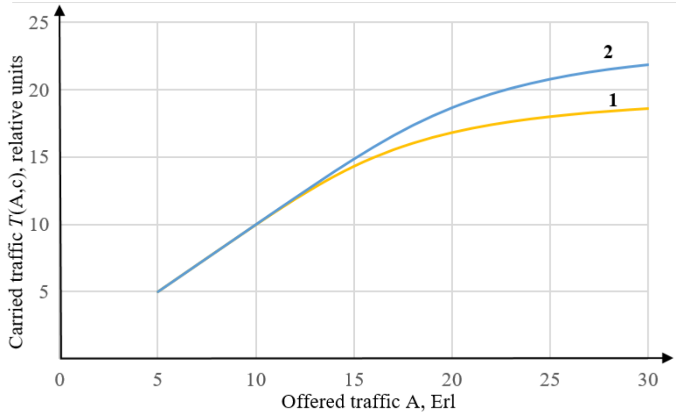

Figure 5 Dependence of the average throughput of a non-intelligent (1) and intelligent (2) system on the load.

The results confirm that intelligent resource allocation improves overall system utilization, allowing hybrid networks to support higher traffic loads while maintaining acceptable QoS levels.

4 Discussion

The results obtained use a deliberately simplified M/M/c/c teletraffic model, in which the entire hybrid system is reduced to a single-pool system with failures. This assumption allows for an analytical assessment of the impact of the 'effective' increase in the number of channels caused by intelligent management but ignores a number of important aspects of real hybrid networks, such as channel heterogeneity, differences between the terrestrial and satellite segments, and specific handover mechanisms.

However, a comparison of the c_{non} and c_{int} scenarios shows that even a relative increase in equivalent capacity by 20% leads to a significant reduction in blocking probability and an increase in throughput in the high-load region. These effects are consistent with publications using DRL algorithms for resource allocation in LEO networks and integrated architectures [8, 9, 12-14, 22-24].

It is important to emphasize that the proposed architecture's 'inter-segment SDN/AI controller–local DRL agents' hierarchy allows for the separation of load forecasting and resource slicing tasks from operational channel and power selection at the individual gNB/spoke level. This two-tier approach facilitates the integration of DRL algorithms into the operator's existing infrastructure and reduces the requirements for the volume of telemetry transmitted to the cloud.

A limitation of the current work is the lack of a complete simulation model with realistic LEO dynamics, a physical layer, and a specific implementation of DRL algorithms. This is left to future research, where analytical estimates based on the M/M/c/c model can serve as a benchmark for validating more complex scenarios.

5 Conclusion

This article proposes and analyzes an architecture for intelligent channel management in a hybrid terrestrial-satellite network with a LEO segment. A key feature of the approach is a hierarchical control structure combining an inter-segment SDN/AI controller and a set of local DRL agents in the terrestrial and satellite segments.

A mathematical formulation of the multi-criteria channel management problem was developed, taking into account bandwidth constraints, blocking probability, latency, and energy efficiency. An aggregated teletraffic model based on M/M/c/c was developed, using the concept of equivalent channels. A comparison of scenarios with non-intelligent and intelligent control schemes showed that an effective 20% increase in system capacity significantly reduces blocking and increases throughput under high loads.

The obtained results confirm the potential of integrating DRL approaches into channel management systems of hybrid terrestrial-satellite networks and can serve as a starting point for the development of more detailed simulation models that take into account orbit dynamics, physical layer features, and specific requirements of individual service classes (eMBB, mMTC, URLLC).

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