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Enabling Coexistence: Dynamic Channel Allocation for Scalable LEO-GEO Networks

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***Abstract*—The growing coexistence of LEO and GEO satellite systems within shared frequency bands introduces critical co-channel interference challenges. This paper presents a robust and dynamic framework for evaluating spectrum allocation strategies to mitigate such interference in GEO–LEO satellite networks. We investigate and compare three allocation schemes: random, optimization-based, and Deep Reinforcement Learning (DRL)-driven strategies. A simulation environment modeled on real-world geometries over Australian ground stations is developed, incorporating a OneWeb-style LEO constellation alongside configurable GEO satellites. Performance is assessed using metrics such as Signal-to-Interference-plus-Noise Ratio (SINR), interference power, signal throughput, and spectral efficiency. Results demonstrate that the learning-based allocation reduces interference and enhances system throughput, offering a scalable solution for future multi-orbit satellite networks coexistence.**

***Index Terms*—Frequency allocation, interference, LEO-GEO coexistence, DRL, satellite communication, spectrum sharing.**

I. Introduction

The explosive growth of Non Geostationary Satellite Orbit (NGSO) constellations [1], especially in Low Earth Orbit (LEO) [2], now poses a severe and imminent interference threat to established Geostationary Earth Orbit (GEO) systems. Historically, GEO satellites have benefited from highly predictable frequency planning due to their fixed Earth-relative positions and minimal interference dynamics. However, the unprecedented density of modern NGSO systems has created a critical situation where their downlink beams increasingly intersect with the GEO arc, causing substantial co-channel overlaps that degrade service quality for GEO users [3]. This coexistence crisis [4] represents one of the most urgent challenges in contemporary shared-spectrum management.

Concurrently, surging global demand for broadband connectivity has triggered the aggressive deployment of massive NGSO constellations, including OneWeb [5] and Starlink [6], which deliver low-latency, high-throughput coverage through intensive frequency reuse across numerous spot beams. While this approach maximizes capacity, it substantially escalates the risk of harmful interference with Geostationary Satellite Orbit (GSO) users operating in identical bands. As these constellations rapidly expand in both scale and complexity, effective inter-system interference management becomes increasingly impossible without sophisticated dynamic mechanisms.

To combat this mounting threat, the International Telecommunication Union (ITU) has established stringent regulatory constraints through *Article 22* of the Radio Regulations (RR), imposing strict limits on the Equivalent Power Flux Density (EPFD) emitted by NGSO satellites toward co-frequency GEO earth stations [7]. Rather than mandating specific access protocols, these regulations provide architectural flexibility while firmly placing compliance responsibility on NGSO operators, who must implement robust channel allocation, beam coordination, and power control strategies.

In response, researchers have proposed various interference mitigation approaches, though most exhibit significant limitations. Traditional spectrum coordination techniques rely heavily on static frequency planning or spatial separation—approaches that prove woefully inadequate in dynamic, multi-orbit environments. More advanced strategies incorporate Cognitive Radio (CR) and Deep Reinforcement Learning (DRL) to enhance spectral efficiency. Pourmoghadas et al. [8] presented a range of cognitive interference management techniques, including exclusion zones and power control, for NGSO–GSO coexistence, but their framework relied heavily on static thresholds and failed to address dynamic user distribution and traffic variation, limiting spectral efficiency in dense deployments. In [9], the authors highlighted the need for joint resource management in GEO–LEO coexistence scenarios, yet the work did not detail how resource allocation is performed.

Zheng et al. [10] proposed a DRL-based channel allocation for LEO satellites, demonstrating improved throughput under dynamic network conditions; however, their model did not consider coexistence constraints from GEO systems, overlooking cross-system interference risks. More recently, Song et al. [11] presented a joint beam management and channel allocation algorithm to mitigate interference, showing promising gains in Signal-to-Interference-plus-Noise Ratio (SINR) and fairness; nonetheless, their simulations assumed ideal cooperation among LEO and GEO operators, which is rarely achieved in practice.

This paper presents a dynamic DRL framework to rigorously assess the impact of Dynamic Spectrum Allocation (DSA) strategies on co-channel interference in hybrid GEO–LEO systems, analyzing effects on SINR, throughput, and spectral efficiency. Our advanced environment models a configurable multi-orbit scenario with a OneWeb-style Walker-Star LEO constellation, a GEO satellite at an arbitrary longitude, and 20 distributed Ground Stations (GSs) across Australia. It captures realistic orbital dynamics, visibility constraints, and time-varying spatial–spectral contention in the downlink regardless of the GEO coordination.

Specifically, we develop a novel Asynchronous Advantage Actor Critic (A2C)-based channel allocation algorithm [12], precisely engineered for hybrid multi-orbit networks. Unlike competing DRL methods plagued by instability or sample inefficiency, our approach employs asynchronous updates ideally suited to the highly dynamic link topologies in LEO–GEO networks. A custom-designed advantage function directly addresses the complex temporal credit assignment challenges caused by frequent handovers, while our innovative multi-modal encoder captures intricate spatial, spectral, and temporal dependencies. Our key contributions include:

- Development of a robust and highly configurable simulation framework for hybrid LEO–GEO coexistence, enabling detailed frequency reuse analysis under realistic orbital and link dynamics.
- Rigorous evaluation of three distinct frequency allocation strategies: (i) random assignment as a baseline reference, (ii) an upper-bound scheme representing theoretical performance limits, and (iii) a cutting-edge learning-enabled DSA policy based on the proposed A2C framework.
- Design of an advanced proportional fairness reward function that jointly maximizes LEO spectral efficiency while minimizing co-channel interference to GEO systems, setting a new benchmark for equitable spectrum sharing.
- Exhaustive evaluation using key metrics, including SINR, interference power, user throughput, and spectral efficiency, offering actionable insights into the coexistence trade-offs in next-generation multi-orbit satellite networks.

II. System Model and Framework

This section presents an end-to-end simulation framework designed to evaluate the downlink performance and frequency reuse in hybrid LEO–GEO satellite systems. The framework incorporates satellite constellation modeling, geometric link evaluation, antenna pattern synthesis, received power computation, serving satellite selection, and channel allocation.

A. End-to-End Simulation Pipeline

The proposed framework is structured into modular components, as illustrated in Fig. 1, enabling flexible experimentation with several channel allocation schemes. The system under study includes a LEO constellation and a GEO satellite positioned over Australia, both providing service to a set of fixed GSs distributed across the continent as illustrated in Fig. 2.

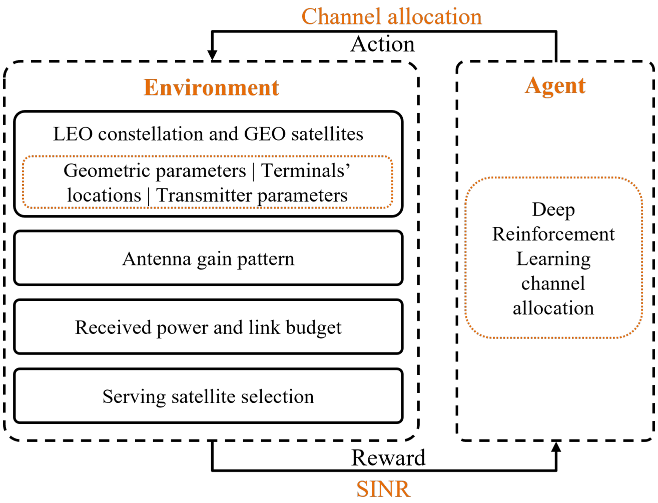

Fig. 1: Framework for LEO-GEO coexistence, including geometry generation, antenna pattern, link budget computation, and channel allocation using DRL environment and agent.

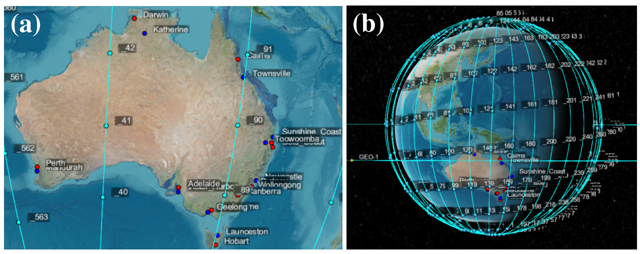

Fig. 2: Hybrid LEO-GEO satellite system and GS layout. (a) Regional view showing Australian GSs. (b) Global view of the Walker-Star constellation and GEO satellite.

The simulation framework begins by defining the orbital elements for both the LEO and GEO satellites using classical Keplerian parameters, namely the semi-major axis a, eccentricity e, inclination i, right ascension of the ascending node Ω, argument of perigee ω, and true anomaly ν. A Walker-Star configuration is adopted for the LEO constellation, consisting of multiple nearly polar orbital planes with a fixed number of satellites per plane to ensure periodic global coverage. The GEO satellite is positioned in a circular equatorial orbit with zero inclination and eccentricity, each located at predefined longitudes to provide continuous coverage over a specific geographic region.

To assess Line-of-Sight (LoS) visibility and propagation conditions, the elevation angle El and the slant range ρ between each GS and satellite are computed. For each GS–satellite pair, El indicates whether the satellite is within the local horizon of the GS, where only links with positive elevation angles are considered valid for downlink transmission. The slant range provides the direct LoS distance required for path loss computation.

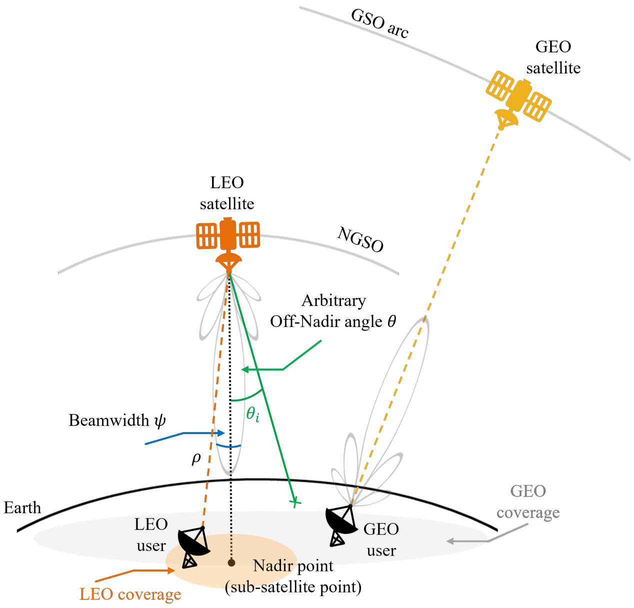

Fig. 3: Geometric representation of an arbitrary off-nadir angle θ from a LEO satellite, illustrating beamwidth ψ, user locations, and coverage overlap with GEO systems.

B. Antenna Gain Modelling

For antenna gain modeling, a directional gain pattern is adopted for LEO satellites to capture realistic beam shaping and angular discrimination. The satellite antenna boresight is aligned with the off-nadir direction, effectively pointing toward the sub-satellite point on Earth. GSs are assumed to employ steerable antennas capable of tracking the satellite during its pass. To compute the resulting direction-dependent antenna gains, the off-nadir angle is calculated from the satellite's perspective toward each GS, as illustrated in Fig. 3.

The off-nadir angle, θ, is defined as the angle between satellite s' Nadir vector $\mathbf{b}_s$ (pointing toward Earth's center) and the line-of-sight (LoS) vector $\mathbf{v}_{g,s}$ connecting satellite s to terminal g, and is given by,

$$\theta_{g,s} = \cos^{-1}\left(\frac{\mathbf{b}_s \cdot \mathbf{v}_{g,s}}{\|\mathbf{b}_s\| \, \|\mathbf{v}_{g,s}\|}\right). \quad (1)$$

Accordingly, the directional gain pattern for the LEO can be modeled as a generic sinc-squared pattern centered at the boresight, formulated as follows [13],

$$G_{\text{tx}}(\theta) = G_{\max} + 10\log_{10}\!\left(\text{sinc}^2\left(\frac{0.2\,\theta}{\psi_{\text{LEO}}}\right)\right), \quad (2)$$

where $G_{\max}$ is the maximum gain at boresight, 0.2 is a shaping constant, and ψ_{LEO} represents the beamwidth in radians. This compact model captures the mainlobe and roll-off behavior in the off-nadir direction. While the antenna pattern for both the GEO and GSs are modeled as a parabolic antenna with fixed gain as, $G_{\max} = 10\log_{10}\left[(\pi D f_o/c)^2 \cdot \eta\right]$, where D is the antenna diameter, f_o is the center frequency, c is the speed of light, and η is the antenna efficiency.

C. Received Power and Link Budget Analysis

The total received power P_{rx} at any GS g from satellite s at time t is modeled as,

$$P_{\text{rx}}^{(g,s)} = P_{\text{tx}}^{(s)} + G_{\text{tx}}^{(s)} + G_{\text{rx}}^{(g)} - \text{FSPL} - L_{\text{atm}}^{(g,s)} - L_{\text{fade}}^{(g,s)}, \quad (3)$$

where $P_{\text{tx}}^{(s)}$ is the satellite transmit power, $G_{\text{tx}}^{(s)}$ is the satellite antenna gain, $G_{\text{rx}}^{(g)}$ is the GS antenna gain, FSPL is the free-space path loss, $L_{\text{atm}}^{(g,s)}$ is the total atmospheric attenuation (including rain, cloud, and gaseous components) based on the ITU-Recommendations defined in [14], and $L_{\text{fade}}^{(g,s)}$ is the fading loss due to multipath effects [15].

D. Serving Satellite Selection Strategy

A key component of the proposed methodology is the selection of the optimal serving satellite for each GS at every time step, based on the maximum expected received power. This process is performed independently for LEO and GEO users, ensuring that only visible satellites corresponding to the user's category are considered. For LEO users, the received power from all candidate LEOs is computed using the link budget model described in (3). The satellite yielding the highest received power among the eligible candidates is then selected as the serving satellite for each GS as shown in Fig. 4.

Let $P_{\text{rx}}^{(g,s)}(t)$ denote the received power at terminal g from satellite s at time t. The serving satellite is determined as,

$$s_g^*(t) = \arg\max_{s \in \mathcal{S}_g} P_{\text{rx}}^{(g,s)}(t), \quad (4)$$

where $\mathcal{S}_g$ denotes the set of visible (based on the El angle) to user g based on its classification (LEO or GEO). The corresponding received power P_g^{serv} from the identified satellite s_g^* is stored and subsequently used to record its channel assignment and SINR evaluation stages.

E. Channel Allocation Strategies

This section presents and compares three channel allocation strategies—random, ideal, and learning-based to evaluate their effectiveness in managing co-channel interference, improving throughput, and enhance system SINR.

1) Random Allocation: The random allocation strategy represents an uncoordinated access policy in which channels are independently assigned from a predefined pool without consideration of interference. The total set of available channels is partitioned such that a subset is reserved for GEO users, while the full pool is accessible to LEO users. Each GEO user is assigned a unique channel from the reserved subset to avoid intra-GEO interference. In contrast, LEO users randomly select from the entire pool at each time step, introducing potential interference with other LEO users and GEO terminals. Assignments are made per-user and per-LEO satellite, allowing the same channel to be reused by different users across satellites. This lack of coordination serves as a baseline to assess the performance benefits of more sophisticated allocation schemes.

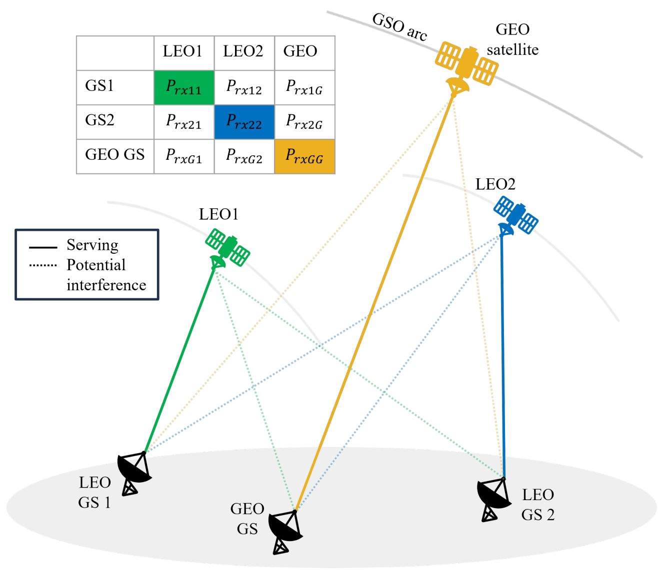

Fig. 4: Serving satellite selection and interference in a multi-satellite network. Each GS connects to the satellite with the strongest received power; interference arises from others satellites reusing the same channel.

2) Greedy-GA Hybrid: Similar to random allocation, the available frequency channels are partitioned such that a reserved subset is dedicated to GEO users, while the entire channel pool remains accessible to LEO users. To provide an upper-bound benchmark for evaluating learning-based approaches, we implement a two-stage hybrid optimization scheme that combines a fast greedy heuristic with a computationally intensive Genetic Algorithm (GA) under centralized optimization and ideal channel knowledge defined as follows:

(i) Greedy SINR-based initialization: A fast, low-complexity heuristic assigns each LEO terminal the channel that maximizes its received SINR, considering interference from co-channel LEO users and overlapping GEO signals. Links below a minimum SINR threshold remain unassigned. This ensures feasible allocations that satisfy basic interference constraints and serves as a warm start for global optimization.

(ii) Global optimization refinement via genetic algorithm (GA): To further enhance throughput and overall spectral efficiency, the greedy solution is refined using a GA on the top 20% most active time steps. The GA jointly optimizes channel assignments for all LEO users using a composite objective function that balances two goals: maximizing system throughput and minimizing harmful interference on GEO-reserved channels. Throughput is modeled using $\log_2(1+\mathrm{SINR})$, where links exceeding the SINR threshold contribute full credit, and sub-threshold links contribute partial credit via a shaping function. Interference penalties are activated when LEO-induced interference exceeds the GEO noise floor, with a tunable weighting parameter λ used to prioritize GEO protection. This hybrid approach allows the system to balance local throughput maximization with global spectrum coexistence constraints.

3) Advanced Dynamic Spectrum Allocation: To dynamically optimize channel allocation in a hybrid LEO-GEO satellite network, a DRL framework based on A2C [12] is developed. An actor-critic architecture learns optimal channel assignments from inputs such as time, frequency, and satellite geometry, guided by a multi-objective reward function $r(t)$ balances proportional fairness among LEO users with interference protection for GEO users defined as,

$$r(t) = \underbrace{\sum_{i=1}^{U_{\mathrm{LEO}}} \log_{10}(\mathrm{SINR}_i(t))}_{\text{Proportional fairness}} + \lambda \underbrace{\sum_{i=1}^{U_{\mathrm{GEO}}} \log_{10}(\mathrm{SINR}_i(t))}_{\text{GEO penalty term}}, \tag{5}$$

where $\mathrm{SINR}_i(t)$ is the SINR of the i-th LEO or GEO user at time t, λ is a penalty scaling factor, U_{LEO} and U_{GEO} are the number of LEO and GEO users respectively.

The proportional fairness term satisfies both marginal utility [16] and Nash bargaining [17] principles, and is formally justified by the axiomatic fairness framework in [18], where logarithmic utility functions are shown to uniquely satisfy the proportional fairness criterion under a set of reasonable axioms. The main objective is to maximize the sum of the logarithms of SINR values, which is mathematically equivalent to maximizing the product of individual SINRs.

The marginal utility for each user, which quantifies the additional benefit obtained relative to others, is defined as,

$$U_i(\mathrm{SINR}_i) = \frac{d}{d(\mathrm{SINR})_i} \log{(\mathrm{SINR})_i} = \frac{1}{(\mathrm{SINR})_i}, \tag{6}$$

representing the rate of change of a user's utility with respect to their SINR. This logarithmic relationship exhibits diminishing returns, wherein users with higher SINR values experience lower marginal gains. Consequently, the system inherently promotes a more equitable and efficient distribution of channel resources by prioritizing improvements for users with poorer link quality.

The second term serves as a penalty term for degraded GEO performance. It discourages co-channel reuse by LEO users in regions where such reuse causes harmful interference to protected GEO terminals. The penalty ensures that the agent not only seeks throughput gains but also learns to avoid harmful spectrum-sharing configurations, striking a balance between performance and coexistence.

The Greedy-GA runs in polynomial time per reallocation, requiring at most $\mathcal{O}(N_{\mathrm{u}}N_{\mathrm{ch}})$ evaluations to assign N_{u} users over N_{ch} channels, with no offline training cost. In contrast, the DRL approach incurs a one-time training cost that scales with the number of episodes and environment steps (roughly $\mathcal{O}(E\,N_{\mathrm{u}}N_{\mathrm{ch}})$ during learning for our setting). Once trained, policy evaluation (inference) is a sequence of fixed matrix–vector operations whose cost scales with the total number of network parameters; for a fixed architecture, this is constant with respect to N_{u} and N_{ch} (i.e., $\mathcal{O}(1)$ per decision).

While our baseline instantiates a OneWeb-like LEO configuration paired with GEO links, the framework itself

TABLE I: SIMULATION PARAMETERS

Parameter	Symbol	Value
LEO altitude	h_{LEO}	1200 km
LEO inclination	i_{LEO}	87°
LEO number of orbital planes	$N_{P_{\text{LEO}}}$	12
LEO number of satellites per plane	$N_{PS_{\text{LEO}}}$	49
Number of LEO satellites	N_{LEO}	588
GEO Altitude	h_{GEO}	35 786 km
GEO Semi-major axis	a_{GEO}	42 157 km
GEO right ascension of ascending node	Ω_{GEO}	168.64°
Number of LEO users	U_{LEO}	10
Number GEO users	U_{GEO}	10
Center frequency	f_{o}	11.5 GHz
Number of channels	N_{ch}	$[10-30]$
Antenna efficiency	η	0.5
LEO transmitted power	P_{LEO_t}	36.98 dBm
LEO antenna diameter	D_{LEO}	0.6 m
LEO antenna beamwidth	ψ_{LEO}	8°
LEO maximum antenna gain	G_{LEOmax}	34.17 dBi
LEO GS antenna diameter	$D_{\text{GS}_{\text{LEO}}}$	0.5 m
LEO GS antenna gain	$G_{\text{GS}_{\text{LEO}}}$	32.59 dBi
GEO transmitted power	P_{GEO_t}	50 dBm
GEO antenna diameter	D_{GEO}	3 m
GEO maximum antenna gain	G_{GEOmax}	48.15 dBi
GEO GS antenna diameter	$D_{\text{GS}_{\text{GEO}}}$	1.2 m
GEO GS antenna gain	$G_{\text{GS}_{\text{GEO}}}$	40.19 dBi
GAE lambda	λ	0.25

is altitude-agnostic. The same optimization baselines and DRL policy apply to lower-altitude constellations without architectural changes; only the induced link statistics (path loss, footprint size, handover rate, interference dynamics) shift with altitude, for which the agent can be retrained using the new orbital parameters. This provides a concrete resource-allocation mechanism that motivate joint management but leave allocation unspecified.

III. SIMULATION RESULTS AND EVALUATION

A. Scenario Configuration

A hybrid LEO-GEO satellite communication scenario is simulated, comprises 20 GSs uniformly distributed across Australia, with half assigned to LEO and the remaining to GEO as defined in Table I. The LEO constellation has $N_{P_{\text{LEO}}} = 12$ orbital planes, each containing $N_{PS_{\text{LEO}}} = 49$ satellites at an altitude of $h_{\text{LEO}} = 1200\,\text{km}$. A single equatorial GEO satellite is positioned at $\Omega = 168.64°$ longitude to serve all GEO-assigned GSs. All satellites operate within the Ku-band at center frequency of $f_0 = 11.5\,\text{GHz}$ and share a total of $N_{\text{ch}} = 15$ orthogonal channels. The link budget is computed for each satellite-GS pair as explained in Section II-C.

The simulation spans $3\,\text{h}$ with a $30\,\text{s}$ resolution, yielding $T = 361$ time steps. At each step, serving satellites are selected based on maximum received power, and communication channels are allocated using one of three strategies: random, optimized, or DRL-based allocation. The proposed DRL training leverages a hybrid framework in which the satellite simulation and link computations are executed within a MATLAB environment, while the DRL agent is implemented in Python. During DRL training, the agent interacts with the satellite environment, selects actions, receives rewards, and updates policies using generalized advantage estimation. The state includes rich temporal, spectral, and spatial embeddings. Training proceeds over multiple epochs with periodic model saving and evaluation, enabling adaptive, interference-aware spectrum management. System performance is assessed using the SINR and mean throughput for both LEO and GEO users.

B. Performance Metrics

1) Interference Identification: To assess co-channel interference, the SINR at each GS and time step is computed by first identifying the serving satellite and its assigned channel. All other GSs reusing the same channel via different satellites are then examined. Their received interference power is cumulatively added only if it drives the resulting SINR below a predefined threshold, SINR_{th} (e.g., 5 dB). This approach ensures that mild co-channel reuse, which maintains acceptable SINR, is not unnecessarily counted as interference. The total interference and noise are used to compute SINR as,

$$\text{SINR}^{(g)}(t) = \frac{P_{\text{rx}}^{(g)}(t)}{I_{\text{LEO}}^{(g)}(t) + I_{\text{GEO}}^{(g)}(t) + N_0}, \tag{7}$$

where $I_{\text{LEO}}^{(g)}(t)$ and $I_{\text{GEO}}^{(g)}(t)$ denote LEO and GEO interference, respectively, and N_0 is the thermal noise. This is repeated for all GSs over time to evaluate link quality under various channel allocation strategies.

2) System Throughput: At each time step, total system throughput is the sum of all users' throughput, computed as,

$$R_{\text{b}}(t) = \log_2(1 + \text{SINR}(t)) \quad [\text{bps/Hz}]. \tag{8}$$

This captures network capacity under different frequency allocations and interference scenarios.

3) Spectral Efficiency in Cognitive Reuse: In a cognitive setup with Primary Users (PUs) (GEO) and Secondary Users (SUs) (LEO), spectral efficiency SE quantifies the balance between reuse and interference defined as follows,

$$SE(t) = \frac{N_{\text{Uch}}(t)}{N_{\text{ch}}}, \tag{9}$$

where $N_{\text{Uch}}(t)$ is the counts of useful channels without interference, and N_{ch} is the total available channels.

C. Evaluation Results

This section presents a system evaluation of the proposed DRL-based spectrum sharing framework against random allocation and optimization-based benchmarks under various network conditions. The results focus on key performance indicators, including mean SINR, mean throughput, and overall spectral efficiency, to demonstrate how each strategy manages the trade-offs between interference mitigation and spectral reuse in hybrid LEO-GEO satellite networks. Fig. 5 presents the Cumulative Distribution Functions (CDFs) for mean SINR and mean throughput for LEO and GEO users under three allocation strategies: random, Greedy-GA, and DRL. As seen in Fig.5(a), the DRL-based allocation significantly improves LEO SINR distribution compared to random

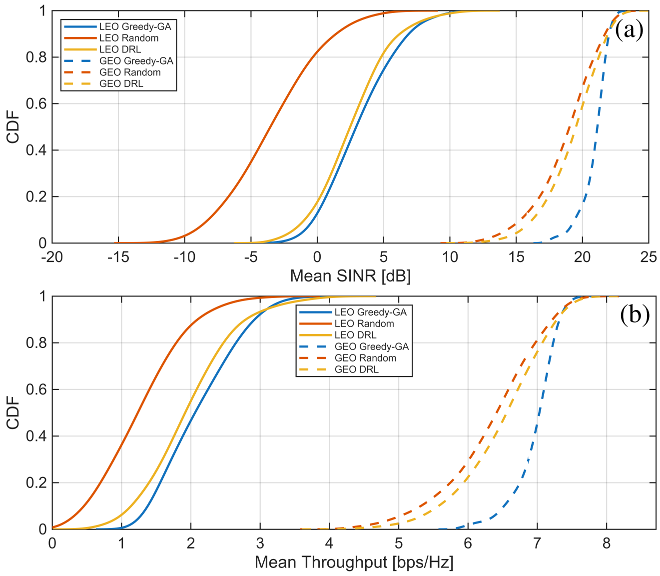

Fig. 5: CDFs for LEO and GEO performance with 15 allocated channels under different allocation schemes: (a) mean SINR, (b) mean throughput.

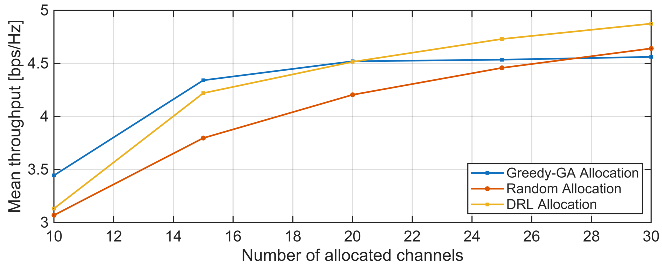

Fig. 6: Mean throughput versus number of allocated channels for different allocation strategies.

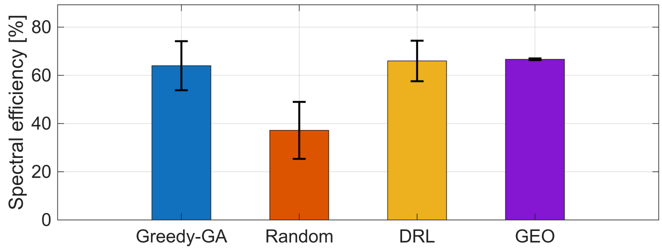

Fig. 7: System spectral efficiency for different allocation strategies for 15 channels, highlighting the performance stability and effectiveness of each method.

allocation and performs competitively with the Greedy-GA benchmark, while maintaining low interference toward GEO users. In Fig. 5(b), DRL achieves superior throughput for LEO users across the entire distribution, closely approaching the performance of the Greedy-GA solution, but with significantly lower computational complexity.

To further evaluate the scalability of the proposed framework, system performance was analyzed as the total number of available frequency channels increased. This complements the default configuration of $N_{\text{ch}} = 15$ channels by extending the evaluation to a wider range ($N_{\text{ch}} \in \{10, 15, 20, 25, 30\}$). The objective is to assess the framework's adaptability under varying spectral resource conditions, reflecting realistic scenarios in which spectrum allocation may fluctuate due to regulatory or operational constraints. Figure 6 illustrates the variation of mean throughput with the number of allocated channels. All allocation strategies benefit from increased spectral resources; however, the DRL policy consistently outperforms random allocation and closely approaches the Greedy-GA upper bound, demonstrating its ability to adapt intelligently to spectrum availability while mitigating interference. Notably, mean throughput continues to increase slightly even when the number of available channels N_{ch} exceeds the number of active users. This effect results from the interference-limited nature of the hybrid LEO–GEO network, in which additional channels reduce co-channel overlap and inter-beam interference rather than enabling multi-channel transmission per user. As interference diminishes, the overallSignal-to-Interference Ratio (SIR) ratio improves, yielding incremental throughput gains until the curves converge to a saturation point.

Finally, Fig. 7 presents the average system spectral efficiency with 15 allocated channels. Reserving the spectrum solely for GEO users (purple) leads to moderate but consistent efficiency, serving as a reference to highlight the cost of under-utilization. The DRL framework (yellow) significantly improves mean efficiency and demonstrates strong reliability with relatively low variance. The random strategy (orange) yields the lowest performance and highest variability. Notably, the DRL approach closely rivals the Greedy-GA method (blue), suggesting that learning-based policies approach near-optimal allocation while maintaining stable operation across time.

In summary, these results underscore the effectiveness of our proposed DRL framework in providing robust interference management and efficient spectrum sharing in hybrid LEO-GEO satellite systems, achieving promising performance. Finally, Greedy-GA is cheaper per reallocation with no training cost, whereas DRL has a higher upfront cost but near-constant-time decisions thereafter, becoming preferable when decisions are frequent or the system scales.

IV. Conclusions

This work introduced a robust simulation framework to evaluate DSA in hybrid LEO-GEO satellite networks. The system performance was evaluated across random, ideal, and DRL-based channel allocation strategies. Among these, the proposed A2C-driven method demonstrated effective interference mitigation and throughput performance, while also enhancing spectral efficiency, promoting scalable coexistence in future multi-orbit satellite systems.

While the results are promising, several aspects remain open for future investigation. First, the current setup assumes a geographically localized deployment with 20 fixed ground stations over Australia. Extending the analysis to globally distributed, mobile, and clustered traffic scenarios will improve the generalizability of the findings to real-world multi-region systems. Second, the channel and fading models have been simplified; future work will incorporate more detailed propagation effects such as Rician fading, multipath, and rain attenuation dynamics to better assess performance robustness under realistic Ku-band conditions. Finally, although the current framework assumes centralized access to user information, future extensions may explore decentralized or federated learning strategies to enhance scalability and autonomy in distributed satellite networks.

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