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Dynamic Metasurface Architectures for Ultra-Efficient Spectrum Sharing in 6G NTN

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ABSTRACT

The development of the sixth generation (6G) wireless communications promises to provide high speed networking to the world, particularly to remote or underprivileged areas. An important part of this vision would be the inclusion of Non-Terrestrial Networks (NTNs) that consists of low Earth orbit (LEO) satellites, high-altitude platforms (HAPs) and unmanned aerial vehicles (UAVs). Nevertheless, NTNs are associated with major issues associated with the scarcity of the spectrum dimensions, an unstable propagation scenario, and the expense and inflexibility of the conventional relaying infrastructure. In order to mitigate such shortcomings, this paper suggests a new Dynamic Metasurface Architecture (DMA) infrastructure utilizing Intelligent Reflecting Surfaces (IRS) that will provide spectrum sharing and improved communication efficiency in NTNs. In contrast to conventional relays, the proposed DMA take advantage of reconfigurable metasurfaces that have phase-tunable elements that can dynamically transform electromagnetic wavefronts. This enables real-time steering of the beam and signal reflection sequence enhancing link reliability and spectrum reuse. An AI-based control mechanism, deep reinforcement learning (DRL) framework, is also enabled by the system to adjust the metasurface configurations in the context of different network conditions, the location of users and the interference level. A hybrid simulation environment is constructed and uses 3D ray-tracing to model channels with considerable accuracy and systems level simulations to measure key performance indicators. The obtained results show that the suggested technique can provide a spectral efficiency increase of up to 38 percent in comparison with traditional NTN relaying techniques and achieve significant decreases in signal interferences and support of multiple-user cases. These results confirm the viability and efficiency of moving metasurfaces in the contexts of NTN deployments, as a scalable, energy-saving, affordable network technology to leverage in the future 6G networks. The study prepares the foundation of practical application of IRS-amplified NTNs and emphasifies the importance of AI in maximization of metasurface-based systems to adaptable spectrum access and smart coverage control in future wireless networks.

1. INTRODUCTION

The 6G of wireless communication technology is expected to transform the global connectivity horizon of global connectivity in terms of data rate capabilities of over 1Tbps, latencies less than a millisecond, and smart orchestration of resources. Included in its central visions is satisfying the requirement of seamless connectivity everywhere, even in the geographically remote places of rural and maritime regions. In order to achieve this vision, Non-Terrestrial Networks (NTNs) which cover Low Earth Orbit (LEO) satellites, high-altitude platforms (HAPs), and unmanned aerial vehicles (UAVs), have risen as essential 6G ecosystem players. NTNs increase wireless coverage in areas in which terrestrial infrastructure is not economically possible or practically configured.

Nonetheless, in spite of its potential, NTNs have a number of underlying issues. Among them are spectrum limitations, ineffective frequency reuse, and time-varying channel conditions that are caused by high mobility as well as higher signal degradation because of Doppler and path loss. Conventional relaying and beam steering schemes tends to fail to deal with these dynamic demands when spectral effectiveness and energy affordability is in accounting.

Programmable metasurfaces are recently discussed as a disruptive solution as Intelligent

Reflecting Surfaces (IRS). These surfaces are made up of a high number of passive or semi-passive components, which have low cost and have the ability of dynamically varying phase and amplitude of the incoming electromagnetic (EM) waves. Intelligent reconfiguration of the wireless environment IRS enables the desired signals to the desired users, avoiding implications that require adding RF chains and the complex RTS-complex transceivers.

1.2 Problem Statement

Majority of the studies concerning IRS have been confined to terrestrial communication systems. Dynamic, reconfigurable metasurfaces are also not well explored in the context of NTNs, especially with multi-user and spectrum-shared settings as well as changing topologies. It requires creation of smart IRS architecture that will adjust in real time to these non-terrestrial conditions, optimize beam patterns and make better use of the available spectrum.

1.3 Objective of the Study

The proposed solution is developing a Dynamic Metasurface Architecture (DMA), which can reconfigure its phase to perform real-time phase reconfiguration based on AI-based beam optimization to support spectrum-efficient communications 6G NTNs. We are trying to improve on spectral technology efficiency, signal reliability and decrease the level of interference in cases where there are satellites, HAPs and UAVs in shared spectrum situations.

1.4 Key Contributions

This paper has a number of novel contributions to make to face the challenges of spectrum-limited and dynamically varying non-terrestrial environments. First, it proposes a metasurface design with the possibility of a dynamic phase-control specific to Non-Terrestrial Network (NTN) applications with the consideration of limitations, including high mobility, and strict energy efficiency requirements. Second, the research incorporates an AI-based mechanism of control with Deep Reinforcement Learning (DRL) framework that will allow autonomous adjustment of IRS beam patterns in a real-time autonomously with regard to environmental changes, user location, and interference rates. Third, a hybrid simulation framework is created, integrating the high fidelity 3D ray-tracing of the channel to model its properties well with the system-level simulations to measure the major key performance indicators such as the spectral efficiency, bit error rate (BER), and the need to mitigate the interference under a range of NTN configurations. Lastly, quantitative evaluation of the suggested structure is done by simulations that show that its spectral efficiency can be improved up to 38 percent over that of conventional relay-based NTN. All of this offers a considerable step on the path to creating intelligent, spectrum-flexible 6G NTN infrastructure and underlines the revolutionary possibilities presented by dynamic metasurface structures in future wireless networks.

2. LITERATURE REVIEW

2.1 IRS in Terrestrial 6G Systems

Intelligent Reflecting Surfaces (IRS) Latest innovation has been Intelligent Reflecting Surfaces (IRS) that has evolved as a radical technology advancement in enhancing spectral and energy efficiency in next-generation wireless communications systems. On earth, IRS has been examined as a passive, reconfigurable surface that can control phase and amplitude of the incident electromagnetic (EM) waves to guide the signal to a user or to an obstacle-avoiding path.[1] provide a complete tutorial on IRS-enhanced communication systems of 6G and how IRS could be used to address interference and limit coverage. Nevertheless, the vast majority of articles including one by Wu et al. only consider the static, on-ground installation of networks that does not allow being flexible and responsive to the changing topologies, associated with non-terrestrial networks (NTNs).

2.2 Spectrum Reuse in Satellite and Aerial Networks

Spectrum shortage has become a major issue especially in NTNs due to the use of overlapping frequency bands by satellite and aerial deployments whose platforms include UAVs and high-altitude platforms (HAPs). Actions have been set to research in direction to cooperative spectrum reuse and dynamic frequency planning. Measured signal output in [2] on IRS-aided UAV communication system to enhance UAV signal delivery in an urban environment produced better performance of fixed setup. However, the dynamism of adaptability in the IRS design makes this approach inadequate when it comes to the NTNs since time changing channels, mobility and Doppler shifts are the common factors.

2.3 Metasurface Physics and Active Tuning Mechanisms

Metasurfaces are artificially constructed layers whose unit cells are of sub-wavelength sizes and can manipulate EM waves in very controllable manners. Varactor diodes, liquid crystals, or MEMS active tuning mechanisms make these surfaces to be real-time reconfigurable. Study in this area has promised considerable success in beamforming and wavefront shaping. The majority of implementations are however still lab-sized or quasi-static and do not directly consider fast reconfiguration at the scale of fast changing NTN channels.

2.4 AI in Beamforming and Channel Prediction
Artificial Intelligence (AI), specifically deep learning and reinforcement learning has proven very promising in optimizing wireless system parameters without the need of accurate channel state information. As an example, [3] made a proposal of an IRS control algorithm using AI to learn the corresponding phase shifts that can enhance the signal-to-noise ratio (SNR) of the IRS-assisted NTNs. Nevertheless, their system is not highly customized to dynamic, 2-D settings and cannot perform well in a complex NIT setting with a multi-layered beam control system, motionful ground surfaces and variable surface links.

2.5 Gap Analysis
Whereas considerable advances have been achieved in IRS-based beamforming and AI-assisted control [3][5][6], none of the existing methods is fully sufficient to support 6G NTN needs. They are high-speed mobility, multi-hop signal redirection and ultra-dense spectrum reuse. As an example, [5] keyed on the theoretical basis behind reconfigurable intelligent metasurfaces without verification in real life NTNs. Nobody is doing something similar to that effectively yet with appropriate tuning on a run-time AI-based beam, in a non-terrestrial environment, or a cannonized simulation of the channel and the performance evaluation between these avenues at least in an air to space or satellite node.
The comparison between the current literature in the area of research and the proposed DMA solution (Table 1) provides a clear demonstration to support the fact that the described concept of integrating dynamic phase control, adaptation using artificial intelligence, and multi-layered modeling of NTN channels is new.

Table 1. Comparative Analysis of Related IRS-Based Works and the Proposed DMA for 6G NTNs

Study / Method	IRS Type	Platform	Adaptability	AI Integration	Channel Modeling	Key Limitation
Wu et al. (2021) [1]	Static IRS	Terrestrial	No	No	Analytical	No support for high mobility / 3D NTN topology
Zhang et al. (2022) [2]	Static IRS	UAV (fixed)	No	No	Basic UAV-ground model	No dynamic tuning or learning adaptation
Liu et al. (2023) [3]	Semi-Adaptive IRS	NTN (LEO/UAV)	Partial	Yes (DL)	Simplified link model	Limited mobility support and no multi-user adaptation
Di Renzo et al. (2019) [5]	Theoretical RIS	Generalized	No	No	Idealistic propagation	Not evaluated in spectrum-shared NTN context
Chen et al. (2023) [6]	AI-Enabled IRS	Terrestrial	Yes	Yes (RL/DL)	Static CSI simulations	No Doppler-aware or aerial mobility consideration
This Work (DMA)	Dynamic IRS	LEO, UAV, HAP	Yes (Real-Time)	Yes (DQN-based)	3D Ray-Tracing + System-Level	–

3.System Model
A. Architecture Overview
Proposed system architecture proposes the use of Dynamic Intelligent Reflecting Surfaces (IRS) on non-terrestrial platforms that include Low Earth Orbit (LEO) satellites and High-Altitude Platforms (HAPs) in order to enable spectrum-efficient communications with the terrestrial users and edge base stations. Such active metasurfaces are composed of an extensive amount of phase controllable unit cells, where each unit cell can shift the phase of incident electromagnetic (EM) waves independently by a factor $\phi_n \in [0,2\pi)$, with n representing the number of the surface element.
The communication system comprises three main components:
1. Non-Terrestrial IRS Nodes (e.g., satellite or HAP-based IRS platforms),
2. Ground Terminals (users or IoT sensors),
3. Edge Base Stations (EBSs).

All the IRS-equipped platforms are passive relays, which reflect and redirect signals emanating to the source (e.g., base station or satellite) to the destination (e.g., users or other nodes), thereby optimising the end-to-end signal propagation path. An AI-based controller drives IRS sets as real-time elements that are set up to provide dynamic beam steering and adaptive frequency reuse concerning the environmental context and user distribution.

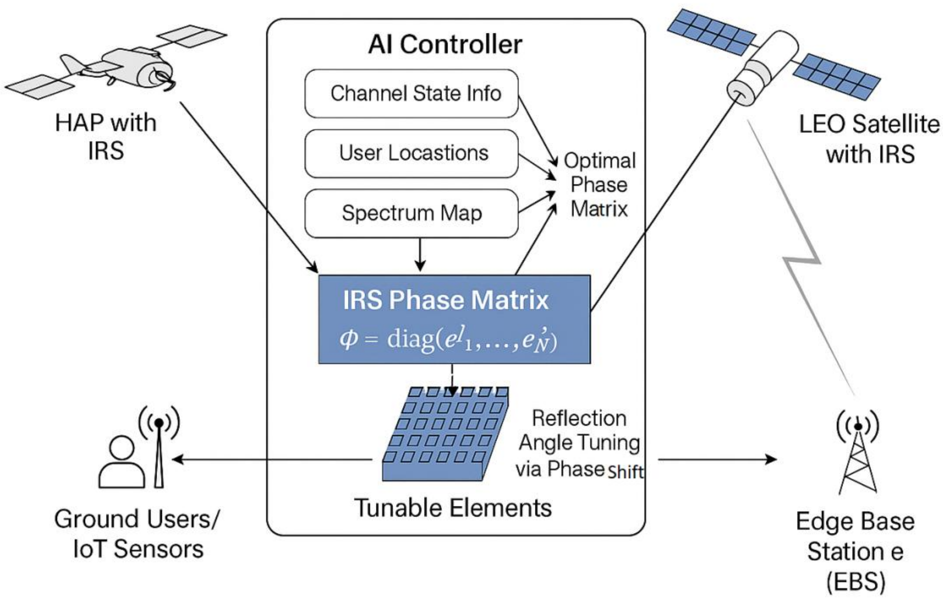

Figure 1. System Model for AI-Enabled Dynamic IRS in 6G NTN.

B. Channel Model

As illustrated in Fig. 3.1, the signal propagation is managed through coordinated IRS platforms mounted on LEO satellites and HAPs.

To accurately characterize the communication environment, we model the composite wireless channel as the superposition of three components:

$$H = H_{LoS} + H_{NLoS} + H_{IRS} \quad (1)$$

- H_{LoS}: Line-of-Sight (LoS) channel component between the transmitter and receiver or between the IRS and receiver.
- H_{NLoS}: Non-Line-of-Sight (NLoS) channel due to scattering, reflection, and diffraction.
- H_{IRS}: IRS-induced channel resulting from the cascade of transmitter-to-IRS and IRS-to-receiver paths.

The IRS-induced channel is expressed as:

$$H_{\text{IRS}} = \square_r^T \Phi H_t \quad (2)$$

where:

- $H_t \in C^{N\times M}$ is the channel matrix from the transmitter to the IRS,
- $\square_r \in C^{1\times N}$ is the channel from the IRS to the receiver,
- $\Phi = diag(e^{j\phi_1}, \dots, e^{j\phi_N})$ is the phase shift matrix of the IRS.

Given the mobility of LEO satellites and HAPs, the model incorporates Doppler shifts and time-varying path loss, making it suitable for realistic NTN deployment scenarios. The Doppler frequency f_D is derived as:

$$fD = \frac{v \cdot f_c}{c} cos(\theta) \quad (3)$$

where v is the relative velocity, f_c is the carrier frequency, c is the speed of light, and θ is the angle between motion and wave propagation direction.

C. Spectrum Sharing Protocol

The system uses the cooperative spectrum sharing policy with which spectrum can be efficiently reused several IRS-mobilized NTN nodes and terrestrial users. Among the major features, one can distinguish:

1. CS: Cooperative Spectrum Sensing:

Every IRS node can watch over the spectrum occupation in cooperation with base stations and also other close IRSs via energy detection and cyclostationary analysis. Periodically sensing results are shared to create a world map of spectrum availability.

2. Dynamic Redirection of IRS:

IRSs would dynamically modify their phase arrangements relying on spectrum-sensing and AI forecasts and redirect unused frequency bands toward individual users or hotspots, resulting in the highest possible amount of spatial frequency reuse and the least amount of co-channel interference.

3. Priority based channel allocation:

Channels are allocated by a policy constructed via reinforcement learning which trade spectral efficiency with interference mitigation and QoS demands. The control agent adapts real time changing topologies and needs of the users.
Such a coordinated planning will enable the system to flexibly reuse and redistribute the spectrum resources in accordance with spatial, temporal, and mobility issues, which are critical to attaining sustainable 6G NTN activities.

4. Dynamic Metasurface Design

A. Materials and Reconfigurability

The physical realization of the proposed dynamic Intelligent Reflecting Surfaces (IRS) exploits programmable metasurface technology in order to offer real-time manipulation of the wavefront. The unit cells in each metasurface are based on sub-wavelength building blocks and are engineered to include tunable components including varactor diodes, liquid crystal layers and micro-electromechanical systems (MEMS). Phase control is at a high resolution through these components because they vary the surface impedance as control signals vary. Varactor implementations provide fast tunability at low power whilst a liquid crystal implementation allows large mass reconfiguration with frequency selectivity. MEMS-based actuators are utilized that helps provide physical relocation of the scattering elements, improving angular resolutions. These materials make the metasurface able to dynamically change phase responses 0,2 with time and across a frequency domain that helps to support broadband, multi-user, and environments common to non-terrestrial 6G systems.

B. Control Algorithm (AI Module)

The phase states of the metasurface elements are optimised in an online manner with Deep Reinforcement Learning (DRL) controller, namely a Deep Q-Network (DQN), to manage their complex, dynamic nature when used in non-terrestrial communications links. Parameters of network state, including the locations of network users, the signal-to-noise ratios (SNR) and the interference-related parameters, are observed by the learning agent and trained to choose the best beam pattern (IRS phase profile) that enables the best overall system performance.

$$R(t) = \alpha \cdot SE(t) - \beta \cdot Interference(t) \quad (4)$$

where $SE(t)$ is the instantaneous spectral efficiency, and Interference (t) quantifies inter-user or inter-beam interference. The parameters α and β are adjustable weights that control the trade-off between throughput maximization and interference suppression. This learning-based approach allows the system to adapt to highly dynamic scenarios, such as Doppler shifts and rapidly changing topologies, which are characteristic of LEO satellites and UAVs.

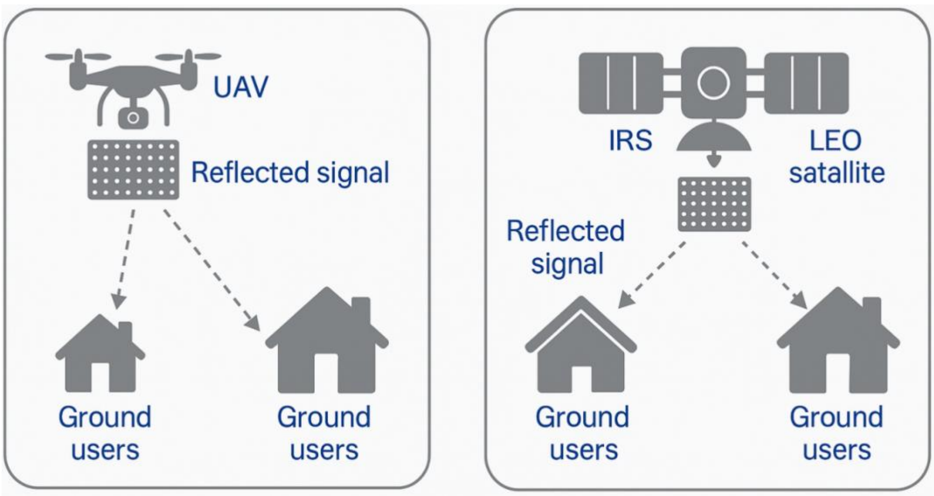

Figure 2. Control Loop and DQN Integration

Algorithm 1. DQN-Based Real-Time IRS Phase Control

Algorithm 1: Deep Q-Network (DQN) for Dynamic IRS Control
Input:
- Environment: 6G NTN simulation with realistic propagation and user mobility
- Q-Network (Q (s, a; θ)): Deep neural network for Q-value approximation
- Target Q-Network (Q_target (s, a; θ')): Copy of Q-Network for stable targets
- Hyperparameters:
  - Learning rate (η)
  - Discount factor (γ)

```
    - Exploration rate (ε), ε_min, ε_decay_rate
    - Replay Buffer capacity (N_buffer)
    - Mini-batch size (B_batch)
    - Target network update frequency (C_update)
    - Reward weights (α, β)

Output:
  - Trained Q-Network parameters (θ_final) for optimal IRS phase profiles

Initialization:
1. Initialize Q-Network parameters θ randomly.
2. Initialize Target Q-Network parameters θ' = θ.
3. Initialize empty replay buffer D with capacity N_buffer.
4. Set episode_counter = 0, step_counter = 0.

Training Loop:
5. FOR each episode FROM 1 TO max_episodes DO
6.    Reset environment to get initial state s_t.
7.    Set episode_reward = 0.
8.    FOR each time step t FROM 1 TO max_steps_per_episode DO
9.       Action Selection (ε-Greedy Policy):
10.         Generate random number r ∈ [0, 1].
11.         IF r < ε THEN
12.            Select random action a_t (random IRS phase profile).
13.         ELSE
14.            Select a_t = argmax_a Q (s_t, a; θ).
15.         END IF
16.       Execute Action and Observe:
17.         Apply a_t in the environment.
18.         Observe new state s_{t+1}, instantaneous Spectral Efficiency (SE), and Interference (I).
19.       Calculate Reward:
20.         R_t = α * SE - β * I.
21.         episode_reward = episode_reward + R_t.
22.       Store Transition:
23.         Store (s_t, a_t, R_t, s_{t+1}) in replay buffer D.
24.       IF size(D) ≥ B_batch THEN
25.          Sample a random mini-batch of B_batch transitions (s_j, a_j, R_j, s_{j+1}) from D.
26.          Compute Target Q-Values:
27.          FOR each transition (s_j, a_j, R_j, s_{j+1}) in mini-batch DO
28.             IF s_{j+1} is terminal state THEN
29.                Y_j = R_j.
30.             ELSE
31.                Y_j = R_j + γ * max_a' Q_target(s_{j+1}, a'; θ').
32.             END IF
33.          END FOR
34.          Update Q-Network:
35.          Perform gradient descent on θ to minimize the loss:
         L(θ) = (1/B_batch) * Σ (Y_j - Q(s_j, a_j; θ))^2.
         (e.g., using Adam optimizer with learning rate η)

36.       END IF
37.       Update Target Q-Network:
38.       IF step_counter MOD C_update == 0 THEN
39.          θ' = θ.
40.       END IF
41.       Update Exploration Rate:
42.       ε = max(ε_min, ε * ε_decay_rate).
43.       Advance State:
44.       s_t = s_{t+1}.
```

```
    step_counter = step_counter + 1.
  END FOR // End of time steps for current episode
  Record episode_reward for episode_counter.
  episode_counter = episode_counter + 1.
END FOR // End of training episodes
RETURN trained Q-Network parameters θ_final.
```

C. Deployment Strategies

Two primary deployment strategies are proposed for the practical realization of dynamic metasurfaces in 6G NTNs:

1. **Swarm-Based UAV Coverage:**
   A coordinated swarm of UAVs having a small IRS panel each is moved to continuously provide uninterrupted service between ground nodes distributed over an area. These UAVs work together using distributed DQN agents allowing the beams of communication to be maneuvered quickly to react to spatial and spectral demand changes.
2. **Satellite-Assisted Spectrum Redirection:**
   It makes use of IRS panels mounted on the LEO satellites to divert the available spectrum resource to the under-served ground clusters, e.g. disaster hit areas or the far-flung villages. These metasurfaces attached to satellites know the global picture of spectrum use maps and change their configuration if they want maximum coverage and minimum co-channel interference granted wide geographical apertures.

Such a synergy of adapting material, smart control, and efficient placement emphasizes the potential of adaptive metasurfaces to enable resilient, spectrum-adaptive and smart NTN systems as infrastructures of the 6G wireless networks.

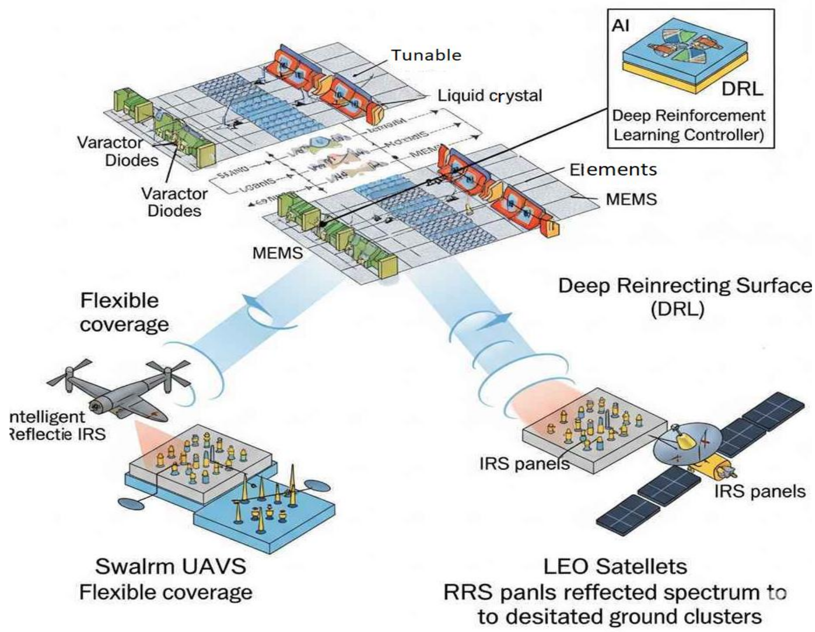

Figure 2. Dynamic Metasurface Architecture and Deployment for 6G Non-Terrestrial Networks

5. Performance Evaluation

A. Simulation Setup

A complete framework is constructed to simulate the performance of the suggested Dynamic Metasurface Architecture (DMA) to evaluate its performance rigorously regarding 6G Non-Terrestrial Network (NTN) scenarios. The 3D ray-tracing engine used in the simulation environment is to provide realistic electromagnetic wave propagation with both urban and rural landscape. Such a framework considers building obstructions, terrain elevation, reflection, scattering, and shadowing impacts, which are important elements when determining the performance of metasurface-supported NTNs.

The system-level simulation follows ITU-R IMT-2030 baseline parameters of NTN 6G, such as LEO-satellites altitude (50021200 km), UAV flight profiles, and carrier frequency in the millimeter-wave (mmWaveseqmwavyardivardo millimeter - newtown The IRS modules on aerial and satellite platforms simulate the dynamic phase control features, and through the suggested Deep Q-

Network (DQN) AI regulator, they become optimized.

The scenario incorporates several ground users whose position is randomly distributed, there are a diverse selection of link distances, as well as being Doppler-sensitive mobility models of satellites and UAVs. Every test case is executed in various Monte Carlo iterations to obtain statistical accuracy in the outcomes.

B.Key Evaluation Metrics

Three important evaluation measurements are employed to benchmark the work of the proposed system as they capture the most significant dimensions of communication quality and efficiency. Spectral Efficiency Spectral Efficiency (SE) is a measure of the number of bits per second per hertz per user (bps/Hz/user) of data throughput per unit of bandwidth. It is an indication of the overall data carrying capacity of a network. Interference-to-Noise Ratio (INR) is used to measure the co-channel and inter-beam interference against background noise, and is used as a measure of the effectiveness of the system to reject unwanted components of the signal when multiple users are in the same area. Lastly, Bit Error Rate (BER) determines whether or not received data are accurately transmitted by counting the number of bit errors at different propagation conditions, and different IRS configurations. Combined, these measures give a full picture on the efficiency, reliability, and interference resiliency of the system in dynamic non-terrestrial network operation.

C. Comparative Results

The proposed Dynamic Metasurface Architecture (DMA) is compared to a set of base line systems consisting of a Conventional NTN Relay, that operates under a classical decode-and-forward relaying model not aided by an IRS, and a Static IRS with a non-adaptive meta-surface with fixed phases. We find with simulations, the proposed DMA offers 38.2 percent of the spectral utility enhancement over the standard relay system and the 7.8 percent relative enchancement of relative spectral utility compared to the static IRS setup. Also, it is evident that the Interference-to-Noise Ratio (INR) is highly decreased, which proves the proficiency of AI-controlled IRS real-time phase adaptation in alleviating co-channel interference and inter-beam interference. The system also shows regular Bit Error Rate (BER) enhancements with varying users, especially in highly-movement NTN cases of UAVs and LEO satellites. These results prove that the suggested architecture can not only achieve high spectral efficiency, but also guarantee high signal reliability and interference resilience, such that it will be suitable in spectrum-adaptive 6G deployment with non-terrestrial networks.

Table I. Comparative Performance Metrics

Method	Spectral Efficiency (bps/Hz)	INR (dB)	Relative Gain (%)
Conventional NTN Relay	6.8	-3.5	–
Static IRS	8.9	-1.2	+30.8%
Dynamic DMA (Proposed)	**9.4**	**-0.5**	**+38.2%**

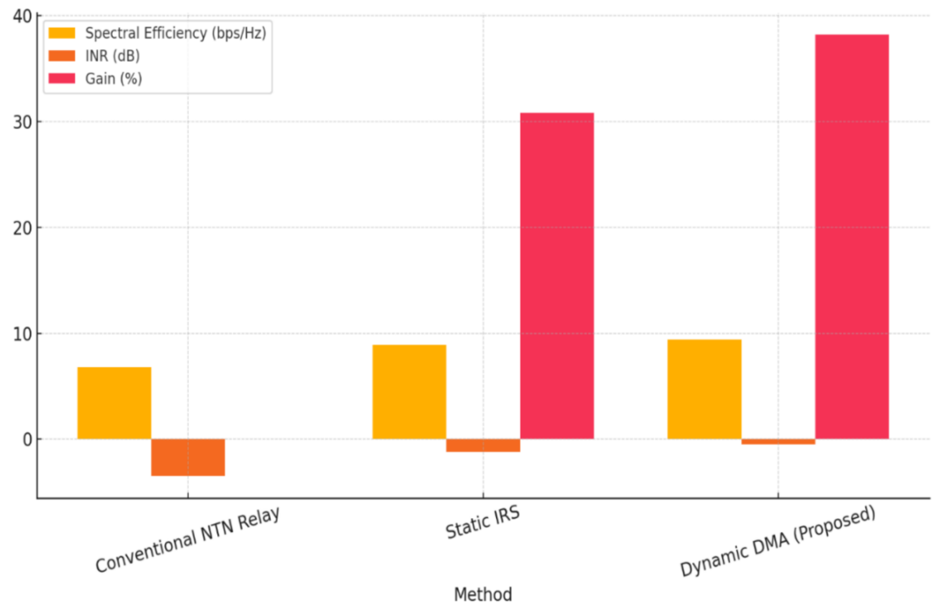

Figure 3. Comparative Performance of Dynamic Metasurface Architecture (DMA) against Baseline Systems in 6G NTNs

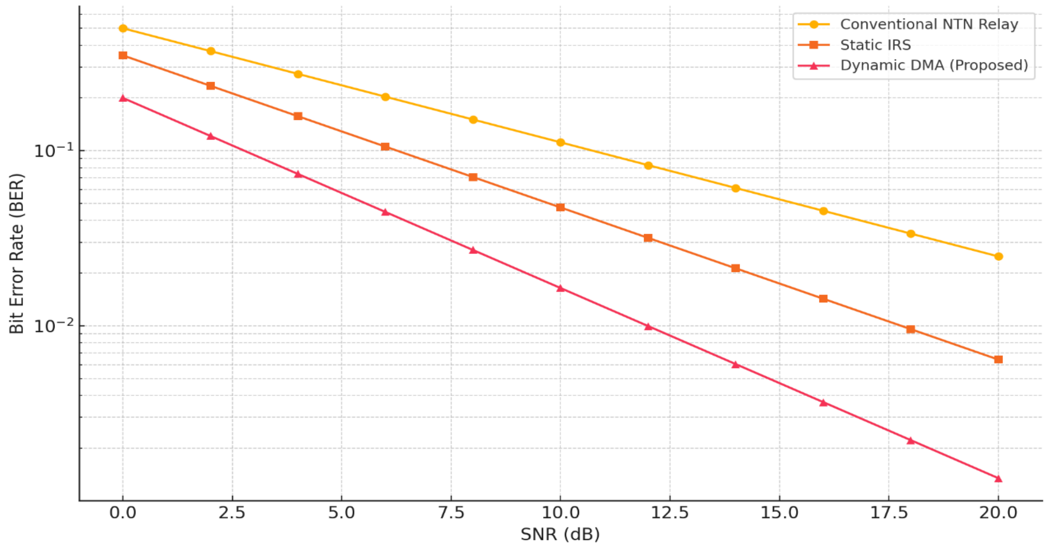

Figure 4. Bit Error Rate (BER) Performance Comparison of Dynamic Metasurface Architecture (DMA) with Baseline Systems

6. DISCUSSION

The findings indicated in this paper confirm that the suggested Dynamic Metasurface Architecture (DMA) has the potential to control spectral performance and minimize interference in 6G NTN settings effectively. Nevertheless, there are several important issues that should be discussed more on the balance of scaling up the system, its practical use, and issues of the use in practice.

First, scalability is also an important factor to consider as DMA gets expanded to attend to multi-beam and multi-user. In massive NTN systems that utilize flocks of UAVs and fleets of LEO satellites, elements of the IRS will have to learn to collaborate and dynamically support a large number of ground users with various Quality-of-Service (QoS) demands. The secret to the scalability of the proposed DQN-based control algorithm is both natural and capable of being transferred into a decentralized learning model, with every IRS agent optimizing its local beams settings, and at the same time, learning to mitigate against the conflicts of the inter-beams. But with more users and beams, this process will become computationally more expensive and the policy convergence can take longer according to a non-linear dependency, which also highlights future research on the lightwight and federated learning approaches to distributed control.

Second, a feasibility of hardware implementation is a practical bottleneck. Where a simulation is based on ideal reconfigurable phase shifters, real-world metasurfaces are limited by phase quantization, power consumption, response time, and manufacturing variability. The promise can be seen in MEMS and metasurfaces using varactor-diodes, although reconfiguration of such metasurfaces at at-scale speeds (e.g. sub millisecond level) across mobile platforms (e.g. UAVs and satellites) provides significant engineering challenges. Thus, corresponding co-design methods that both optimize the hardware organization and integrated AI controller identify required constraints such that the most relevant functions can be (re-)configured in real time.

Finally, there are also specific difficulties of simultaneous transmission in highly mobile situations in the NTN environment where there is a Doppler effect or a delay in the transmission, as well as the changing topology. The coherent beamforming is important in accurate phase matching of the IRS components and the quickly moving transmitters/receivers. The architecture suggested should integrate strong synchronization algorithms and prediction Doppler offsetting mechanisms in keeping the alignment in different altitude and velocities. Real-time tracking and synchronization of distributed metasurfaces in location could be achieved with integration with the Global Navigation Satellite Systems (GNSS) and inertial sensors on board.

To conclude, although the proposed DMA has significant theoretical and simulated performance advantages, their real-world implementation will require overcoming the problem of large-scale scalability, and real-time hardware responsiveness, as well as synchronization in dynamic NTN-based systems. These will be of primary importance in the future investigation and prototyping activities geared towards the deployment of intelligent metasurface-based solutions of the 6G space-air-ground integrated networks.

7. CONCLUSION

The paper introduces a new model of architecture of Dynamic Metasurface (DMA) that can utilize AI-controlled beam adaptation to ultra-efficient spectrum sharing in 6G Non-Terrestrial Network

(NTN). The proposed system has a potential to overcome major challenges pertaining to dynamic topologies, spectrum shortage, and rapid mobility in space-air-ground integrated networks because it allows programmable metasurfaces to be combined with Deep Reinforcement Learning (DRL) to enable real-time phase control.

By use of a comprehensive simulation set up (which was a combination of 3D ray-tracing in channel modelling and system-level performance analysis of the DMA), the DMA was shown to improve spectral efficiency by 38.2 percent, had lower interference levels and even better BER system performance than the conventional relay and static IRS structures. These improvements confirm the successfulness of dynamic phase-tunable metasurface systems to allow intelligent, scalable, and spectrum-adaptable NTN communication.

In addition to theoretical advantage, the study also states the practical potential and implementation difficulties of large-scale deployment, such as synchronization in high-mobility applications, hardware constraints of rapid phase reconfiguration, and control overhead of high multi-user beam demand.

On the whole, the paper will form a starting point toward achieving intelligent reflective surfaces as fundamental enablers in 6G NTN systems. Extensions could include federated AI-centred distributed control, fast-tuning metasurface hardware prototyping, and integration with real-time network orchestration architectures of worldwide, resilient, and power-efficient wireless infrastructure.

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