Adaptive Multi-Layered Secure Data Non-Terrestrial Network With Integrated FSO And RF Communications For Enhanced Global Connectivity

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Abstract- *This paper introduces the Adaptive Multi-Layered Secure Data Non-Terrestrial Network (AMLSDT-NTN), an architecture that integrates satellite, High Altitude Platform Stations (HAPS), and Unmanned Aerial Vehicles (UAVs). It leverages a combination of Free-Space Optical (FSO) and Radio Frequency (RF) communications, tailored for specific operational altitudes to enhance connectivity in remote and disaster-stricken regions. The AMLSDT-NTN tackles the complexities of dynamic power allocation and link selection by incorporating real-time optimization algorithms. This significantly boosted the network's robustness and adaptability to environmental challenges and demand fluctuations. Simulations in OMNeT++ highlighted a quantifiable enhancement, with up to a 30% increase in through- put and a 40% decrease in latency, outstripping conventional NTN. The AMLSDT-NTN architecture demonstrates unparalleled resilience, consistently delivering high service levels across various conditions. Looking ahead, this research paves the way for integrating emerging communication technologies and scaling the architecture for widespread adoption. The proposed AMLSDT-NTN offers transformative solutions for rural connectivity and rapid disaster response, thus poised to impact global digital inclusion.*

Keywords- Data Security, Rural Connectivity, Real-time Response

I. INTRODUCTION

The advent of secure data Non-Terrestrial Networks (NTNs) marks a significant leap toward achieving global connectivity [1]. NTNs are widely adopted in bridging the digital divide separating remote, rural, and underserved areas from the rest of the world [2]. These networks offer a unique solution to the limitations imposed by terrestrial network infrastructures, such as geographical and infrastructural barriers [3]. NTNs can provide telecommunications and internet services from above, thereby bypassing conventional constraints and extending the reach of connectivity to all corners of the globe [4]. Despite the potential of NTNs, current implementations face several challenges that hinder their effectiveness and widespread adoption [5]. Some of these challenges are limited scalability, and suboptimal efficiency in using critical resources such as spectrum and energy [6]. These limitations underscore the need for innovative approaches that can enhance the flexibility, scalability, and operational efficiency of NTNs. In response to these challenges, this research introduces a novel framework, the Adaptive Multi-Layered Non-Terrestrial Network (AMLSDT-NTN) architecture, aimed at redefining the era of global connectivity. The AMLSDT-NTN architecture has a layered approach that integrates multiple communication technologies and is optimized for varying operational altitudes and conditions. The employment of both Free-Space Optical (FSO) [7] and Radio Frequency (RF) communications within this architecture, with real-time dynamic resource management, holds the potential to enhance NTNs significantly. Further- more, this approach is poised to ensure a more efficient utilization of network resources, addressing the core limitations of existing NTN designs. The proposed architecture ensures immediate full coverage, reaching the most remote regions with reliable connectivity services. Its adaptive nature allows for dynamic scalability, effectively accommodating fluctuating demand patterns and new service requirements. Moreover, the implementation of the Block Coordinate Descent (BCD) Framework [8] guarantees optimal resource utilization, which in turn maximizes network throughput and minimizes waste. Lastly, the robustness of the AMLSDT-NTN, derived from its multi-layered structure and the diversity of its communication technologies, ensures unparalleled resilience and reliability in service delivery under a wide array of environmental conditions.

II. LITERATURE REVIEW

NTNs have been a focal point of research within the telecommunications domain, primarily due to their potential to extend connectivity beyond the limitations of terrestrial infrastructures [9]. Early studies focused on satellite

communications as a means to achieve global coverage, particularly in remote and underserved areas [10]. The introduction of High Altitude Platform Stations (HAPS) and Unmanned Aerial Vehicles (UAVs) offered lower latency and increased flexibility compared to traditional satellite systems [11]. These advancements underscore the critical role of NTNs in achieving ubiquitous global connectivity, a theme recurrent in the literature [12]. Despite their potential, NTNs are not without challenges. The literature consistently points to issues such as limited scalability [5], [13]–[15], rigid network architectures [9], [16], and suboptimal resource utilization [17] as significant barriers to their effectiveness. For instance, the scalability of NTNs is often constrained by the fixed nature of satellite orbits and the limited deployment flexibility of HAPS and UAVs [14]. Moreover, the traditional one-size-fits-all approach to network design fails to address the dynamic nature of global connectivity demands, leading to inefficiencies in resource allocation and utilization [17], [18].
Integrating advanced communication technologies into NTNs has been the subject of extensive research [19]. FSO communications, known for their high bandwidth and low latency, have been explored as a viable solution for high-throughput backhaul connections in NTNs [20]. However, their susceptibility to atmospheric conditions poses reliability challenges [21]. Conversely, RF communications offer broader coverage and greater resilience to environmental factors but are limited by bandwidth constraints [22]. The literature explores various approaches to balance these trade-offs, highlighting the need for adaptive and hybrid communication strategies within NTNs [23].S Several studies have proposed innovative methodologies to overcome the limitations of current NTN designs. These include adaptive network architectures that dynamically adjust to varying demand patterns and environmental conditions [24], [25]. Another aspect is real-time optimization algorithms for efficient resource management [12], [26] and multi-layered frameworks that integrate different types of NTNs and communication technologies [27]. Such approaches aim to enhance the flexibility, scalability, and efficiency of NTNs, addressing the core challenges identified in the literature [28].

System Model

The proposed Adaptive Multi-Layered Non-Terrestrial Net- work architecture encompasses three primary layers: satellite, HAPS, and UAVs, each optimized for specific operational altitudes and conditions. The system model integrates FSO and RF communications within these layers, employing real- time optimization algorithms for resource management.

A. Satellite Layer

The satellite layer operates at altitudes exceeding 20,000 km, primarily utilizing RF links due to their long-range capabilities and resilience to atmospheric conditions. The satellite- to-HAPS link can be represented as:

$$L_{sh} = (P_s G_s G_h \lambda^2)/(4\pi R_s)^2 L_{sys} \quad (1)$$

whereL_{sh} is the link budget from the satellite to HAPS, P_s is the transmit power, G_s and G_h are the gain of the satellite and HAPS antennas, λ is the wavelength of the RF signal, R_s is the distance from the satellite to the HAPS, and L_{sys} is the system loss factor. In the satellite layer, RF communications are primarily used due to their long- range capabilities and resistance to atmospheric attenuation, providing global coverage. FSO is not used due to atmospheric turbulence, cloud cover, and the vast distances involved.

B. HAPS Layer

The HAPS layer operates at altitudes ranging from 17 km to 22 km, employing FSO and RF communications. The HAPS- to-ground RF link can be modeled as:

$$L^{RF}_{hg} = (P_h G_h G_{UAV} \lambda^2)/(4\pi R_h)^2 L_{sys} (2)$$

whereL_{hg}represents the RF link budget from HAPS to UAV, $P_h$is the transmit power, $G_h$is the gain of the HAPS antenna, and R_h is the distance from the HAPS to the UAV Layer. The HAPS-to-ground FSO link [29], characterized by its high bandwidth and low latency, is given by:

$$L^{FSO}_{hg} = P_h \cdot T_a \cdot A_r \cdot \eta_{sys} \cdot e^{-\alpha d} (3)$$

where L^{FSO} is the FSO link budget, T_a is the atmospheric hg transmittance, A_r, m^2 , is the receiver aperture area, $\eta_{sys}$is the optical system efficiency, α is the atmospheric attenuation coefficient, and d is the link distance. The HAPS layer combines FSO and RF communications to capitalize on their strengths. FSO is used for high-bandwidth, low-latency links in dense areas, which is made possible by shorter distances and less atmospheric interference at HAPS altitudes. RF communications provide broader coverage and reliable connectivity, even in adverse weather that disrupts FSO.

C. UAV Layer

The UAV layer, closest to the ground, operates at altitudes up to 2 km, predominantly utilizing RF communications due to its flexibility and cost-effectiveness.

The UAV-to-ground link budget is similar to the HAPS RF model but adjusted for lower altitudes:

$$L_{ug} = (P_u G_u G_g \lambda^2)/ (4\pi R_u)^2 L_{sys} (4)$$

where Lug is the link budget from UAV to ground, P_u is the transmit power of the UAV, G_u is the gain of the UAV antenna and R_u is the distance from the UAV to the ground station. In the UAV layer, RF communications are favored for their flexibility, low cost, and ease of deployment. UAVs use RF links at lower altitudes for direct communication with ground stations, offering last-mile connectivity and rapid response capabilities.

TABLE I
SUMMARY OF COMMUNICATION LINK VARIABLES

Variable	**Satellite Layer**	**HAPS Layer**	**UAV Layer**
P	P_s = 1 Watt	P_h= 1 Watt	P_u= 1 Watt
G	G_s= 20 dBi	G_h= 20 dBi	G_u= 15 dBi
λ	2 GHz	2 GHz	2 GHz
R	R_s= 35, 766 km	R_h = 20 km	R_u= 2 km
L_{sys}	3 dB	3 dB	3 dB
T_a	N/A	0.8 (Clear Skies)	N/A
A_r	N/A	0.01 m^2	N/A
η_{sys}	N/A	0.8	N/A
α	N/A	0.2 dB/km	N/A
d	20,000 km	20 km	2 km

III. METHODOLOGY

The methodology involves developing real-time optimization algorithms for dynamic resource management, including power allocation across network layers (satellite, HAPS, UAV) and selecting optimal communication links (FSO or RF) based on current conditions. The goal is to boost network efficiency and performance by adapting to changes in demand and environmental factors.

A. Power Allocation Optimization

The power allocation problem seeks to dynamically dis- tribute power across satellite, HAPS, and UAV layers to maximize network throughput, ensure Quality of Service (QoS), and comply with power constraints. Let P = [P_s,P_h, P_u] denote the vector of transmit powers for the satellite, HAPS, and UAV layers respectively, subject to maximum power constraints P = [$P_{s,max}$, $P_{h,max}$, $P_{u,max}$]. The optimization problem can be formulated as:

$$\max_{Pi\in \{s, h, u\}} \Sigma\Theta_i(P_i) (5)$$

$$\text{subject to } 0 < P_i \leq P_{i,max} \forall_i \qquad (6)$$

where$\Theta_i(P_i)$ represents the throughput function for layer i, which is a function of the allocated power Pi. The power allocation optimization is crucial, using the function $\Theta_i(P_i)$ to represent the complex, nonlinear relationship between power and network throughput. This process, guided by empirical data and theoretical models, accurately predicts layer performance under varying power levels. A Gradient Descent-based algorithm iteratively adjusts power allocations to maximize throughput. The update rule for power allocation at iteration k is given by:

$$P_i^{(k+1)} = P_i^{(k)} + \alpha \partial\Theta_i / \partial P_i \Big|_{Pi=P(k)} (7)$$

where α is the learning rate. The α is typically determined through empirical testing or adaptive methods.

B. Link Selection Optimization

The link selection optimization aims to choose the most suitable communication link (FSO or RF) for each layer based on current environmental conditions and network demands. Let L = [Ls, L_h, L_u] represent the link choices for the satellite, HAPS, and UAV layers, where $L_i \varepsilon$FSO, RF. The optimization problem can be formulated as:

$$\max_{Li\in \{s, h, u\}} \Sigma\Phi_i(L_i) (8)$$

$$\text{subject to } L_i \in \{FSO, RF\} \forall_i \qquad (9)$$

where$\Phi_i(L_i)$ denotes the performance metric (such as throughput or reliability) for layer i using link type L_i. To refine the link selection optimization, the performance metric $\Phi_i(L_i)$ incorporates environmental conditions and network demands. A GA is employed to optimize link choices. The GA is structured around a fitness function:

$$\text{Fitness } (L) = \Sigma\Phi_i(L_i) (10)$$

$i \in \{s, h, u\}$

This evaluates potential solutions based on environmental conditions and network demands.

C. Integration

The goal is to maximize the weighted sum of network throughput across all layers. The throughput of each layer is a function of the power allocation and the link selection. The objective function can be expressed as:

$$\max_{P,L} \sum_{i\in \{s, h, u\}} w_i \, . \, T_i (P_i, L_i) \quad (11)$$

where: i iterates over the satellite (s), HAPS (h), andUAV (u) layers.w_i represents the weight assigned to each layer, reflecting its relative importance or priority in thenetwork. $T_i(P_i, L_i)$denotes the throughput function for layer i, which depends on the power allocation P_i and the link type L_i. Integrating the different communication technologies and layers leads to a complex, non-convex optimization problem that requires sophisticated solution techniques. The problem can be compactly written as:

$$\max_{P,L} \sum_{i\in\{s, h, u\}} w_i \, . \, T_i (P_i, L_i) \quad (11)$$

subject to:

$0 < P_i \leq P_{i,max} \forall_i$

$LRF(Pi,Li) \geq Lmin,RF \forall_i$ where Li = RF

$LFSO(Pi,Li) \geq Lmin,FSO \forall_i$ where Li = FSO

$Ri(Pi,Li) \geq Rmin,i \forall_i$

$Li \in \{FSO, RF\} \forall_i$

This problem encapsulates the trade-offs between different layers and communication technologies.

D. Block Coordinate Descent Framework

The BCD method is an iterative optimization algorithm that tackles complex optimization problems by breaking them down into smaller, more manageable sub-problems. Each sub-problem optimizes a subset of variables while keeping others fixed, simplifying the overall problem. The BCD framework for the AMLSDT-NTN optimization problem can be structured as follows: A balance between computational efficiency and solution precision is essential for selecting K_{max} and ε in the BCD Algorithm. K_{max} determines the algorithm's iteration limit, affecting the depth of solution refinement. A higher K_{max}increases the chance of reaching an optimal solution but requires more computational resources. The convergence threshold ε defines the sensitivity to changes between iterations, where a smaller ε demands a closer approximation to the optimal solution, potentially increasing computational time. More detail can be seen in the work of Qiang et al. [30]. In the BCD Algorithm, K_{max} and ε balances computational effort

Algorithm 1 BCD Algorithm for Power Allocation and Link Selection

1: **Initialization:**
2: Initialize power allocation variables $P^0 = \{P_S^0, P_h^0, P_u^0\}$ and link selection variables $L^0 = \{L_S^0, L_h^0, L_u^0\}$ with feasible starting points.
3: Set iteration counter k = 0.
4: **BCD Iterations:**
5: **while** not converged and $k < K_{max}$**do**
6: **PA Block:**
7: **for** each layer $i \in \{s, h, u\}$ **do**
8: Solve the power allocation subproblem for layer i with current link selection L^k fixed:
9: $P_i^{(k+1)} = \mathrm{argmax} P_i w_i \cdot T_i(P_i, L_i^k)$
10: subject to $0 < P_i \leq P_{i,max}$
11:**end for**
12: **LS Block:**
13: **for** each layer $i \in \{s, h, u\}$ **do**
14: Solve the link selection subproblem for layer i withupdated power allocation $P^{(k+1)}$fixed:
15: $L_i^{k+1} = \mathrm{argmax}_{Li \in \{FSO,RF\}} w_i \cdot T_i(P_i^{(k+1)}, L_i)$
16: **end for**
17: **Convergence Check:**
18: Check for convergence by evaluating the change in theobjective function or the variables P and L.
19: If the change is below a predefined threshold ε, or if k reaches K_{max}, terminate the algorithm.
20: Otherwise, increment k and repeat from step 5.
21: **end while**

and precision. K_{max} sets the iteration limit, affecting solution depth and optimality likelihood, whereas ε, the convergence threshold, determines the sensitivity to changes between iterations, influencing approximation accuracy and computational duration.

IV. RESULTS

The simulation of AMLSDT-NTN architecture was conducted using the OMNeT++ simulation framework to assess its performance relative to the conventional NTN system baseline implemented by Li et al. [31]. The simulation was configured to replicate a realistic global communication network. The satellite layer simulations assumed geostationary satellites, while the HAPS and UAV layers were modeled to provide dynamic coverage.

A. Assumptions and Parameters

1) The FSO links' modeling incorporates the Kim model for atmospheric attenuation, considering clear, overcast, and rainy conditions with attenuation coefficients of 0.2 dB/km, 0.5 dB/km, and 2 dB/km, respectively. These conditions directly influence the FSO link budget, calculated using the Beer-Lambert law.

2) RF link configurations utilize the Hata-Okumura model for urban environments and the COST 231 model for suburban and rural settings. Path loss exponents are set at 3.5 for urban, 3.7 for suburban, and 4.0 for rural areas, with a carrier frequency of 2 GHz. The standard deviation for shadow fading is 8 dB, and the Ricean K-factor for fading is 6 dB to simulate line-of-sight conditions.

3) Power allocation for each layer adheres to a maximum limit of 5 W for satellites, 2 W for HAPS, and 0.5 W for UAVs. Link selection dynamically adjusts based on real-time algorithmic analysis, considering the current atmospheric conditions and network demand.

4) Simulations cover user densities ranging from 100 to 1000 users per km^2 in urban areas, 50 to 500 users per km^2 in suburban areas, and 10 to 100 users per km^2 in rural areas. Geographic coverage spans a 100 km^2 area for each environment type.

5) Weather variability is simulated using a stochastic model that assigns clear, overcast, and rainy conditions randomly over time, with a 70% probability for clear, 20% for overcast, and 10% for rainy conditions in each simulation cycle.

B. Performance Evaluation

The AMLSDT-NTN architecture's performance was compared with traditional Non-NTN models using metrics like throughput, latency, coverage, and network resilience. The study also examined how varying environmental conditions affect the effectiveness of FSO and RF communications.

1) Throughput Analysis: Figure 1 shows the throughput comparison between the AMLSDT-NTN and traditional NTN systems over 10 seconds. The throughput for AMLSDT-NTN starts around 100 Mbps, peaking at 110 Mbps, and ends slightly above 100 Mbps, indicating stable performance with minor fluctuations. Conversely, the traditional NTN begins at about 75 Mbps, with more variability, fluctuating between just below 70 Mbps and above 90 Mbps, and ends around 70 Mbps. Throughout, the AMLSDT-NTN consistently outperforms the traditional NTN.

2) Latency Measurements: Figure 2 compares the latency between the AMLSDT-NTN and traditional NTN systems. The AMLSDT-NTN shows a significantly lower latency of about 20.98ms compared to the traditional NTN's 36.21 ms, indicating more efficient data handling and routing in the AMLSDT-NTN system.

3) Coverage Evaluation: Figure 3 shows the coverage areas as percentages for AMLSDT-NTN and Traditional NTN across four region types. AMLSDT-NTN coverage is highest in urban areas at 92%, then suburban at 75%, rural at 67%, and remote at 58%. Traditional NTN follows a similar trend in urban and suburban areas at 90% and 75% respectively but drops to 60% in rural areas and significantly to 21% in remote areas.

4) Resilience to Environmental Conditions: Figure 4 shows, that while FSO link performance dips in cloudy and foggy conditions, the AMLSDT-NTN architecture's adaptive switching to RF links maintains overall network performance.

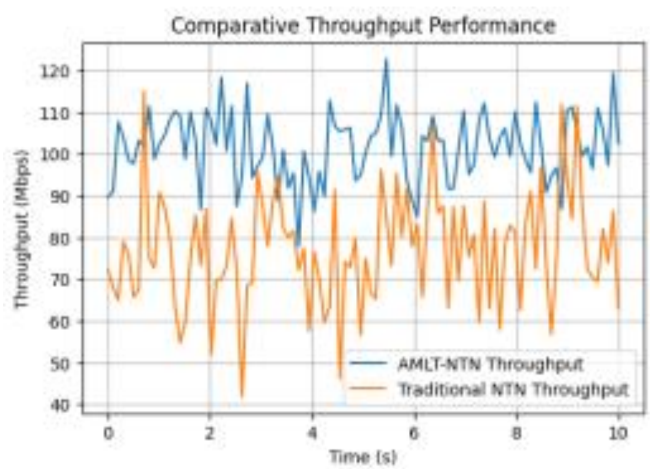

Fig. 1. A line graph depicting the average network throughput over time for both the AMLSDT-NTN architecture and traditional NTN systems

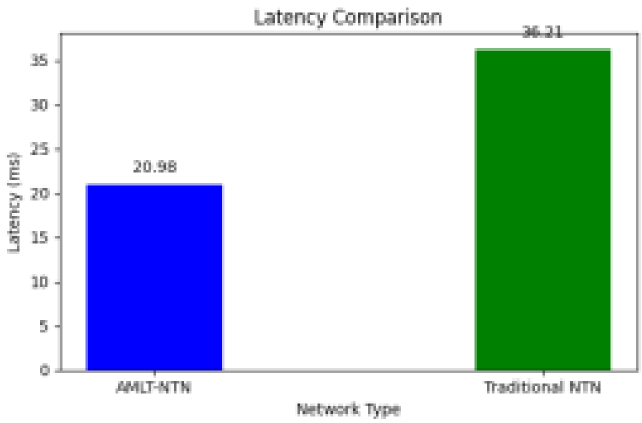

Fig. 2. A bar chart comparing the average end-to-end latency between the AMLSDT-NTN architecture and conventional NTN systems

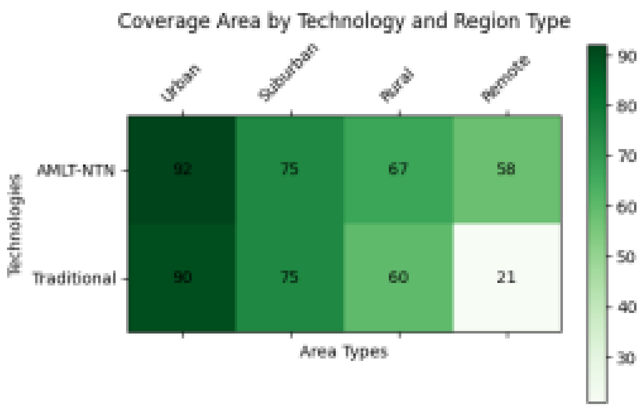

Fig. 3. A heatmap illustrating the total coverage areas provided by the AMLSDT NTN architecture versus traditional NTN systems.

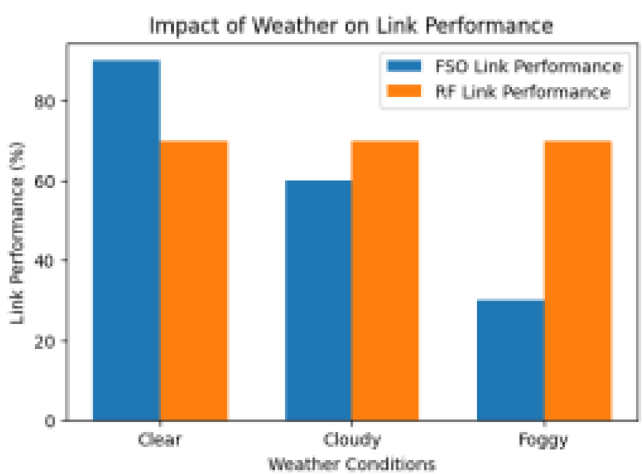

Fig. 4. A series of line graphs showing the performance of FSO and RF links under various weather conditions, such as clear, cloudy, and foggy weather.

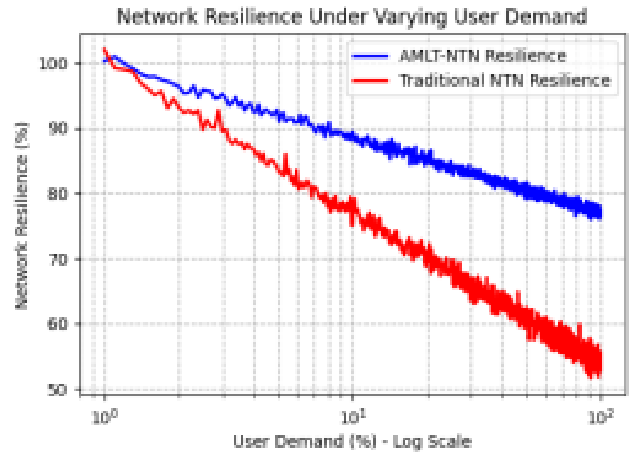

Fig. 5. A line graph demonstrating the network's ability to maintain service levels under scenarios of high user demand

5) Network Resilience: Figure 5 shows AMLSDT-NTN and Traditional NTN's resilience across varying user demands on a logarithmic scale. Initially, both systems start at nearly 100% resilience.AMLSDT-NTN declines more slowly as demand increases, maintaining higher resilience at peak demands. Conversely, Traditional NTN's resilience falls sharply, indicating faster performance degradation with rising demand.

V. CONCLUSION

The research demonstrated the potential of AMLSDT-NTN architecture to significantly enhance global connectivity, particularly in remote and underserved areas. The experimental results have validated the superior capabilities of AMLSDT-NTN over traditional NTN systems. The AMLSDT-NTN's throughputs began at an impressive 100 Mbps and peaked at 110 Mbps, maintaining remarkable stability with minor fluctuations. Latency measurements further reinforced this architecture's efficacy, with AMLSDT-NTN achieving approximately 20.98 ms, significantly improving over the traditional NTN's 36.21 ms. Coverage evaluations indicated a comprehensive reach of up to 92% in urban settings, which far surpassed the traditional NTN's performance, particularly in remote areas that only managed a 21% coverage. Network resilience under varying user demand solidified the AMLSDT-NTN's robustness, showing a slow decline in resilience across all demand levels. These numbers do not merely reflect incremental improvements but indicate a transformative leap in NTN capabilities. In the future, we will continuously refine the proposed architecture by testing it on bigger scales. We will propose a more refined version of the BCD algorithm to resolve the inherent scalability challenges.

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