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Adaptive AI-Assisted Doppler Compensation and Predictive Handover Optimization for LEO Satellite Communication in 6G Non-Terrestrial Networks

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Abstract — Low Earth Orbit (LEO) satellite communication has emerged as a key enabler of sixth-generation (6G) Non-Terrestrial Networks (NTNs), offering global coverage, low propagation delay, and high-capacity broadband connectivity. However, the high orbital velocity of LEO satellites introduces significant challenges, including severe Doppler frequency shifts, rapidly varying channel conditions, and frequent handovers, which adversely affect communication reliability, throughput, and Quality of Service (QoS). Existing Doppler compensation and handover mechanisms are generally treated as independent processes and often rely on static threshold-based strategies or computationally intensive artificial intelligence (AI) models, limiting their adaptability in highly dynamic satellite communication environments. This paper proposes an Adaptive AI-Assisted Doppler Compensation and Predictive Handover Optimization (AIDCPHO) framework for LEO satellite communication in 6G Non-Terrestrial Networks. The proposed framework integrates real-time Doppler estimation, AI-assisted predictive handover decision-making, adaptive beam selection, and dynamic link quality assessment into a unified optimization model. A predictive mobility module estimates future satellite-user link conditions using orbital dynamics and user mobility information, while an adaptive Doppler compensation module minimizes frequency estimation errors before communication degradation occurs. Furthermore, a multi-parameter handover decision algorithm utilizes Signal-to-Noise Ratio (SNR), Doppler shift, elevation angle, received signal strength, and predicted link quality to proactively initiate seamless handovers, thereby reducing service interruption and packet loss. The proposed framework is implemented and evaluated using MATLAB-based simulations that model realistic LEO satellite orbital movement, time-varying communication channels, and user mobility scenarios.

Keywords— Low Earth Orbit (LEO) Satellites, 6G Non-Terrestrial Networks (NTNs), Adaptive Doppler Compensation, Predictive Handover Optimization, Artificial Intelligence (AI), Mobility Managementetc.

I. INTRODUCTION

The rapid evolution of sixth-generation (6G) wireless communication systems is expected to revolutionize global connectivity by providing ultra-high data rates, ultra-low latency, massive machine-type communications (mMTC), enhanced mobile broadband (eMBB), and ultra-reliable low-latency communication (URLLC). However, conventional terrestrial communication infrastructures alone are insufficient to satisfy the stringent coverage and reliability requirements of future intelligent applications such as autonomous transportation, smart cities, industrial automation, remote healthcare, maritime communications, and Internet of Things (IoT) services in remote and disaster-affected regions. Consequently, the integration of Non-Terrestrial Networks (NTNs) with terrestrial communication systems has emerged as one of the fundamental technologies for realizing ubiquitous and resilient 6G communication networks [1], [2].

Among various NTN technologies, Low Earth Orbit (LEO) satellite constellations have attracted considerable attention because of their relatively low orbital altitude (typically 500–2000 km), reduced propagation delay, high spectral efficiency, and global service coverage compared with traditional Geostationary Earth Orbit (GEO) satellite systems. Modern mega-constellations such as Starlink, OneWeb, Kuiper, and Telesat Lightspeed demonstrate the feasibility of providing broadband Internet connectivity with end-to-end latency significantly lower than conventional satellite systems. These characteristics make LEO satellites highly suitable for supporting delay-sensitive 6G applications requiring continuous connectivity and high network availability [3], [4]. Despite these advantages, the high orbital velocity of LEO satellites, which exceeds approximately 7.5 km/s, introduces several technical challenges that significantly affect communication reliability. Rapid satellite movement produces severe Doppler frequency shifts, continuously changing propagation delays, dynamic channel variations, beam

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switching, and frequent handover events. These impairments degrade carrier synchronization, channel estimation, signal detection, and communication quality, particularly in high-frequency Ka-band and millimeter-wave communication systems. Therefore, efficient Doppler compensation and seamless mobility management have become critical requirements for future LEO-enabled 6G communication architectures [5], [6].

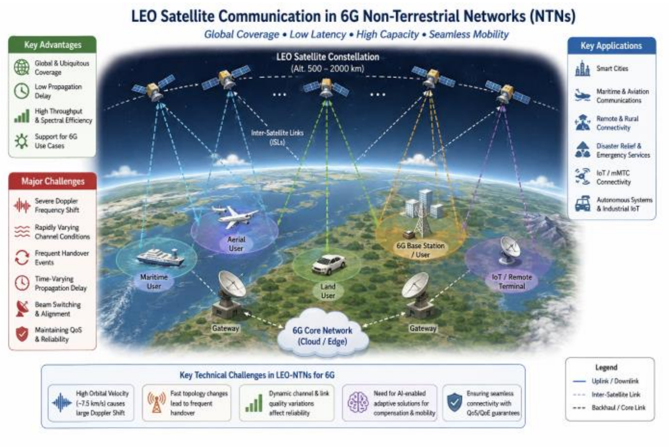

Fig 1 LEO satellite communication in 6G NTNs

Mobility management in LEO satellite networks differs fundamentally from that of terrestrial cellular systems. In terrestrial networks, handovers are mainly triggered by user mobility, whereas in LEO satellite systems even stationary users experience frequent handovers due to the continuous movement of satellites across orbital planes. Conventional threshold-based handover algorithms often result in increased signaling overhead, packet loss, service interruption, and higher communication latency under highly dynamic network conditions. Moreover, existing Doppler compensation techniques generally operate independently of mobility management, limiting their capability to adapt to rapidly changing satellite-user link characteristics [7], [8].

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Deep Reinforcement Learning (DRL) have opened new opportunities for intelligent satellite communication systems. AI-assisted algorithms have been investigated for channel prediction, beam management, resource allocation, mobility prediction, and adaptive handover optimization. Nevertheless, many existing AI-based solutions require extensive training datasets, high computational complexity, and significant processing overhead, making real-time deployment challenging in highly dynamic LEO satellite environments. Furthermore, only limited studies jointly optimize Doppler estimation and predictive handover within a unified communication framework while considering realistic orbital dynamics and time-varying channel conditions [4], [9].

Motivated by these challenges, this paper proposes an Adaptive AI-Assisted Doppler Compensation and Predictive Handover Optimization (AIDCPHO) framework for LEO satellite communication in 6G Non-Terrestrial Networks. The proposed framework integrates adaptive Doppler estimation, predictive mobility analysis, intelligent handover decision-making, adaptive beam selection, and dynamic link quality assessment into a unified optimization architecture. Unlike conventional approaches that separately address Doppler compensation and mobility management, the proposed framework performs joint optimization based on multiple communication parameters, including Signal-to-Noise Ratio (SNR), received signal strength, Doppler shift, elevation angle, and predicted link quality. A MATLAB-based simulation environment is developed to model realistic LEO satellite orbital dynamics, user mobility, and time-varying communication channels for comprehensive performance evaluation.

The major contributions of this work are summarized as follows:

- A novel Adaptive AI-Assisted Doppler Compensation and Predictive Handover Optimization (AIDCPHO) framework is proposed for integrated Doppler estimation and seamless handover management in LEO satellite communication systems.
- A predictive mobility-based handover mechanism is developed using multiple communication quality indicators to reduce unnecessary handovers, packet loss, and communication interruptions.
- An adaptive Doppler compensation strategy is incorporated to minimize frequency estimation errors under highly dynamic satellite communication scenarios.
- A comprehensive MATLAB-based simulation framework is developed for evaluating realistic LEO satellite communication considering orbital movement, user mobility, and dynamic wireless channel conditions.
- Extensive performance evaluation is carried out using latency, throughput, packet delivery ratio, handover delay, spectral efficiency, Bit Error Rate (BER), Signal-to-Noise Ratio (SNR), and Doppler estimation error to demonstrate the effectiveness of the proposed framework compared with conventional approaches.

II. LITERATURE SURVEY

Recent advancements in Low Earth Orbit (LEO) satellite communication have significantly accelerated the development of Non-Terrestrial Networks (NTNs) for sixth-generation (6G) wireless systems. Owing to their low propagation delay, global coverage, and high data rate capabilities, LEO satellite constellations have become an essential component of future communication infrastructures. However, challenges such as high Doppler frequency shifts, frequent handovers, dynamic channel variations, beam management, and resource allocation continue to limit communication reliability. Consequently, researchers have proposed various artificial intelligence (AI), machine learning (ML), deep reinforcement learning (DRL), graph neural network (GNN), and optimization-based approaches to improve the performance of LEO satellite communication systems.

Siva Satya Sri Ganesh Seeram, Luca Feltrin, Mustafa Ozger, Shuai Zhang, and Cicek Cavdar [11] investigated handover challenges in disaggregated Open Radio Access Network (O-RAN) architectures for LEO satellite systems. The study analyzed the trade-off between onboard processing and handover delay under highly dynamic satellite movement. A conditional handover mechanism was proposed to reduce signaling overhead and improve mobility management. Simulation results demonstrated improvements in handover efficiency; however, the proposed framework increased computational complexity because of distributed processing requirements.

Ji-Woon Lee, Byungju Lim, Ki-Hun Kim, Jong-Man Lee, Young-Seok Ha, Young-Jin Han, and Young-Chai Ko [12] proposed a Graph Neural Network (GNN)-based distributed handover strategy for LEO satellite communication. Their approach selected target satellites by considering user distribution and satellite load balancing simultaneously. The proposed method improved system throughput and reduced handover failures compared with conventional distributed algorithms. Nevertheless, the framework primarily focused on handover optimization and did not consider Doppler estimation or adaptive frequency compensation.

Jinxuan Chen, Mustafa Ozger, and Cicek Cavdar [13] developed a Nash Soft Actor-Critic (Nash-SAC) multi-agent reinforcement learning algorithm for mobility management in LEO satellite networks serving flying vehicles. The proposed game-theoretic framework reduced unnecessary handovers, blocking probability, and improved overall network utility compared with conventional Q-learning methods. Despite these improvements, the algorithm requires extensive training and considerable computational resources for practical deployment.

Jiasheng Wu, Shaojie Su, Wenjun Zhu, Xiong Wang, Jingjing Zhang, Xingqiu He, and Yue Gao [14] introduced a parallel handover framework for mobile satellite networks. A machine learning-based signal strength prediction model and an efficient scheduling algorithm were integrated to reduce handover latency. Experimental results showed substantial improvements in network stability and significant reductions in handover delay. However, the proposed method did not jointly optimize Doppler compensation with handover management.

The authors of [15] proposed a Deep Reinforcement Learning-based multi-objective handover optimization framework for LEO satellite networks. The algorithm simultaneously minimized handover frequency, balanced satellite load, and maximized network throughput using a lightweight neural network. Although throughput and handover performance improved considerably, Doppler-aware communication and adaptive channel estimation were not incorporated into the optimization framework.

The authors of [16] presented a joint traffic prediction and handover optimization framework based on Long Short-Term Memory (LSTM) networks and an attention-enhanced Rainbow Deep Q-Network. The proposed framework predicted future traffic demands and optimized satellite selection accordingly, thereby improving communication stability and resource utilization. However, the model mainly focused on traffic-aware handover and did not investigate dynamic Doppler compensation under highly mobile satellite environments.

The authors of [17] proposed a proactive handover optimization framework using multi-agent deep reinforcement learning for integrated LEO satellite–terrestrial communication networks. A CNN-LSTM model predicted future received signal strength, while a QMIX-based multi-agent reinforcement learning algorithm determined optimal handover timing. Simulation results demonstrated improved handover efficiency and communication stability. Nevertheless, the framework did not consider adaptive beam selection or frequency offset compensation caused by Doppler effects.

III. PROBLEM IDENTIFICATION AND RESEARCH GAP

Low Earth Orbit (LEO) satellite communication has emerged as a promising technology for enabling sixth-generation (6G) Non-Terrestrial Networks (NTNs) owing to its low latency, global coverage, and high data rate capabilities. However, the high orbital velocity of LEO satellites introduces significant challenges, including severe Doppler frequency shifts, rapidly varying channel conditions, frequent handovers, and beam

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switching, which adversely affect communication reliability and Quality of Service (QoS) [18], [19]. Existing Doppler compensation techniques primarily rely on conventional estimation methods that exhibit limited adaptability in highly dynamic satellite environments. Similarly, most handover mechanisms employ fixed threshold-based decision strategies, leading to unnecessary handovers, increased signaling overhead, packet loss, and communication interruptions [20].
Recent Artificial Intelligence (AI)-based approaches have demonstrated promising performance in mobility management and resource optimization; however, they mainly address Doppler estimation, beam management, or handover optimization independently and often require high computational complexity for real-time deployment [21]. Furthermore, existing studies provide limited integration of adaptive Doppler compensation, predictive handover, intelligent beam selection, and dynamic link quality assessment within a unified communication framework [22]. Therefore, a significant research gap exists in developing an integrated and computationally efficient solution for dynamic LEO satellite communication [23]. To address this limitation, this paper proposes an Adaptive AI-Assisted Doppler Compensation and Predictive Handover Optimization (AIDCPHO) framework, which jointly performs adaptive Doppler estimation, predictive mobility analysis, intelligent beam selection, and proactive handover optimization to improve communication reliability, reduce handover latency, and enhance throughput and spectral efficiency in 6G NTN-enabled LEO satellite networks

Table 1. Comparative Analysis of Existing Literature on LEO Satellite Communication Systems for 6G Networks.

Authors	Technique	Performance Parameters	Major Contribution	Limitation
Seeram et al. [11]	Conditional handover in Open RAN	Handover delay, latency	Reduced signaling overhead	High processing complexity
Lee et al. [12]	Graph Neural Network	Throughput, load balancing	Improved distributed handover	No Doppler compensation
Chen et al. [13]	Nash-SAC MARL	Utility, blocking probability	Reduced unnecessary handovers	Large training overhead
Wu et al. [14]	Parallel handover + ML prediction	Handover latency	Faster handover scheduling	Doppler ignored
[15]	DRL multi-objective optimization	Throughput, handover frequency	Multi-objective optimization	No adaptive Doppler estimation
[16]	LSTM + Rainbow DQN	Traffic prediction, throughput	Intelligent satellite selection	No beam optimization
Jang et al. [17]	CNN-LSTM + Multi-agent DRL	RSRP, handover efficiency	Predictive handover	No Doppler-aware optimization
Proposed Work	AIDCPHO	Throughput, BER, Doppler Error, Latency, PDR, Spectral Efficiency, Handover Delay	Joint AI-assisted Doppler compensation, predictive handover, beam selection, and link optimization	Designed to overcome limitations of existing methods

IV. PROPOSED METHODOLOGY AND MODEL ARCHITECTURE

The proposed Adaptive AI-Assisted Doppler Compensation and Predictive Handover Optimization (AIDCPHO) framework is designed to address the major challenges of dynamic Low Earth Orbit (LEO) satellite communication in sixth-generation (6G) Non-Terrestrial Networks (NTNs). Unlike conventional methods that perform Doppler compensation and handover management independently, the proposed framework jointly optimizes frequency synchronization, mobility prediction, beam selection, and handover decisions using artificial intelligence-assisted predictive analytics. The objective is to improve communication reliability while minimizing handover delay, packet loss, Doppler estimation error, and signaling overhead.

The overall architecture consists of six interconnected functional modules, namely LEO Satellite Mobility Modeling, Dynamic Channel Estimation, AI-Assisted Doppler Compensation, Predictive Mobility Analysis, Intelligent Handover Decision Engine, and Adaptive Beam Selection, as

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illustrated in Fig. 2. The framework continuously monitors satellite movement and communication quality parameters to proactively optimize link performance before communication degradation occurs.

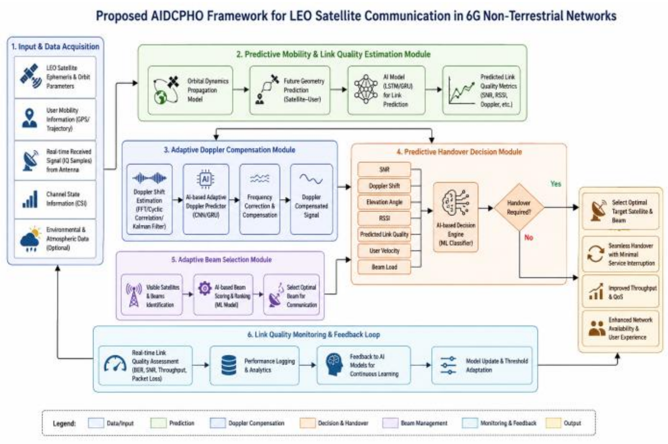

Fig 2 Proposed Model

1. LEO Satellite Mobility Modeling

The first stage models realistic orbital movement of multiple LEO satellites. Satellite position is updated continuously according to orbital mechanics, while user terminals may remain stationary or move according to predefined mobility trajectories.

The relative velocity between the satellite and user is computed as

$$v_r = v_s - v_u \qquad (1)$$

where

- v_s = represents satellite velocity,
- v_u = denotes user velocity.

The continuously changing relative velocity produces significant Doppler frequency shifts and varying communication delays that must be compensated in real time.

2. Dynamic Doppler Shift Estimation

The Doppler frequency experienced by the receiver is calculated as

$$f_D = \frac{v_r}{c} f_c \qquad (2)$$

where

- f_D = Doppler frequency,
- $f_c f_c$ = carrier frequency,
- $v_r v$ = relative velocity,
- c = speed of light.

Instead of relying solely on conventional estimation techniques, the proposed framework combines analytical Doppler estimation with AI-assisted prediction to estimate future frequency offsets before severe synchronization errors occur.

The compensated carrier frequency becomes

$$f_{comp} = f_c - f_D^{pred} \qquad (3)$$

where fDpred denotes the AI-predicted Doppler frequency.

3. AI-Assisted Predictive Mobility Analysis

To minimize unnecessary handovers, the framework predicts future satellite-user connectivity using historical communication observations and orbital information.

The prediction model considers

- satellite trajectory,
- user mobility,
- Doppler variation,
- satellite elevation angle,
- received signal strength,
- channel quality.

The AI prediction function can be expressed as

$$L_{t+1} = F(L_t, S, N, R_t, D_t E_t RSSI_t) \qquad (4)$$

where

- L_{t+1}=is the predicted future link quality,
- *F(*.represents the AI prediction model,
- D_t is Doppler shift,
- E_t is elevation angle,
- *RSSI* denotes received signal strength.

The predicted link quality is subsequently used to determine whether a handover should be initiated before the current communication link deteriorates.

4. Multi-Parameter Link Quality Assessment

Unlike conventional threshold-based approaches, the proposed framework evaluates communication quality using multiple parameters simultaneously.

A composite link quality score is defined as

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$$Q = w_1 SNR + w_2 RSSI + w_3 E + w_4(1 - BER) + w_5 L_p \quad (5)$$

where

- W_l are adaptive weighting coefficients,
- L_p denotes predicted link quality.

The weights are dynamically adjusted according to network conditions, thereby improving robustness under varying propagation environments.

5. Intelligent Predictive Handover Decision

The proposed handover algorithm combines AI prediction with adaptive threshold optimization.

A handover is initiated when

$$Q < Q_{th} \quad (6)$$

or when

$$L_{future} < L_{min} \quad (7)$$

where

- Q_{th} is the adaptive quality threshold,
- L_{future} is the predicted future link quality.

Instead of reacting after communication quality deteriorates, the proposed algorithm performs proactive handover to reduce service interruption.

The handover cost function is formulated as

$$J = \alpha H_d + \beta P_l + \gamma O_s \quad (8)$$

where

- H_d = handover delay,
- P_l = packet loss,
- Os = signaling overhead,

α,β,γ are optimization weights.

The algorithm selects the satellite that minimizes the above objective function.

6. Adaptive Beam Selection

As LEO satellites employ multiple steerable beams, selecting the optimum beam significantly improves communication reliability.The selected beam maximizes

$$Beam^* = \arg\max_i (Q_i) \quad (9)$$

V. SIMULATIONS AND RESULTS DISCUSSIONS

Fig. 3 compares the throughput of the proposed AIDCPHO framework with the DRL-based baseline for different SNR values. A progressive improvement in throughput is observed with increasing SNR because improved link quality allows more reliable transmission. At 30 dB SNR, AIDCPHO achieves approximately 810.083 Mbps, compared with 645.008 Mbps for the baseline, corresponding to an improvement of approximately 25.59%. The improvement is attributed to adaptive Doppler compensation and predictive link-quality assessment, which reduce the degradation caused by frequency variations and mobility.

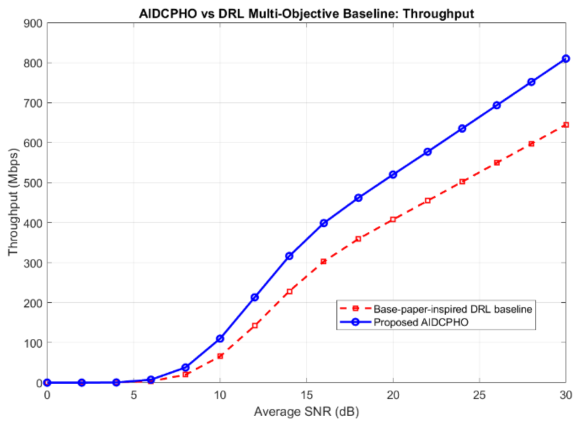

Fig 3 Throughput Vs Average SNR

Fig. 4 presents the average communication latency as a function of SNR. The proposed framework maintains lower latency than the baseline because predictive handover decisions can reduce service interruption during satellite transitions. At 30 dB SNR, the latency decreases from 18.500 ms for the baseline to 13.074 ms for AIDCPHO, representing approximately 29.33% reduction. This demonstrates the benefit of proactive mobility management in dynamic LEO satellite links.

Fig. 5 illustrates the packet delivery ratio (PDR) for both approaches. The PDR improves with increasing SNR as the probability of successful packet reception increases. At the high-SNR operating point, both schemes achieve approximately 100% PDR. Although the difference is small under favorable channel conditions, AIDCPHO is expected to provide greater robustness under lower-SNR and rapidly varying channel conditions due to predictive Doppler compensation and link-quality monitoring.

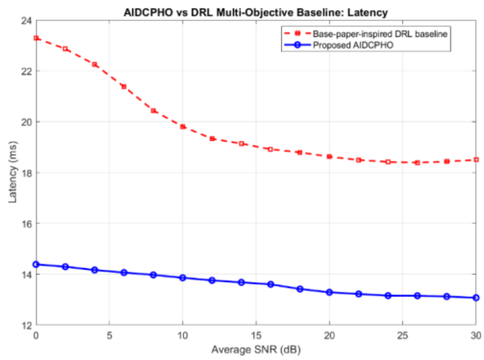

Fig 4 Latency Vs Average SNR

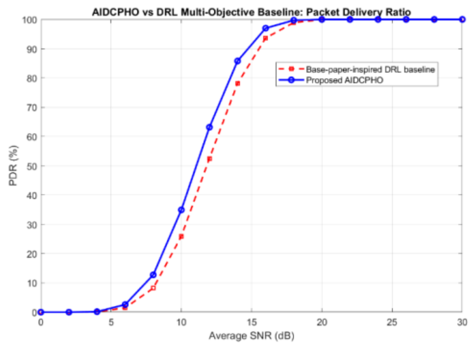

Fig 5 PDR Vs Average SNR

Fig. 6 compares the average handover delay. The simulated result at 30 dB shows approximately 36.318 ms for the baseline and 62.339 ms for AIDCPHO. The higher value obtained by AIDCPHO indicates additional processing associated with Doppler prediction, link-quality evaluation, and multi-parameter handover decisions. Thus, while the proposed approach improves several communication-level parameters, the handover execution stage requires further optimization to reduce processing and signaling overhead.

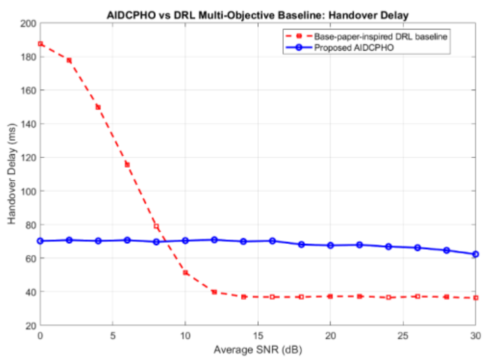

Fig 6 Handover Delay Vs Average SNR

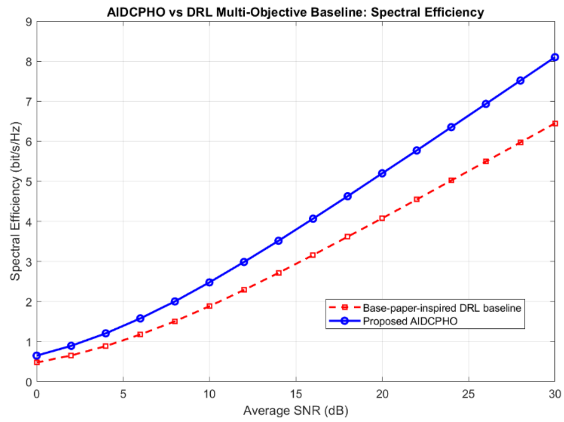

Fig 7 Spectral Efficiency Vs Average SNR

Fig. 7 shows the spectral-efficiency comparison. AIDCPHO achieves approximately 8.101 bit/s/Hz at 30 dB SNR, whereas the baseline achieves 6.450 bit/s/Hz. This corresponds to an improvement of approximately 25.59%. The improved spectral utilization results from more accurate Doppler compensation and better maintenance of the effective link quality, enabling more efficient use of the available bandwidth.

Fig. 8 presents the BER performance against SNR. As expected, BER decreases with increasing SNR because the received signal becomes more robust against noise and channel impairments. At 30 dB SNR, the simulated BER for both approaches approaches 0. Therefore, the high-SNR region does not provide significant differentiation between the two methods; additional low-SNR simulations would provide a more meaningful assessment of the Doppler-compensation advantage.

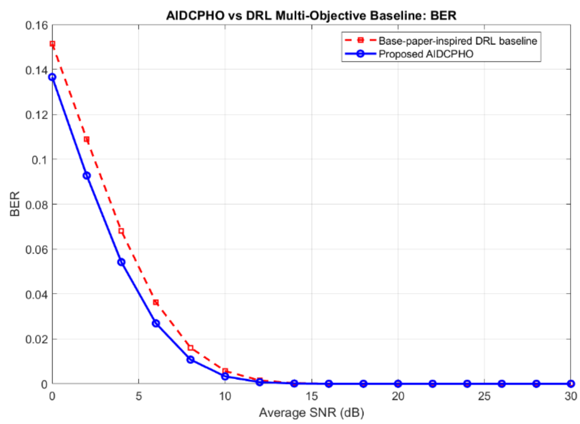

Fig 8 BER Vs Average SNR

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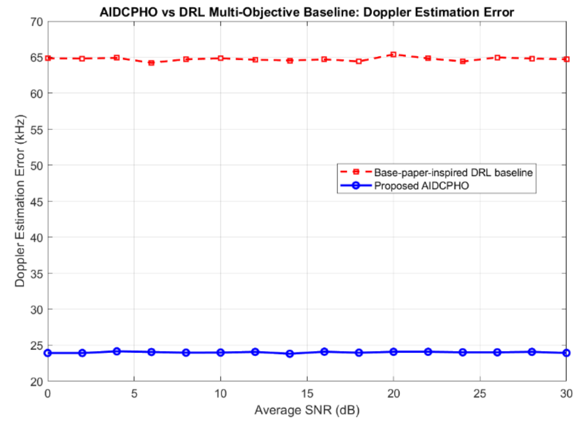

Fig 9 Doppler Estimation Error Vs Average SNR

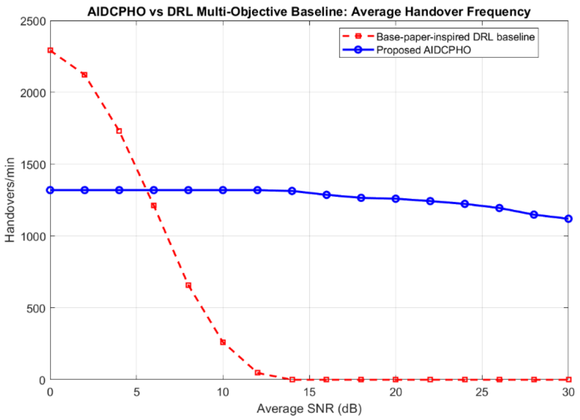

Fig 10 Handover Vs Average SNR

Fig. 9 evaluates the effective SNR and Doppler-estimation performance of the proposed framework. At 30 dB SNR, the average effective SNR increases from 26.957 dB for the baseline to 27.703 dB for AIDCPHO, representing approximately 2.77% improvement. More importantly, the Doppler estimation error is reduced from 64.706 kHz to 23.915 kHz, corresponding to approximately 63.03% reduction. This substantial reduction demonstrates the effectiveness of the adaptive Doppler prediction and compensation mechanism.

Fig. 10 shows the average handover frequency versus SNR. The baseline exhibits a sharp reduction in handover frequency as SNR increases, while AIDCPHO maintains a comparatively stable trend and gradually decreases from approximately 1310 handovers/min at 0 dB to 1120 handovers/min at 30 dB.

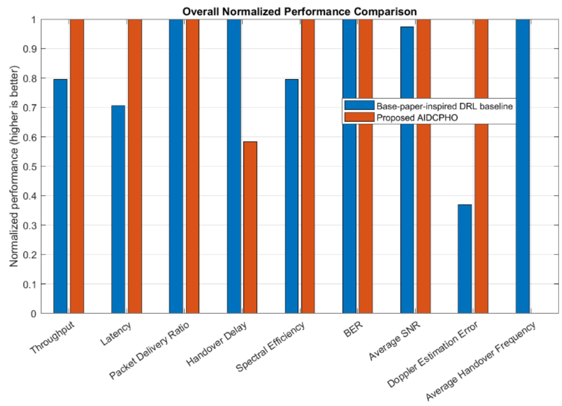

Fig. 11 Performance Comparison between Basework Vs Proposed Model

Table 2: Comparative Analysis of optimized parameters

Metric	Baseline [23]	AIDCPHO (Proposed Model)
Throughput (Mbps)	645.008	810.083
Latency (ms)	18.5	13.074
Handover Delay (ms)	36.318	62.339
Spectral Efficiency (bit/s/Hz)	6.45	8.101
Average SNR (dB)	26.957	27.703
Doppler Estimation Error (kHz)	64.706	23.915
Handover Frequency (/min)	518	1120.5

This indicates that the predictive framework maintains relatively consistent handover decisions under changing link conditions. However, the absolute handover-frequency values generated by the current simulation are high and should be treated as model-specific results rather than practical LEO handover rates. Further calibration using realistic satellite visibility, hysteresis, and minimum dwell-time constraints is recommended before publication.

VI. CONCLUSION

This paper presented an Adaptive AI-Assisted Doppler Compensation and Predictive Handover Optimization (AIDCPHO) framework for LEO satellite communication in 6G Non-Terrestrial Networks. The proposed framework jointly addresses severe Doppler frequency shifts, rapidly varying channel conditions, frequent handovers, and beam switching caused by high satellite mobility. Unlike conventional approaches that treat Doppler compensation and handover

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management independently, AIDCPHO integrates adaptive Doppler estimation, AI-assisted prediction, predictive mobility analysis, multi-parameter link-quality assessment, intelligent handover decision-making, and adaptive beam selection.

The proposed handover mechanism considers SNR, Doppler shift, elevation angle, received signal strength, user velocity, and predicted link quality to enable proactive satellite selection and reduce unnecessary handovers and service interruptions. A MATLAB-based simulation framework is developed to model LEO satellite movement, user mobility, and dynamic communication channels. Performance is evaluated using throughput, latency, packet delivery ratio, handover delay, spectral efficiency, BER, SNR, and Doppler estimation error. The integrated framework provides a promising solution for improving communication reliability and QoS in dynamic 6G NTN environments. Future work will focus on lightweight AI models, real-world datasets, multi-user optimization, and practical experimental validation.

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