Predictive QoS for Cellular-Connected UAV Communications

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***Abstract*—Unmanned aerial vehicles (UAVs), or drones, are transforming industries due to their affordability, ease of use, and adaptability. This emphasizes the need for reliable communication links, especially in beyond-line-of-sight scenarios. This paper investigates the feasibility of predicting future quality of service (QoS) in UAV payload communication links, with a special focus on 5G cellular technology. Through field tests conducted in a suburban environment, we explore challenges and trade-offs that cellular-connected UAVs face, particularly in the context of frequency band selection. We employed machine learning models to forecast uplink (UL) throughput for UAV payload communication, highlighting the significance of diverse training data for accurate predictions. The results reveal the effect of frequency band selection on UAV UL throughput rates at varying altitudes and the influence of integrating diverse feature sets, including radio, network, and spatial features, on ML model performance. These insights provide a foundation for addressing the complexities in UAV communications and enhancing UAV operations in modern networks.**

***Index Terms*—UAV, 5G, 6G, Machine Learning (ML), QoS**

I. Introduction

In recent years, unmanned aerial vehicles (UAVs) have seen significant growth in use across various civilian applications, including aerial surveillance, traffic control, photography, package delivery, and communication relaying. Current UAV systems often rely on point-to-point communication in unlicensed bands, offering limited data rates and range while being susceptible to interference and security concerns. Therefore, several technical challenges must be addressed before the full potential of UAVs can be utilized. A critical requirement is the establishment of high-capacity, low-latency, and ultra-reliable two-way wireless communications between UAVs and ground entities. This is pivotal for ensuring the safety of both UAV operations and the effective transfer of mission-specific payload data. UAVs typically depend on two distinct communication channels: the command and non-payload communication link for control instructions and the payload communication link for transmitting data such as video and sensor information. As the number of UAVs continues to rise, there is a pressing need for innovative wireless technologies to enhance UAV-ground communications.

One promising solution is cellular-connected UAVs, where UAVs are integrated with existing and forthcoming cellular networks. This approach presents numerous advantages, such as ubiquitous availability, enhanced performance, simplified monitoring and management, robust navigation, and cost-effectiveness. Leveraging the extensive global coverage of cellular networks, this integration facilitates remote UAV control, live video streaming, and large-scale air traffic monitoring [1]. However, challenges exist in adapting existing cellular network designs primarily intended for ground users to meet the unique requirements of UAVs such as air-to-ground channel models and frequent handovers.

Previous studies have evaluated the performance of uplink (UL) throughput in LTE-A and 5G networks for UAVs, emphasizing the impact of altitude or the three-dimensional (3D) movement of UAV on data transmission and network-related issues such as network planning challenges [2] [3] [4]. Therefore, the dynamic wireless channel conditions and network-related issues pose significant challenges in maintaining uninterrupted data transmission. To achieve uninterrupted data transmission, we propose the use of future QoS prediction. Specifically, we aim to predict the future UL throughput QoS parameter in the UAV's payload communication link using machine learning (ML) techniques. This proactive approach enables application adaptation based on the anticipated QoS.

ML-based QoS prediction has been recently considered also in the context of vehicular communications [5]. Predictive quality of service (PQoS) has been examined within the context of the vehicle to everything (V2X) applications in [6], specifically in teleoperated driving scenarios. However, PQoS considerations for UAV use cases have not received any attention in the existing literature. Aerial users and ground users need to be treated differently, primarily because UAVs require comprehensive 3D coverage due to their operations in airspace. Therefore, in this paper, we evaluate the feasibility of using PQoS for UL throughput prediction in 5G networks for UAV mobility scenarios. We collect physical layer radio metrics and UL throughput data by flying a drone at different altitudes and employing time series ML models to make predictions. We compare various centralized ML models to determine the most accurate predictor by validating the models using a test dataset derived from practical experiments.

This paper is organized as follows: in Section II we provide an overview of the challenges associated with cellular-connected UAVs and explore the concept of PQoS for cellular-connected UAVs. Section III delves into the field trial setup, data collection, and analysis process. In Section IV, we discuss the implementation of ML techniques and evaluate the obtained results. Finally, Section V concludes the paper with a summary of the main results.

II. Background

A. Characteristics and Challenges of UAV Propagation Over Network

Communication channels between UAV and base station (BS) are subject to various influencing factors, including flight altitude, environmental conditions, and obstacles, resulting in varying propagation characteristics. Line of sight (LoS) links are more common for smaller UAVs, reducing signal fading and enabling the use of lower transmit power levels. These channels exhibit small-scale fading often modeled as Ricean fading when LOS components coexist with multipath components. UAV velocity introduces Doppler shifts, mobility-induced changes in the channel impulse response, and antenna effects also play a significant role in the UAV communication quality [7]. Higher altitudes generally provide better LoS connectivity with the BS, reducing shadowing and path loss [8]. However, an optimal UAV operation altitude remains challenging to determine. UAVs operating at higher altitudes necessitate BSs to provide 3D communication coverage. UAVs require specific antenna configurations since existing base stations, which have downward-tilted antennas, are primarily designed for terrestrial users [9]. One should also consider the potential of UAVs to cause harmful interference to the ground system unless well-designed [10]. Performance evaluations reveal that UAVs experience frequent handovers due to their mobility, leading to increased latency and data transmission challenges. UAVs are estimated to undergo approximately five times more handovers than ground-level UEs [3]. Network planning challenges include the provision of coverage for aerial users and addressing issues like Physical Cell Identity (PCI) allocation. In the context of 5G, the number of available PCIs has doubled in comparison to 4G. These distinct PCIs complicate allocation, especially for UAVs flying at higher altitudes, where they may have LoS connectivity to multiple cells sharing the same PCI [2]. Additionally, Channel State Information (CSI) exchange between UAVs and BSs is crucial for resource allocation. However, communication delays (feedback delay) can hinder adaptive scheduling, potentially leading to inefficient resource allocation. An underestimation of channel quality can result in spectral resource wastage, while overestimation can lead to transmission failures [4]. UAVs owing to their mobility necessitate more frequent transmission of CSI information. In high-mobility scenarios, narrow beams can also restrict the duration for which the UAV remains within a particular beam, posing challenges for channel estimation and link adaptation. This increased beam switching can lead to decreased performance, requiring more resources and resulting in longer data transmission times. It is evident from these considerations that the unique UAV propagation channel characteristics present both opportunities and challenges for cellular-connected UAV communication.

B. Predictive QoS

In the context of cellular-connected UAV communication, perception data which includes sensor, video, and image

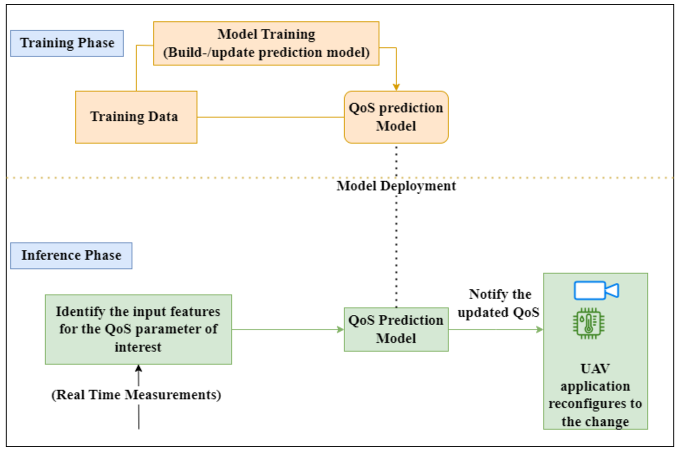

Fig. 1. PQoS Model.

data, is transmitted to a remote control station via a cellular network. The configuration of this data transmission relies on factors such as drone speed, environmental conditions, and QoS requirements. Achieving the desired QoS is influenced by various factors, including user equipment (UE) density, interference, mobility, and handovers. For mission-critical UAV services such as safety and automated piloting, it is essential to avoid sudden session interruptions arising from QoS degradation. Traditional networks employ reactive QoS management which responds to QoS changes as they occur. However, this approach presents significant challenges for automated piloting, where uninterrupted data transmission is critical. By proactive QoS management, the system predicts potential changes in QoS levels during established communication sessions and promptly notifies the UAV application of anticipated QoS changes (improvements or degradation) before they occur. In response to these predictions, the UAV application adjusts its communication strategy, for instance, opting for a low-bandwidth approach for UL payload transmission when QoS levels are expected to decrease and switching to a high-bandwidth approach when QoS levels tend to increase. Alternatively, in video transmission, the bitrate of the encoder can be adjusted based on the prediction. Fig. 1 illustrates the PQoS model. The accurate prediction of QoS parameters depends upon the selection of relevant features. Specifically, different QoS metrics, such as latency and throughput, may be influenced by distinct set of features. This distinction holds true for both uplink and downlink scenarios. The prediction horizon, which represents the duration during which a prediction remains valid needs to be chosen carefully. This horizon can vary depending on the specific use cases of UAVs. The prediction horizon is inherently tied to factors such as the mobility speed of the UAV and the nature of the use case. For instance, in mission-critical applications where split-second decisions are crucial, a relatively shorter prediction horizon is essential. This ensures that the predictions made align with the rapidly changing conditions and meet the strict requirements of mission-critical tasks.

III. Data Collection and Analysis

A. Data Collection

The drone flights for data collection were conducted in the outskirts of Oulu, Finland. Traficom's civil aviation regulations were adhered to during the trials to ensure safety and compliance. The trials were carried out below the maximum flying limit of 120 meters in a non-prohibited flying area, with the drone remaining within the operator's LoS throughout the flights. Permission for the trials was obtained from a mobile network operator, referred to as 'Operator A'. The available networks were primarily 5G Non-Standalone networks. For data collection MediaTek prototype phones, equipped with SIM cards from Operator A, were utilized for data collection. Measurements were systematically collected along a predefined drone route that instructed the drone to make a 90-degree turn every 300 meters. The MediaTek device was attached to one of the legs of a DJI M300 drone to replicate the scenario of a cellular-connected drone, as commercially available cellular-connected drones are not yet available. Data was collected at a frequency of 3 seconds, and flights were conducted at various altitudes with multiple repetitions to ensure data accuracy. The UL throughput configuration was set to maximum for all measurements. Two phones, UE1 and UE2, were employed for data collection. UE2 was used for drone flights at altitudes of 100 meters and for manual flights due to battery constraints in UE1. We used UE1 to collect measurements at altitudes of 50, 70, 80, and 90 meters. UE1 generated a total of 1677 data points, while UE2 collected 581 data points during the data collection process. Each round of measurements lasted approximately 5 minutes, and data collection concluded when the drone's battery was depleted.

B. Data Analysis

In this paper, we focus on 5G-related metrics as illustrated in Table I, and we selected these metrics based on prior research in QoS prediction. The data collected during flights includes physical layer radio metrics, some network features, and spatial information such as location and speed. Fig. 2 illustrates that UE2 exhibited higher NR_RSRP values compared to those of UE1. It could also be observed from Fig. 2 that, UE2 consistently achieved higher UL throughput rates, ranging from 70 to 100 Mbps throughout its flight. In contrast, UE1's UL throughput peaked when the drone was at 50 meters, with throughput declining as the drone ascended to 70, 80, and 90 meters. Therefore, UE1's UL throughput exhibited a clear inverse relationship with increasing altitude.

UE2 outperformed UE1 in several key aspects. UE1 experienced an increase in the number of handovers as the drone flew at higher altitudes, UE2 demonstrated notably different behavior despite sharing identical hardware. Fig. 3 which corresponds to handover events, i.e., the changes in NR_PCI as the drone moved both vertically and horizontally. Handover decisions for UE1 are primarily influenced by variations in the RSRP values received from different BS antennas. UAVs rely on the side lobes of the BS antennas for communication, and they often encounter similar RSRP values from different cells. Even minor fluctuations in RSRP could trigger frequent

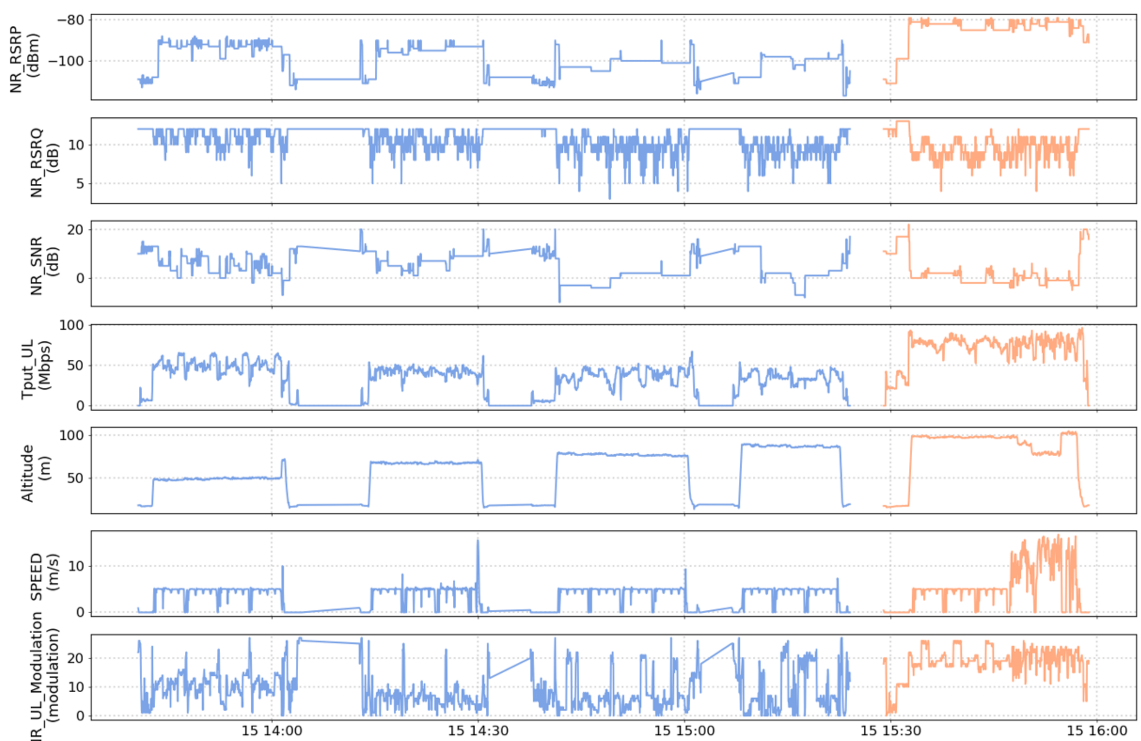

Fig. 2. Overview of Measurements (UE1 is shown with blue and UE2 with orange lines).

TABLE I
MEASUREMENTS COLLECTED

Column Name	Meaning
timestamp	Timestamp of the observation
NR_PCI	Physical Cell ID of NR network
NR_RSRP	Reference Signal Received Power in NR
NR_RSRQ	Reference Signal Received Quality in NR
NR_SNR	Signal-to-Noise Ratio in NR
Tput_UL	Uplink Throughput in Mbps
ULBLER	Uplink Block Error Rate
NR_UL_Modulation	Uplink Modulation in NR
Altitude	Altitude of drone
Latitude	Latitude of the drone
Longitude	Longitude of the drone
SPEED	Speed of the drone

handover events, as the UAV struggles to identify the optimal cell providing the best RSRP value to meet its connectivity requirements [3]. However, even when operating at an altitude of 100 meters, UE2 experienced no handovers. Drones flying at 100 meters are likely to have LOS connectivity with multiple BSs in the network. However, UE2 remained consistently connected to the same cell throughout its flight. One could also see from Figs. 2 and 3 that UE2's performance surpassed that of UE1, showcasing superior connectivity stability and throughput.

C. Performance Discrepancy Analysis Between UE1 and UE2

Table II presents a summary of the BSs and frequency bands to which the UEs connected during the flight trials. UE2 established connections with both n78 3500 MHz time division duplexing (TDD) and n28 700 MHz frequency division duplexing (FDD) frequency bands, whereas UE1 remained connected exclusively to the n78 (3500 MHz TDD) band

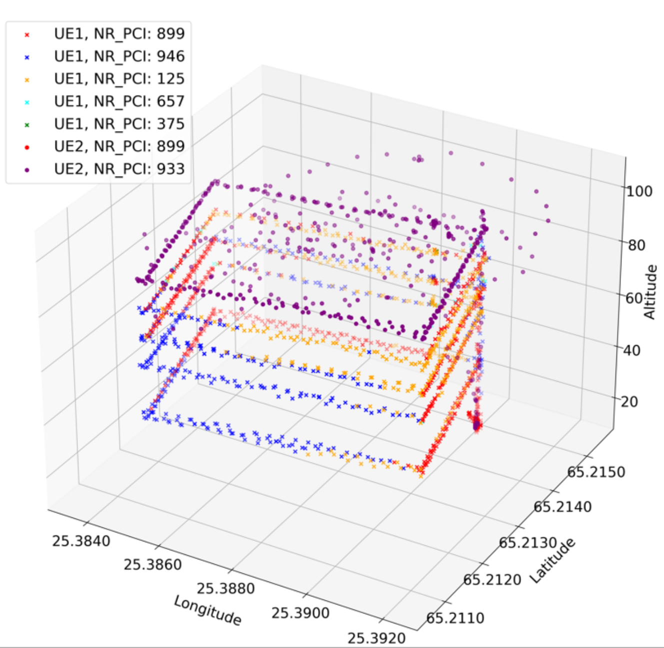

Fig. 3. 3D plot that shows the handover events.

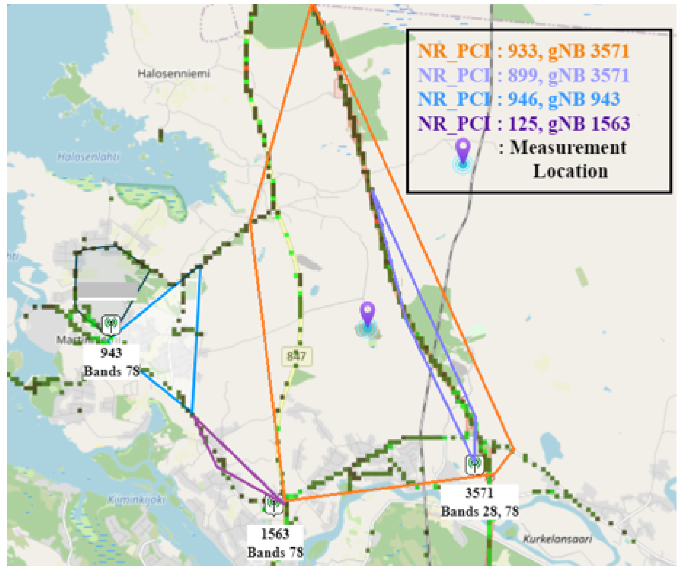

Fig. 4. Cell coverage.

throughout the flight trials. The identification of these BSs is based on NR_PCI data obtained from CellMapper.

TABLE II
UE1 AND UE2 BASE STATION CONNECTIONS AND FREQUENCY BANDS

Base station	NR_PCI	Frequency band (MHz)	UE connected
gNB ID 3571	899	3500 (n78 TDD)	UE1, UE2
gNB ID 3571	933	700 (n28 FDD)	UE2
gNB ID 1563	125	3500 (n78 TDD)	UE1
gNB ID 956	657	3500 (n78 TDD)	UE1
gNB ID 943	946	3500 (n78 TDD)	UE1
gNB ID 2074	375	3500 (n78 TDD)	UE1

We noticed that at altitudes above 80 meters, UE1 occasionally connected to the distant gNB 2074 (NR_PCI 375), which was an unexpected occurrence considering the distance from the measurement location. This highlights the influence of unexpected BS interference on UAV handovers. The performance difference between UE1 and UE2 can be attributed to the frequency bands they were connected. UE2 supported both n28 and n78 bands and maintained stable performance without handovers due to the n28 band's wider coverage and better interference tolerance. Fig. 4. shows the coverage area of the main cells to which the UEs were connected during measurements. On the other hand, UE1's connectivity was limited to the n78 band and hence experienced more handovers at higher altitudes.

The n78 band, operating at 3500 MHz is categorized as C-Band 5G spectrum, bridging the gap between low band and high-band frequencies. It offers faster data speeds compared to low band frequencies and wider coverage compared to high band frequencies, making it suitable for various scenarios like fixed user connections and slow moving indoor users. While it strikes a favorable balance between speed and coverage for ground based 5G applications, it may not be the optimal choice for aerial applications like UAVs.

The 700 Mhz n28 band frequency band is particularly well-suited for mobile broadband users in rural areas who may be moving at medium to high speeds. It's ideal for scenarios where maintaining communication with mobile subscribers in conditions of high Doppler carrier frequency shift is crucial. The lower frequency of the 700 MHz band offers advantages for communicating with subscribers moving at higher speeds. As evidenced by Fig. 4, n28 provided excellent coverage and stable performance during UAV flight operations at higher altitudes. Therefore, it appears to be a promising frequency band for UAV operations, providing consistent performance even at higher altitudes. However, further research is needed to determine the optimal n28 frequency for UAV applications across different traffic conditions and locations.

IV. ML BASED PREDICTION METHODS

We employ different ML techniques to enhance QoS at the application layer by predicting the QoS parameter UL throughput at the next time step. UL throughput signifies the data transmission rate from UE to the network. This parameter plays a pivotal role in shaping the performance of applications on the user's device. Accurate QoS prediction is of paramount importance to ensure seamless and reliable data transmission, as well as efficient resource allocation.

The collected dataset is used to train ML models, which include ensemble methods like random forest and XGBoost, as well as recurrent neural networks (RNNs) such as long short-term memory (LSTM) and gated recurrent unit (GRU). These model choices are based on insights from related research in V2X applications like teleoperated driving, autonomous system and video transmission. To assess the model's performance, we employed several key metrics, including mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). Lower values for MAE, MSE, and RMSE signify higher model accuracy, while achieving a lower MAPE, typically below 10%, is considered good. The dataset required minimal cleaning, involving outlier removal and handling null values. Data was transformed into sequences of length 5 for the RNN model, with 90% used for training and the last 10% for testing. The MinMaxScaler function was utilized for data normalization, and Python, TensorFlow, and Keras were used for model implementation.

A. Feature Engineering

The features used for training the ML model are grouped into four distinct sets. Table III illustrates each feature set containing specific subsets of columns from the original dataset which captures different aspects of the data.

- **Feature set A** includes all available features in the dataset, providing the most comprehensive set of features for analysis and model training.
- **Feature set B** comprises essential radio-related features, along with location and speed information. These features are important for evaluating radio signals while considering spatial and speed characteristics.

TABLE III
FEATURE GROUPS

Features	Feature set A	Feature set B	Feature set C	Feature set D
NR_RSRP	x	x	x	x
NR_RSRQ	x	x	x	x
NR_SNR	x	x	x	x
Tput_UL	x	x	x	x
ULBLER	x			
UL Modulation	x			
NR_PCI	x			
Altitude	x	x	x	
Latitude	x	x		
Longitude	x	x		
SPEED	x	x	x	

- **Feature set C** consists of features selected based on strong correlations with the target variable (UL throughput at the next time step) based on Pearson's correlation coefficient.
- **Feature set D** focuses only on radio-related metrics and throughput, while excluding spatial and speed characteristics. This aids in assessing whether spatial factors have a positive or negative impact on the model's predictions.

B. Model Training and Evaluation Using UE1 Data

Test data comprises of the last 140 data points from the dataset. The drone maintained an altitude of approximately 90 meters above sea level for most of the data points. These data points exhibit both rapid increase (e.g., 33, 46 Mbps) and decrease (e.g., 16, 21 Mbps) in UL throughput values, indicating significant fluctuations over short periods as well as instances of minor fluctuations. Among the models considered, we found that RF from the ensemble category and GRU from the RNN category demonstrated slightly better performance. Fig. 5 and 6 provide an informative overview of RF and GRU model performance on the test data.

The analysis of the RF model's performance on the test data, illustrated in Fig. 5, demonstrates that predicted throughput values generally closely align with actual values. Despite deviations during rapid changes, the model captures the overall trend effectively. The RF model exhibits its best performance when trained with all feature columns (*Feature set A*), with the lowest MAE (1.888 Mbps) as indicated in Table IV. The results in Table IV highlight that the RF regressor consistently

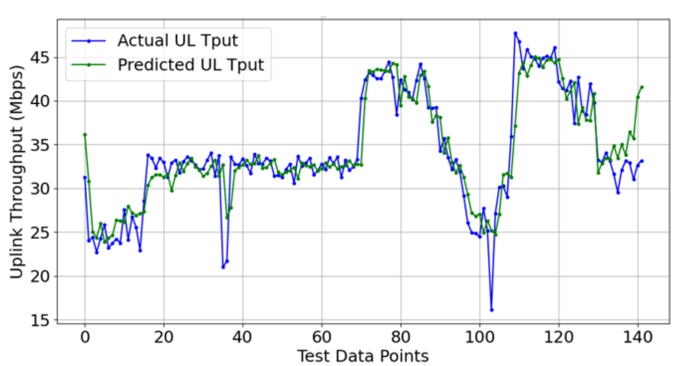

Fig. 5. Best RF model predictions (*Feature set A*) on UE1 data.

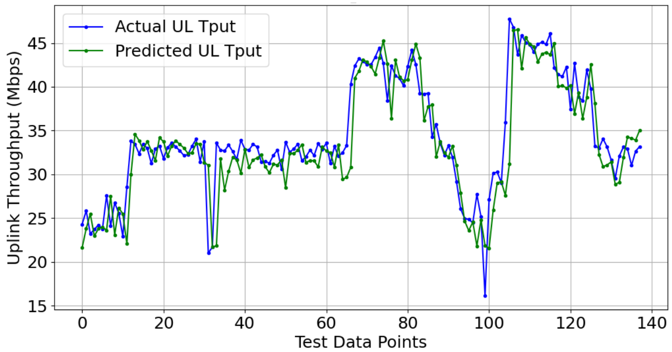

Fig. 6. Best GRU model predictions (*Feature set C*) on UE1 data.

TABLE IV
REGRESSION MODEL PERFORMANCE METRICS

Model	Feature set	MAE	MSE	RMSE	MAPE
RF	A	1.888	7.601	2.757	0.060
RF	B	2.235	8.919	2.986	0.071
RF	C	2.172	9.216	3.036	0.069
RF	D	2.310	9.976	3.158	0.073
XGB	A	2.389	9.936	3.152	0.078
XGB	B	2.397	9.936	3.152	0.079
XGB	C	2.427	10.571	3.251	0.079
XGB	D	2.381	10.566	3.250	0.076
GRU	A	2.906	13.326	3.650	0.089
GRU	B	3.165	16.642	4.079	0.099
GRU	C	2.148	10.166	3.188	0.065
GRU	D	2.232	11.220	3.349	0.068
LSTM	A	3.002	14.593	3.820	0.092
LSTM	B	3.142	17.310	4.161	0.100
LSTM	C	2.588	11.462	3.386	0.080
LSTM	D	2.171	11.395	3.376	0.068

performs well across all feature sets, demonstrating low MAE, MSE, RMSE, and MAPE values, indicating its robustness and versatility for this dataset. The evaluation of different feature sets provides insights into feature relevance, for instance, as illustrated in Table IV, *Feature set D*, which includes radio metrics and UL throughput, performs well across models, emphasizing the importance of these radio-related metrics for accurate predictions.

While the performance of LSTM and GRU models is competitive with RF and XGBoost regressors, they tend to exhibit slightly higher MAE, MSE, RMSE, and MAPE values, particularly in certain feature sets. This suggests that, for this specific task, simpler models like the RF regressor can achieve comparable or better performance.

In our study, we found that training ML models on a diverse set of flying scenarios and altitudes improved predictive performance. However, in rapidly changing environments, shorter prediction horizons may be more effective. The quality of training data significantly influences accuracy, emphasizing the need for a wider variety of scenarios.

V. CONCLUSIONS

This paper introduced the concept of PQoS in cellular-connected UAV and demonstrated how ML techniques can predict UL throughput, emphasizing the importance of diverse training data for accuracy. Analysis of frequency bands revealed that lower-frequency bands, like the 700 MHz band, offer superior signal propagation characteristics compared to higher-frequency bands, highlighting the importance of frequency selection in optimizing UAV communication. Based on our measurements, 700 MHz proved to be a promising choice for UAV operations than 3500 MHz, delivering robust performance and improved throughput at higher altitudes without performance trade-offs. We found that the RF model, trained with a comprehensive feature set that included radio, network, and spatial information, exhibited better performance compared to other ML models. This research provides valuable insights for designing reliable UAV communication systems and emphasizes data-driven approaches to tackle UAV-specific challenges, offering a foundation for further advancements in UAV communication integration into modern networks.

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