An Enhanced Path Loss Prediction Approach for the A2A Channel in UAV Communications

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Abstract **—Recently, unmanned aerial vehicles (UAVs) have found numerous telecommunication applications due to their high feasibility and low cost. Optimizing the UAV communications system requires determining the characteristics and sensitivity of wireless signals to propagation effects in different environments, and frequency bands. Hence, accurate path loss prediction models are vital for planning, evaluating, and optimizing UAV-based communication networks. This research proposes a path loss prediction model for UAV-to-UAV channels using two variants of the LSTM deep learning algorithm: bidirectional long short-term memory (LSTM) and encoder-decoder LSTM with hyperparameter tuning. The proposed model has been assessed using metrics such as mean absolute error (MAE), root mean square error (RMSE), and R-squared (R2). The proposed model has higher accuracy when compared with a traditional empirical model, and earlier machine learning models.**

Keywords**—air to air, bidirectional LSTM, deep learning, LSTM, encoder-decoder LSTM, path loss, UAV**

I. INTRODUCTION

In recent years, Unmanned Aerial Vehicles (UAVs) have been increasingly utilized in telecommunications, thanks to their high mobility and deployment flexibility. Future wireless systems will require more diverse applications with orders-of-magnitude capacity improvement than current systems. So leveraging UAVs for wireless communication shows great promise as an essential element in upcoming wireless systems. UAV communication links differ significantly from terrestrial links. Key factors influencing UAV links include Line of Sight (LoS), Non-Line of Sight (NLoS), Doppler frequencies, and carrier frequency...Therefore, thoroughly studying the UAV links in communication is essential [1].

The propagation channel in a communication system refers to the reduction in signal power between the transmitter (Tx) and receiver (Rx). Accurately modeling this channel is crucial for evaluating wireless coverage and analyzing interference. Parameters such as path loss, propagation delay, Doppler frequency shift, and the arrival and departure angles of individual multipath components are derived from the channel impulse response (CIR). Path loss modeling is essential for assessing both the signal strength of the desired transmission and the interference levels from unwanted signals in wireless communication systems. Path loss values are typically obtained using a channel sounder or through simulations based on ray-tracing principles [2].

Various established statistical path loss models in typical environments, such as outdoor urban-macro, urban-micro, rural, and indoor settings, have been introduced in previous works [3–7]. These models have achieved standardization in both 3GPP and the International Telecommunication Union (ITU) [8, 9]. Among them, the floating-intercept (FI) model and the close-in (CI) model stand out as the two most widely used statistical path loss models [10, 11]. Typically, these models have been constructed based on the one-dimensional (1D) affine function of a log-scaled distance between the transmitter (Tx) and receiver (Rx), with the residue from the fitted line further modeled as shadow fading. However, traditional log-distance path loss models fall short of capturing the complete complexity of the propagation environment, primarily due to their one-dimensional structure. For instance, path losses are considered identical for receiving points situated at the same distance from a fixed transmitter (TX) along the fitted line. Additionally, in traditional path loss models, the shadow fading of closely located receiving points is regarded as independent [12]. These traditional models might not adequately represent particular environments or circumstances since they are frequently generalized. Because of this, their forecasts could not be entirely accurate and could cause issues when put into practice. Furthermore, path loss models usually consider perfect circumstances and ignore dynamic phenomena like multipath propagation, fading, and shadowing. These elements have the potential to greatly affect signal reception and quality, which is why the current models need to be substantially improved and expanded upon [13, 14].

To enhance both accuracy and efficiency, machine learning (ML)-based propagation models have emerged as promising tools. Achieving offline training for these

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models can be realized through the utilization of either measured or synthetic (simulated) data. Moreover, their distinctly non-linear characteristics position them as excellent candidates for predicting propagation parameters, such as path loss [15]. Various algorithms, including Random Forest and KNN, Support Vector Regression (SVR), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) have been applied to train predictive models for path loss in UAV communication scenarios [16–18]. Besides, Mohamed et al. compared the major machine-learning-based path loss models for enclosed indoor channels. Their findings indicate that the RNN-LSTM algorithm achieves the best root-mean-square error (RMSE) performance [19]. This paper focuses on using deep learning to construct prediction models for path loss in the A2A scenario. The feasibility of the proposed models is assessed using MAE, RMSE, and R2 parameters. Additionally, the prediction accuracies of proposed models are also compared with the log-distance path loss model in the same public dataset. The results indicate that the models proposed in this study outperform traditional empirical models.

In this study, we investigate the use of deep learning for modeling path loss in air-to-air communication networks. Our main contributions are:

i) Identifying suitable features for the deep learning model based on an analysis of the impact of system parameters on channel loss.

ii) Proposing a path loss prediction model for channel estimation in A2A-based UAV communication, utilizing Bidirectional LSTM and encoder-decoder LSTM algorithms. This model has been implemented and its accuracy evaluated on a publicly available dataset.

The rest of the paper is structured as follows: Section II delves into problem formulation. Section III provides details proposed approach. In Section IV, a thorough analysis of the numerical results is conducted. Finally, Section V serves as the conclusion of the study, summarizing key findings and insights.

II. Problem Formulation

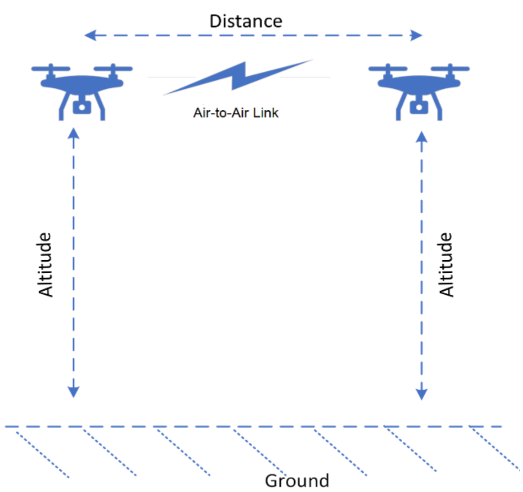


Fig. 1. A2A Chanel in UAV communications.

The air-to-air (A2A) communication channel refers to the communication between two unmanned aerial vehicles (UAVs), where one acts as the receiver and the other as the transmitter, with a direct line of sight between them. The A2A link is illustrated in Fig. 1. This study focuses on predicting the path loss of the A2A communication channel between two UAVs operating at the same altitude above the ground.

A. The Log-distance Path Loss Model

The most used model for calculating path loss is the log-distance path loss model. In this model, path loss depends greatly on the distance between the receiver and the transmitter [20]. This value on a dB scale is calculated according to the following formula:

$$PL_{CI}(d,f) = PL(d_0) + 10\alpha log_{10}\left(\frac{d}{d_0}\right) + \chi_\sigma \quad (1)$$

where:

$PL(d)$ is the path loss value at distance d

$PL(d_0)$ is path loss at the reference distance d_0

χ_σ is a shadow fading term that follows Gaussian distribution with zero mean and deviation σ the path loss exponent set as α

If d_0=1m; $PL(d_0)$ can be calculated using Friis' law by:

$$\boldsymbol{PL(d_0) = 20log_{10}\left(\frac{4\pi f}{c}\right)}. \quad (2)$$

where *f*: carrier frequency

c: light's speed

According to UAV communication, the height of the UAV is also a parameter that affects the channel loss. Zhu et al introduced the altitude-dependent mmWave path loss model as follows:

$$PL(f_c, d, h_{UAV}) = PL(d_0) + 10Ah_{UAV}^B log\left(\frac{d}{d_0}\right) + \chi_\sigma \quad (3)$$

where: $\boldsymbol{h_{UAV}}$ is the altitude of the UAV

The parameters A and B are dependent on the environment [21].

B. Path Loss Model Using Machine Learning

In recent years, machine learning has seen significant advancements, with AI technology being applied across various fields to address challenges involving big data or problems where precise formulas are difficult to establish. The development of path loss models using machine learning has also garnered attention from researchers [17, 22].

Table I presents results from recent studies that have addressed the prediction of path loss in UAV communication using machine learning. These findings demonstrate that machine learning techniques offer greater accuracy compared to traditional channel loss prediction methods. This study proposes two machine learning models based on the Bidirectional LSTM algorithm and the encoder-decoder LSTM to estimate path loss in UAV-to-UAV communication.

TABLE I. RESULTS OBTAINED FROM SOME RECENT STUDIES

Study	Scenario	Algorithm	Evaluation error (dB)	
			MAE	RMSE
Yan Zhang *et al.* [16]	Helsinki urban scenario A2A communication Frequency f = 2.4Ghz	Random Forest	2.27	3.06
		KNN	4.56	8.9
Ashraf Tahat *et al.* [22]	Urban Environment A2G communication Frequency *f* = 433 MHz	KNN	3.515	4.49
		ANN	3.306	4.616
		Regression Trees (RT)	3.726	5.373
	Frequency *f* = 900MHz	KNN	3.155	4.465
		ANN	3.766	5.466
		RT	3.869	6.413
	Frequency *f* =5.8GHz	KNN	4.705	6.383
		ANN	5.408	7.265
		RT	5.475	7.317
Sarun Duangs-uwan *et al.* [17]	Napier cenarios for GS-to-UAV Frequency *f*= 2.4 Hz Altitude = 5m	SVR	2.125	4.782
		ANN	2.025	4.439
Guanshu Yang *et al.* [23]	Ottawa urban/ Helsinki urban Frequency 28 GHz; 2.4; 5.8; 28; 37 GHz	Random forest		1.64
		KNN		3.85
P.T.Q. Trang *et al.* [18]	Full LOS conditions A2A communication Frequency *f* = 60GHz	LSTM	1.48	1.98

III. PROPOSED APPROACH

A. The Dataset

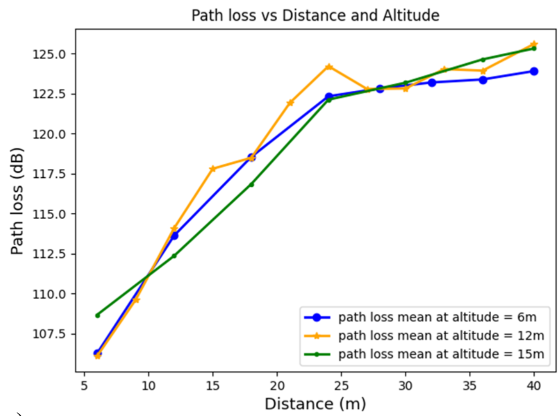
The data utilized in this paper is sourced from a publicly available dataset hosted on GitHub [24]. This dataset was collected during a measurement campaign lasting over three days using Facebook Terragraph channel sounders. The communication system operated between two UAVs at a 60 GHz carrier frequency under full line-of-sight (LOS) conditions. The measurement results were compared with 3GPP channel models to verify the data's reliability [25].

The dataset comprises 6,889 rows saved in a CSV file. The data preprocessing involved two steps. First, records with errors or missing fields were filtered out, and the empty or erroneous cells were filled with the median values of the respective fields. Next, the dataset was divided into two sub-datasets: 80% for training and 20% for testing, achieved through uniform random sampling. In the second step, the sub-datasets were normalized to reduce processing time and mitigate bias.

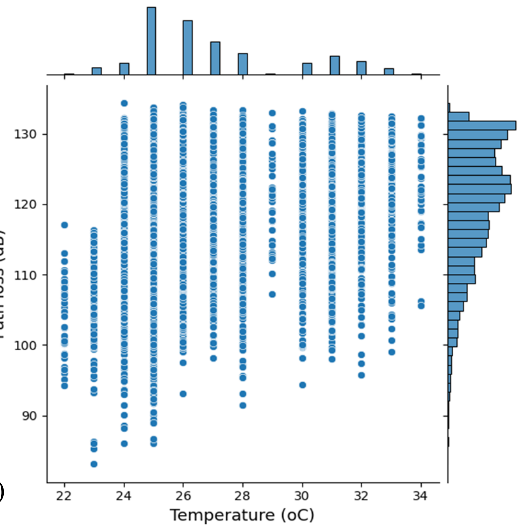
B. Features Selection

In traditional path loss prediction methods, signal strength loss is primarily determined by the distance between the transmitter and receiver. However, other factors—such as the characteristics of the transmitting and receiving antennas and the surrounding environment—also impact the communication channel. In UAV (unmanned aerial vehicle) communication, the altitude of the drones further influences this factor. Moreover, selecting the appropriate features is crucial in determining the effectiveness of a deep learning model. To achieve an accurate model, meticulous data analysis is crucial in crafting a suitable learning model. In this section, the data is analyzed to determine the influence of each parameter on path loss. The primary goal is to select appropriate features to input into the model.

Fig. 2. depicts the impact of various parameters on path loss within the dataset.



a)



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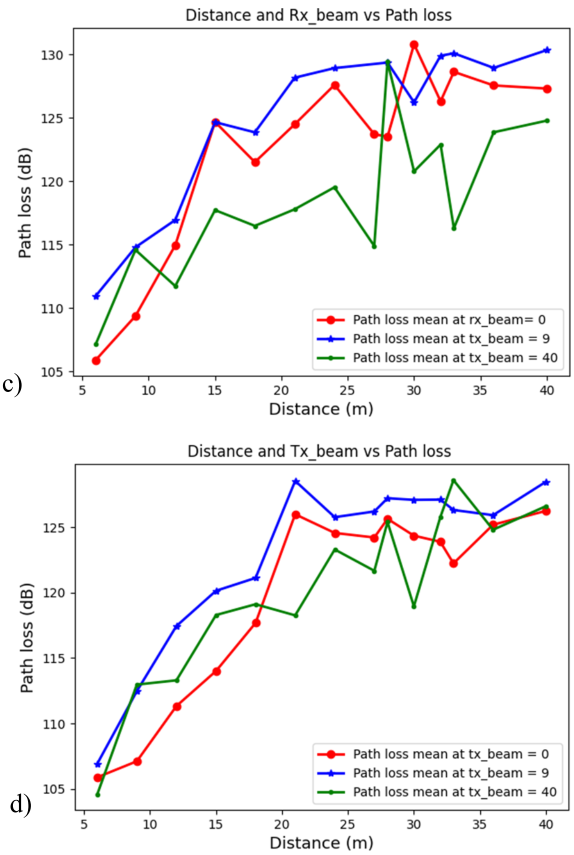


Fig. 2. The relationship between distance and path loss considering other parameters of the system.

In Fig. 2a, the influence of UAV altitude on path loss is demonstrated. The dataset encompasses channel parameters at three distinct altitudes: 6m, 12m, and 15m. The line graphs indicate that changes in the UAV's altitude do not alter the path loss trend, but there is a noticeable deviation in this value with varying drone altitudes.

TABLE II. THE SELECTED FEATURES

Features name	Description
distance	The distance between 2 UAV (m)
altitude	The altitude of UAV compared to ground (m)
tx beam	Transmitter beam indices used for scanning
rx beam	Receiver beam indices used for scanning.
tx gain idx	Transmitter gain indices.
rx rf gain idx, rx if gain idx	The receiver gains indices from the Automatic Gain Control (AGC).
tx temp	Transmitter junction temperature
rx temp	The receiver node's junction temperature

Fig 2b illustrates the impact of temperature at the transmitter/receiver positions on path loss. The bar graph shows that most data were collected within the temperature range of 24 °C to 28 °C. In temperatures below 24 °C, path loss values tend to be lower compared to those in temperatures above 30 °C. Fig 2c and 2d demonstrate that alterations in the receive and transmit antenna beam index do not impact the transmission loss trend with distance. However, a significant change in transmission loss is observed when the index of the antenna beams is altered. This change is more pronounced at the receiver and slightly less prominent at the transmitter. Based on these findings, selected features for the learning and testing model are defined and presented in Table II.

C. Performance Evaluation Criteria

To investigate the performance of the path loss model, R2 (R-squared), MAE (mean absolute error), Mean Squared Error (MSE), and RMSE (root mean square error) have been used [26]. These performance indicators can be calculated by formulation following:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| . \quad (4)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}. \quad (5)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (6)$$

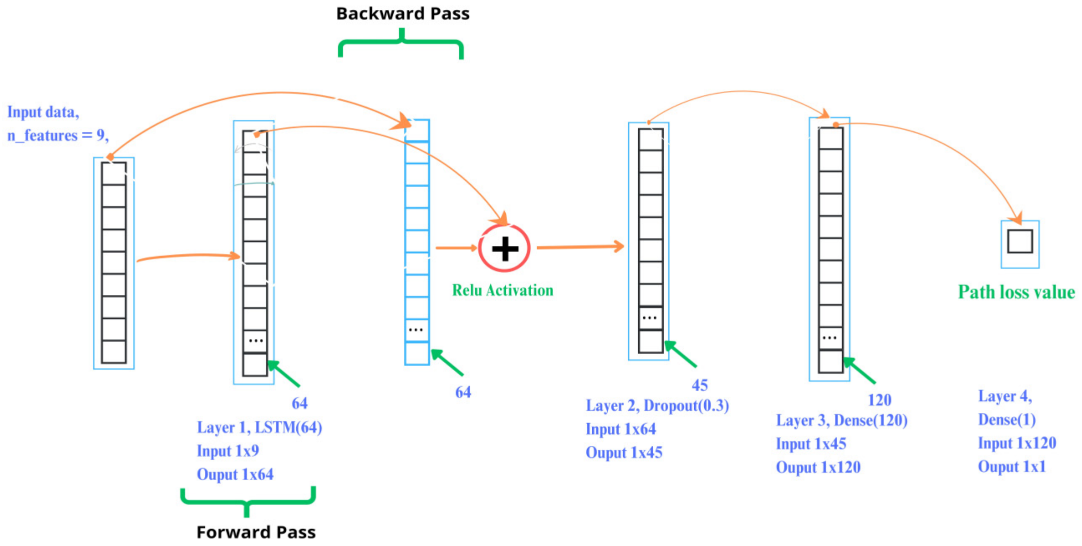
$$R2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - avg(y))^2} \quad (7)$$

where: $\hat{y}_i$ is the ith predicted value, y_i is the ith observed value.

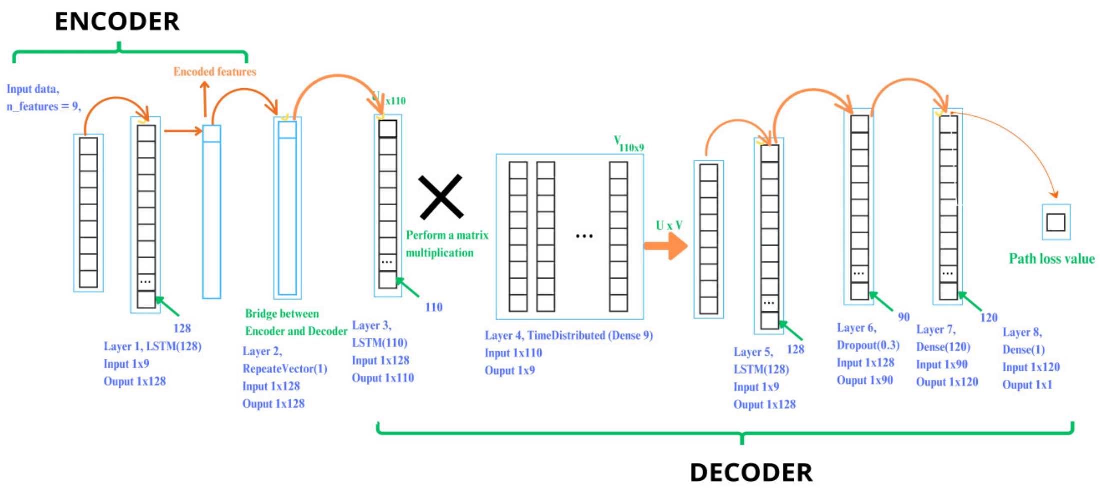
D. Proposed Path Loss Model

A sequence model featuring two LSTM layers—one processing input in the forward direction and the other in the backward direction—is commonly known as a "Bidirectional LSTM" or "BiLSTM." Frequently applied in NLP-related tasks, this method involves processing data in both directions, enabling the model to enhance its understanding of relationships within sequences. The Encoder-Decoder LSTM, designed for forecasting variable-length output sequences, is particularly tailored for sequence-to-sequence problems in prediction tasks. Comprising two fundamental sub-models—the decoder and the encoder [26, 27]—this model addresses the challenges of such tasks. As recommended, LSTM, Bidirectional LSTM, and Encoder-Decoder LSTM algorithms are suitable for solving sequential problems. Notably, input data presented in different orders will yield varying effects on the output results. Leveraging this characteristic, we employ these algorithms to estimate path loss in UAV communication. Given that the output data (path loss) is primarily influenced by the transmission distance, this parameter holds a central position in the "long-sort" series of LSTM.

Two models based on Algorithm 1 have been developed to address path loss prediction. The creation of this model involved three key steps: (i) Data Preprocessing—this includes normalization, and splitting the data into training and testing sets; (ii) Model Training—involving the training of bidirectional LSTM and encoder-decoder LSTM models specifically designed for path loss prediction; and (iii) Hyperparameter Tuning—where appropriate hyperparameters were selected for the bidirectional LSTM and encoder-decoder LSTM models to achieve targeted performance metrics, such as a specific RMSE value.



a) Bidirectional LSTM model



b) Encoder-Decoder LSTM model

Fig. 3. The proposed path loss model

Algorithm 1: Algorithm for developing a path loss model based on deep learning

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Input: Draw: Raw dataset
  RMSEmax: Maximum acceptable Root Mean Square Error (RMSE)
Output: Mpred: Predicted path loss model
Preprocessing Data:
  Randomly split Draw into:
  𝓓train: Training dataset, 𝓓test: Testing dataset
Normalize 𝓓train and 𝓓test:
  𝓓train_norm=Normalize(𝓓train)
  𝓓test_norm=Normalize(𝓓test)
Set initial values for parameters:
  N← Initial number of neurons, LR← Initial learning rate
  Epochs← Initial number of epochs, RMSEinitial←∞ (initialize RMSE to a large value)
Training Phase:
  Train the model M using 𝓓train_norm with parameters {N, LR, Epochs}.
  Calculate the initial performance metrics:
    MAEinitial according to formula (4)
    RMSEinitial according to formula (5)
Hyperparameter Tuning and Model Optimization:
  While RMSEinitial>RMSEmax do:
    Tune the hyperparameters {N, LR, Epochs} using Random Search:
    Nnew,LRnew,Epochsnew} ← RandomSearch(N, LR, Epochs)
    Retrain the model M using 𝓓 train_norm with the new hyperparameters:
    M←Train_Model(𝓓train_norm,Nnew,LRnew,Epochsnew)
    Predict the path loss on 𝓓test_norm:
    Predictions←M(𝓓test_norm)
    Update the performance metrics:
      MAEupdated according to formula (4)
      RMSEupdated according to formula (5)
    Update RMSEinitial←RMSEupdated
  End while

The proposed model predicts path loss through the utilization of the Bidirectional LSTM algorithm and the Encoder-Decoder LSTM algorithm, as depicted in Fig. 3a and 3b. Although the Bidirectional LSTM model is less intricate, it demonstrates lower prediction accuracy compared to the Encoder-Decoder LSTM model.

IV. Numerical Results

In this section, the performance of the proposed approach is assessed. This includes evaluating path loss with distance, the cumulative distribution function (CDF) of path loss, mean absolute error (MAE), root mean square error (RMSE), and computation time

Firstly, in Fig. 4, the path loss values are illustrated using the log-distance path loss model, the log-distance altitude-dependent model, and the proposed deep learning model. The green line and dotted line depict the relationship between path loss and the distance and altitude of UAVs based on the close free space model and altitude-dependent model. The results suggest that the path loss differences among these models are not substantial, but they deviate significantly when compared to the measured values. The red dots represent predicted values using the proposed model, and these values closely align with the true values.

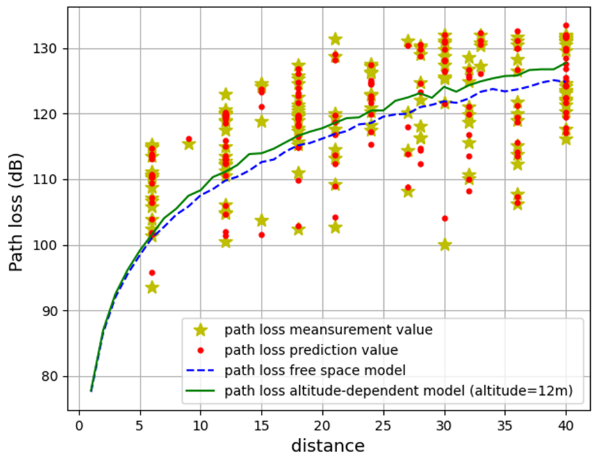

Fig. 4. The relationship between distance and path loss.

Secondly, the discernible contrast in the accuracy of the deep learning model, as opposed to the log-distance model and KKN regression model, in predicting path loss is vividly portrayed in the cumulative distribution function (CDF) presented in Fig. 5. In a comprehensive comparison, both bidirectional LSTM and Encoder-Decoder LSTM models outperform the benchmarks, encompassing path loss in free space, path loss altitude-dependent, and KNN regression.

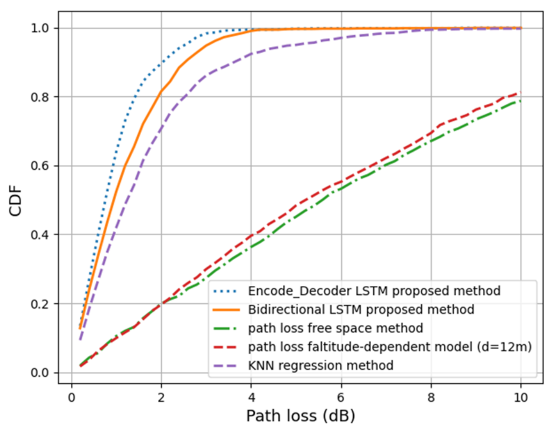

Fig. 5. The CDF among models.

Delving into specifics, the cumulative density of path loss errors smaller than 4 dB attains 100% when employing either bidirectional LSTM or Encoder-Decoder LSTM models. In contrast, when utilizing the log-distance model, the cumulative density of errors less than 10 dB only reaches 80%. Achieving a path loss of less than 2 dB is confined to a cumulative probability of 20% with the log-distance model alone. However, this figure significantly escalates to 80% when employing the bidirectional LSTM model and rises even further to approximately 90% with the use of the Encoder-Decoder LSTM model.

Thirdly, the model's accuracy is evaluated using metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE). Table III compares the MAE, MSE, and RMSE values of the proposed model against those of the log-distance model. The proposed models demonstrate significantly higher accuracy, with an MAE of 1.183 dB for the bidirectional LSTM and 0.939 dB for the Encoder-Decoder LSTM. In contrast, the log-distance model, Altitude dependent model, and KNN model result in much higher errors, with values of 6.521 dB, 6.944 dB, and 1.662 dB, respectively. The MSE, RMSE values of the proposed model also achieved better values than the traditional models. Furthermore, Table III also highlights the effectiveness of the proposed models through their R2 values. The Encoder-Decoder LSTM model achieves an R2 of 0.979, and the bidirectional LSTM model achieves an R2 of 0.968, both indicating superior predictive performance in UAV communication path loss estimation.

TABLE III. THE MODEL'S ACCURACY

Model	MAE	MSE	RMSE	R2
Encoder-Decoder LSTM	0.939	1.511	1.229	0.979
Bidirectional LSTM	1.183	2.357	1.535	0.968
KNN	1.662	5.304	2.303	0.928
Close Free Space	6.521	63.773	7.985	0.161
Altitude dependent	6.944	73.684	8.583	0.018

Finally, However, a drawback of machine learning methods, when compared to traditional approaches, is the computation time. Table IV presents the training time and predicting time of the proposed deep learning models. While the calculation time for the traditional model is negligible, the Bidirectional LSTM model requires 0.581 seconds, and the LSTM Encoder-Decoder model takes 0.821 seconds. (These results were simulated using the Python 3.9 programming language on a Lenovo ThinkPad with a Core i5 processor and 8GB RAM).

TABLE IV. EVALUATING ALGORITHM COMPUTATION TIME

Model	Number of records in test data	Test time (seconds)
Bidirectional LSTM	1380	0.581
Encoder-Decoder LSTM		0.821
KNN regression		1.219

V. CONCLUSION

This paper proposes two deep-learning models for path loss prediction of air-to-air channels in UAV communication systems, aiming to enhance the precision of channel estimation. The outcomes underscore the superior accuracy of our proposed models in addressing the challenges of path loss prediction. The accuracy of our proposal has been assessed in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), with the LSTM Encoder-Decoder model achieving the best performance at 0.939 dB and 1.183 dB, respectively. This proposal exhibits promise for the application of AI in UAV communication systems. Moreover, further research is needed to look into the intricacies of deep learning-based path loss predictions, specifically focusing on minimizing computation time to meet the real-time demands of upcoming applications.

DATA AVAILABILITY

The data used to support this study are downloaded from the website https://github.com/wineslab/uav-to-uav-60-ghz-channel-model.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Trinh Anh Vu proposed an idea, Pham Thi Quynh Trang, and Dinh Trieu Duong contributed to the simulation and analyzed the data. All authors had written the paper and approved the final version.

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