Millimeter Wave Path Loss Modeling for UAV Communications Using Deep Learning

Pham Thi Quynh Trang[1,2](✉), Duong Thi Hang[1], Ha Xuan Son[2], Dinh Trieu Duong[2], and Trinh Anh Vu[2]

[1] University of Industry, Hanoi, Vietnam
{pham.trang,hangdt}@haui.edu.vn
[2] VNU University of Engineering and Technology, Hanoi, Vietnam
{duongdt,vuta}@vnu.edu.vn

Abstract. Unmanned Aerial Vehicles (UAVs) and millimeter waves are pivotal technologies in the sixth-generation (6G) mobile communication systems. Effective path loss modeling for UAV-based millimeter wave communications is critical for rapid and accurate data transmission. Traditional methods, such as deterministic, empirical, and machine learning-based approaches, are commonly used. This paper presents a ground-breaking approach that harnesses the power of deep learning, specifically the Long Short-Term Memory (LSTM) algorithm, to predict path loss in UAV-based millimeter wave communications, with a particular focus on UAV-to-UAV scenarios. Our experimental results demonstrate the exceptional performance of our deep learning model, achieving a remarkable term root-mean-square error (RMSE) of only 1.98 dB when compared to measurement results in test scenarios. This remarkable outcome underscores the profound significance of employing deep learning methodologies in predicting path loss, surpassing the capabilities of traditional methods. By leveraging deep learning, we advance the field of UAV-based millimeter wave communication modeling, enabling more precise and efficient data transmission in 6G networks.

Keywords: UAV · Deep Learning · path loss · LSTM algorithm

1 Introduction

The fifth-generation (5G) technology brings with it the significant promise of delivering ultra-fast data rates, extremely low latency, and vastly improved spectral efficiency. In the future, the emergence of data-intensive applications and the expansive wireless network will necessitate the development of sixth-generation (6G) communication technology. Both in the current 5G networks and in the forthcoming 6G networks, millimeter-wave technologies will assume a crucial role in achieving the envisioned network performance and communication objectives [1]. Because of their extensive bandwidth and elevated carrier frequencies, mmWave communications exhibit reduced scattering effects and more pronounced blocking effects in non-line-of-sight (NLoS) paths [2].

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In addition, unmanned aerial systems have significant promise as technological enablers for wireless communication. They offer a cost-effective and efficient solution for temporarily connecting ground users in situations where ground infrastructure is unavailable. Within this field, establishing a high-capacity backhaul network with interconnectivity between unmanned aerial vehicles (UAVs) is a large challenge. Besides their capacity enhancement roles, UAV-BSs can serve vital functions during emergency situations such as earthquakes, floods, and similar events, when fixed infrastructure is either entirely or partially compromised and non-operational. Nevertheless, despite the advantages it offers, UAV-assisted networking also presents specific design challenges. These include issues related to energy efficiency (EE), trajectory planning, positioning, resource management, privacy, and more [3].

When multiple UAVs depend on one another to transmit data in an aerial multi-hop manner, conventional sub-6 GHz technologies are inadequate for handling high-load traffic aggregation. Therefore, the millimeter wave (mmWave) spectrum emerges as a comprehensive solution for completely wireless nodes, providing unparalleled bandwidth [3]. Combining millimeter wave communications with UAV networks can respond to the high throughput demands of the majority of UAV applications. Implementing mmWave communications within UAV networks offers two primary advantages:

1) The wide coverage of mmWave technology significantly increases the capacity of UAV networks, effectively meeting the demand for rapid response capabilities.
2) Through the utilization of mmWave technology, the data traffic of UAV network can be significantly augmented, as mmWave communications excel in providing high throughput for short-range transmissions [4].

For designing and developing wireless communication systems, it is essential to have a transmission channel model that describes the transmission of radio waves using channel parameters. Path loss is one of the most fundamental characteristics among the channel parameters, as it describes the power reduction of a signal traveling between the transmission device (Tx) and receiving device (Rx) in a propagation channel. Precise modeling of path loss is of utmost importance during the deployment of a system as it directly influences the received power of the intended signal and the levels of interference from unwanted signals in wireless communication systems. These parameters are indispensable for assessing wireless coverage and conducting interference analysis [5]. There are three conventional approaches for modeling path loss: empirical methods, deterministic methods, and machine learning-based (ML-based) methods [6]. Modeling the path loss of mmWave communications is a complex task due to their heightened susceptibility to transmission environments. Consequently, path loss modeling for mmWave propagation assumes a critical role in the design and analysis of communication systems.

In this paper, a path loss model is suggested, which employs a deep learning approach using Long Short-Term Memory networks (LSTM) for 60 GHz mmWave communication in UAV-to-UAV scenarios. The proposed model attains a satisfactory level of performance when predicting path loss in test scenarios with a public dataset. Experimental results demonstrate that the proposed LSTM path loss model in this study surpasses conventional empirical methods in accuracy.

The rest of the paper is structured in the following manner. In Sect. 2, we present the related works. Section 3 describes the data and proposed method in detail. Experimental results are discussed in Sect. 4. Lastly, Sect. 5 serves as the conclusion of the paper.

2 Related Works

2.1 The Free Space Reference Path Loss Models

The publications on transmission models have introduced various experimental path loss laws that depend on distance and frequency parameters. In free space reference (CI), the path loss models can be expressed in the following way [7]:

$$PL_{CI}(d,f) = PL_{FS,ref}(f) + 10n_{CI}\log_{10}(d) + \xi_{\sigma,CI} \tag{1}$$

In this, $PL_{FS,ref}(f)$ represents the route loss determined at a reference distance of one meter using Friis' law for free space propagation.

$$PL_{FS,ref}(f) = 20log_{10}(\frac{4\pi f}{c}) \tag{2}$$

In this:

c: speed of light
f: carrier frequency
n_{CI}: the path loss exponent (PLE)
$\xi_{\sigma,CI}$: the shadow fading obey Gaussian distribution with zero mean o and standard deviation of σ. The foundational equation provided in Eq. (1) applies for all most path loss models based on measurements.

2.2 Path Loss Modeling Method Based on Machine Learning

Machine learning-based methods acquire insights from statistical information derived from measurement data, empirical models, or preprocessed inputs generated from field simulations in the domain of radio propagation. These methods are then used to make predictions related to path loss values. Numerous studies in the field of path loss modeling with machine learning have been presented. They encompass a variety of approaches, such as neural networks, support vector regression, These methods encompass Convolutional Neural Networks (CNN) and decision tree-based approaches. The capacity to capture intricate relationships between inputs and outputs in machine learning-based methods makes them well-suited for path loss modeling. H. Cheng et al. introduced an attention-enhanced convolutional neural network (AE-CNN) path loss model for 5G communications in suburban settings. In order to overcome the constraints of local feature extraction and extract global information from input images, dilated convolution is utilized. The attention mechanism plays a key role in enabling the attention-enhanced convolutional neural network (AE-CNN) model to extract important properties relevant to propagation contexts by using global information from inputs. In test cases, the AE-CNN model demonstrates superior performance in terms of root mean square error compared to the most advanced deterministic and empirical approaches. [8]. Jo et al. present a machine-learning framework for path loss modeling that combines three key techniques: variance analysis based on Gaussian processes, principle component analysis (PCA)-assisted feature selection, and multi-dimensional regression based on artificial neural networks (ANNs). When compared to the traditional linear path loss plus log-normal shadowing mode, the combined path loss and shadowing model is more precise and adaptable [9]. Figure 1 shows our proposed procedure for predicting path loss based on deep learning. In this paper, our proposed procedure consists of three steps: preprocessing data, training, and evaluating results via test data.

3 Data and Path Loss Model

3.1 Data Collection and Preprocessing

The data used in this paper is sourced from a publicly available measurement dataset hosted on GitHub [10]. The dataset was collected from an actual measurement campaign using Facebook Terragraph channel sounders. The communication system was set between two UAVs at 60 GHz of carrier frequency [11].

The accuracy of a learning model depends on the training data introduced to it. To obtain an accurate model, it is necessary to have a well-distributed, large, and accurately measured dataset in addition to its computational and tuning parameters. Thus, preparing the data is a crucial step in creating an appropriate learning model. We divided the data preprocessing into two steps: The first step involves filtering out records with errors or missing fields. We address missing data by filling in the empty cells with the median values of the respective fields. In the second step, we also perform normalization to reduce processing time and mitigate bias. To prepare the training data, we partition all the measured data into two sets: the training set, which comprises 80% of the data, and the testing set, which constitutes 20%. Our method of achieving this division is uniform random sampling. During model optimization, the data for testing is specifically utilized to modify hyperparameters.

3.2 Feature Selection and Hyper-parameter

From the dataset, detailed features used in the training and testing model are shown in Table 1.

In this study, we used the LSTM model. Because path loss does not depend on time, the number of steps in the parameter is set = 1. The hyper-parameter, and optimization algorithms are shown in Table 2.

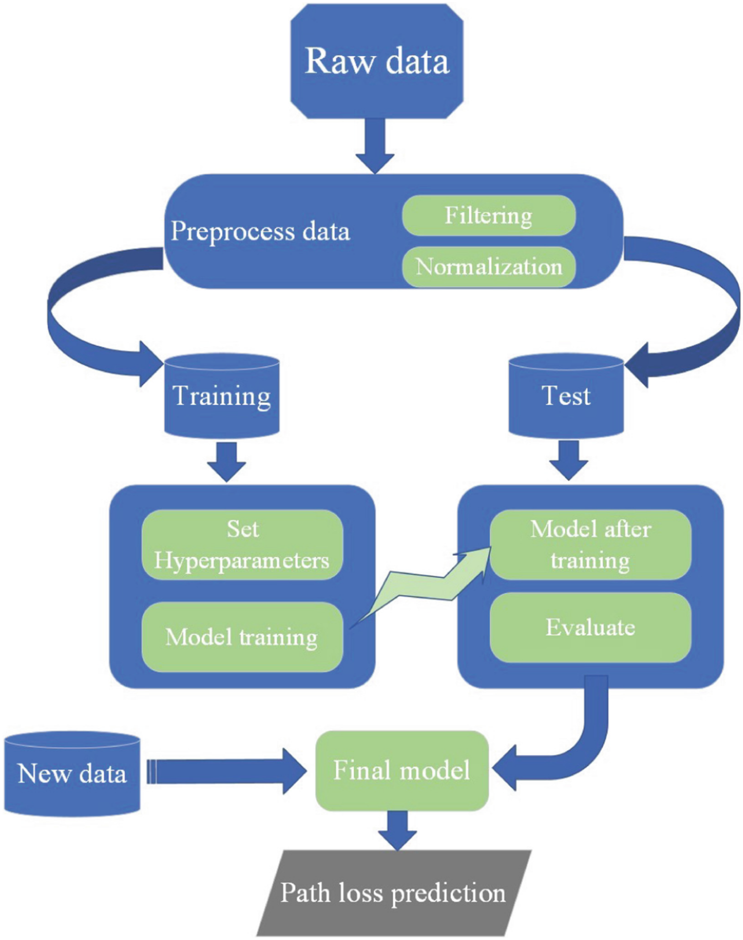

Fig. 1. Procedure of machine-learning-based path loss prediction.

Table 1. The features for training and testing.

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

Table 2. Hyper-parameter and optimization algorithm.

Hyper-parameter	Optimization algorithms
epochs = 50	LSTM layer: activation ='relu'
verbose = 0	Output layer: activation ='linear'
Dropout = 0.3	optimizer ='adam'
number of steps in =1	loss = 'mse'.
number of steps out = 1	

3.3 Performance Evaluation

The accuracy of the prediction findings is assessed using three statistical metrics: R2 (R-squared), MAE (mean absolute error, and RMSE (root mean square error [12]. These indicators, which are defined as follows, can be found by comparing the test dataset's actual values to the projected values:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y_i}| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y_i})^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y_i})^2}{\sum_{i=1}^{N}(y_i - avg(y))^2} \tag{5}$$

where $\hat{y_i}$ is the i^{th} predicted value, y_i is the i^{th} observed value.

3.4 Path Loss Model

A type of recurrent neural network (RNN) architecture in the deep learning space is called LSTM (Long Short-Term Memory). Because LSTM has feedback connections, as opposed to traditional neural networks, it can handle complete data sequences as opposed to simply individual data points. [13]. We applied the LSTM networks with hyperparameters and activation functions are described in Table 1. The proposed path loss prediction model for the mmWave Channel of UAV-to-UAV Communications scenario is shown in Fig. 2.

The Algorithm 1 returns a trained LSTM model. This trained LSTM model was then passed and used for the prediction phase of the path loss model as shown in Algorithm 2.

4 Results and Discussion

Figure 3 shows the path loss from the empirical models, the measured, and the predictions versus distance. Regarding the trend, the path loss values in the

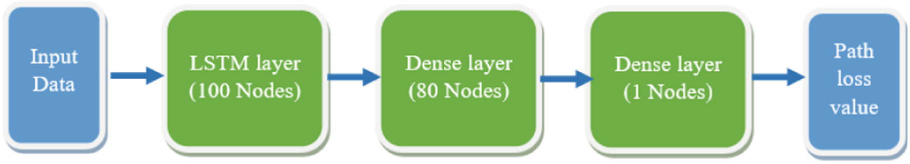

Fig. 2. LSTM path loss model based machine.

Algorithm 1. Training LSTM path loss model

1: Collect channel data from the public dataset.
2: Extract channel characteristic data for use as the training dataset.
3: Establish the prediction model of path loss based on the LSTM algorithm.
4: **for all** *epoch* = 1 to 50 **do**
5: Train model
6: Calculate RMSE, MAE and R2
7: **end for**
8: Return trained LSTM model

dataset are acquired through real measurements, and the predicted values generated by the proposed LSTM model align with the simulated loss graph based on Friis' law. According to Friis' law, the path loss value depends only on the carrier frequency and the distance between the transmitting device and the receiving device. However, from the results of the actual measurement campaign and analysis from [11], the path loss is also greatly influenced by the receive/transmit antenna beams, the height of the UAV as well and the environmental temperature. Observing Fig. 3, it is evident that our proposed model's predicted path loss closely aligns with the actual measured values. This result is obtained because, in addition to distance, the LSTM model considers input features such as the location vectors of Tx and Rx beam pairs, UAV altitude, and node junction temperature.

To provide a thorough evaluation of the LSTM model's performance, we calculated several key metrics, including the mean absolute error (MAE), root mean square error (RMSE), and R2 (R-squared), by comparing the predicted data with the true data. The results of this evaluation are presented in Table 2, where we examine the performance at different altitudes of the UAV. Notably, the results clearly demonstrate the LSTM model's effectiveness, as indicated by the RMSE values at each altitude being consistently smaller than those obtained through all-altitude calculations. According to the result from (1) with carrier frequency = 60GHz and Gaussian random variable with standard deviation σ

Algorithm 2. Predicting from the LSTM mode

1: Set input data.
2: Predict path loss from the LSTM model with given input data.
3: Return path loss value.

= 3.56 dB [11], the RMSE of the empirical model and measured values get at 7.66dB, MAE = 6.42. Table 3 demonstrates that the machine learning approach surpasses the empirical method, as indicated by all error metrics displaying lower values and yielding higher correlation results.

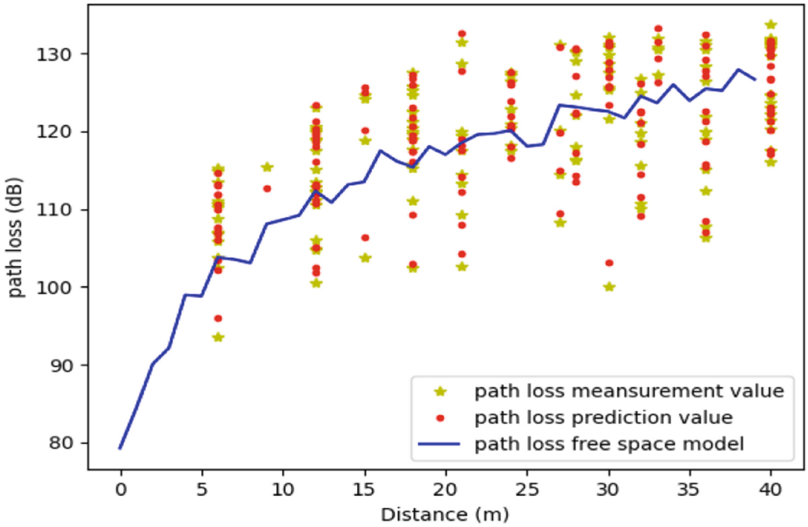

Fig. 3. Path loss prediction values based on LSTM model.

Table 3. MAE, RMSE, and R2 value of measurement path loss and predict path loss.

Altitude(m)	MAE (dB)	RMSE (dB)	R^2
All altitude(m)	1.48	1.98	0.95
H = 6 (m)	1.67	1.92	0.95
H = 12 (m)	1.58	1.95	0.95

Figure 4 illustrates a comparison of error rates using the MAE and RMSE indices with varying numbers of features applied to the identical training model. By examining Fig. 4, it becomes evident that the proposed features yield the lowest values for the MAE and RMSE indices, with MAE at 1.48 dB and RMSE at 1.98 dB. Meanwhile, if using only one feature which is a distance like the free space model, the highest error rates for MAE and RMSE are observed, reaching 5.45 dB and 6.66 dB, respectively. Even though considering the influence of each UAV's altitude, the error rate also reduces insignificantly.

In addition, Fig. 4 also shows the R2 value for different cases, including scenarios with only one feature (distance between two UAVs), two features (distance and altitude of UAVs), and multiple features as outlined in Table 1. The R2 value

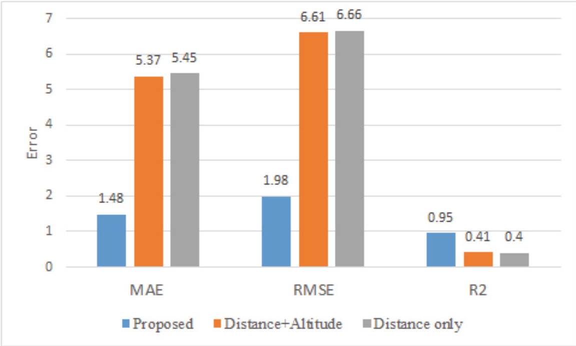

Fig. 4. The MAE, RMSE, and R2 vs number of feature

reaches its peak at 0.95 when the model's input aligns with the recommendations in Table 1, while the input data includes both the distance and altitude of the UAVs, the R2 value only reaches 0.41. This result shows the suitability of the selection of input parameters with the proposed LSTM model.

5 Conclusion

In this paper, we proposed an LSTM model designed to predict path loss in UAV-to-UAV transmission scenarios, operating at a carrier frequency of 60 GHz, based on publicly available measurement data. Our proposed LSTM model exhibited its superiority over the traditional empirical Free Space path loss method. Notably, machine learning-based path loss methods offer the advantage of incorporating a wider range of parameters compared to empirical techniques. In our proposed model, we harnessed parameters such as distance, Tx and Rx beam pairs, UAV altitude, and node junction temperature as input variables, showcasing the flexibility and effectiveness of machine learning in addressing the complex challenges of path loss modeling in UAV-based millimeter wave communications.

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