Channel Modeling for Millimeter-Wave UAV Communication based on Explainable Generative Neural Network

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Abstract

This paper proposes an enhanced method for channel modeling in millimeter-wave wireless UAV-assisted communication networks. It addresses the need for accurate, data-efficient, and interpretable channel models for user-centric networks, obtained by integrating the Generative Adversarial Network (GAN) framework with eXplainable AI (XAI) systems. The methodology incorporates Deep SHAP to optimize the generator's gradient descent process, improving model accuracy. By comparing metrics such as Kullback-Leibler divergence and Wasserstein Distance, the model demonstrates superiority in capturing real parameter distributions. Moreover, it indicates robust performance with significantly fewer training samples, making it a promising solution for real-world deployment.

Keywords

Unmanned aerial vehicles, Channel modeling, Generative neural network, XAI, Shapley additive explanations

1. Introduction

Unmanned Aerial Vehicles (UAVs) have emerged as integral components in various industries due to their remarkable maneuverability, adaptability, and cost-effectiveness. Functioning as aerial Base Stations (BSs) or mobile relays within three-dimensional (3D) wireless communication networks, they ensure the provision of ubiquitous connectivity for the ground User Equipment (UE), even in challenging environments where direct Line-Of-Sight (LOS) transmission links are not feasible. Integrating UAVs into cellular networks represents a significant step toward advancing fifth-generation (5G) and beyond 5G (B5G) mobile networks, ensuring continuous, high-capacity broadband connectivity even in catastrophic scenarios.

The rise of time-critical communication services alongside the proliferation of internet users and IoT devices, has led to a surge in data traffic, straining traditional radio spectrum resources. Leveraging higher frequencies such as the millimeter Wave (mmWave) spectrum not only addresses the issue but also offers advantages such as enhanced throughput and lower latency, making them a promising solution for UAV networks. Moreover, accurate

Late-breaking work, Demos and Doctoral Consortium, colocated with The 2nd World Conference on eXplainable Artificial Intelligence: July 17–19, 2024, Valletta, Malta

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channel modeling is crucial in designing optimized air-to-ground (A2G) or air-to-air (A2A) UAV-based communication systems. It involves developing a model that predicts or simulates the parameters of mmWave links, considering phenomena including reflection, diffraction, and scattering. However, the inherent susceptibility of mmWave to atmospheric absorption and blockage significantly complicates their channel modeling in UAV-assisted networks.

Numerous studies have been conducted to develop accurate channel parameter models. Conventional approaches are categorized into empirical, deterministic, and stochastic models. For ground-to-air (G2A) communication, [1] proposed a mathematical path loss prediction model, while [2] examined an empirical path loss two-ray model and modified Log-Distance model for A2A communication. [3] introduced a map-based model for A2G mmWave communication, considering all three direct, reflection, and diffraction rays. The work of [4] developed a hybrid parameter estimation method for UAV-to-Vehicle (U2V) communication, integrating geometric-based and stochastic approaches. Moreover, [5] presents a geometry-based stochastic model for Multiple-Input Multiple-Output (MIMO) UAV communications, considering the movement of the transmitter, receiver, and all reflectors within the propagation environment by using a two-stage continuous-time Markov model.

In recent years, Machine Learning (ML) methods have gained great popularity in the channel modeling domain. The ML approaches excel in generalizing to new data and adapting to changing environmental conditions. In the study [6], a deep Long Short-Term Memory (LSTM) model was proposed for predicting path loss in A2A UAV communication. In [7] authors utilized Random Forest and K-nearest-neighbors techniques, along with a feature selection scheme, for path loss and propagation delay predictions. [8] introduced a neural network-based model for path loss prediction, focusing on the relationship between reflection angle, path delay, and path loss factor. Additionally, [9] shows a rapid Angle-Of-Arrival (AOA) estimation approach employing a Support Vector Machine (SVM) tailored for MIMO beamforming in dynamic vehicular communication scenarios.

ML-based approaches, particularly Neural Networks (NNs), have proven to be valuable tools for channel modeling, with Generative Neural Networks, such as Variational AutoEncoder (VAE) and Generative Adversarial Networks (GAN) standing out for their ability to capture the complex dynamics of mmWave UAV channels [10, 11, 12]. However, these models typically require extensive training datasets, exceeding 10,000 records, which are costly and time-consuming to acquire. Addressing this challenge, this paper exploits the potential of eXplainable Artificial Intelligence (XAI) to enhance the training process of Conditional GANs (CGAN) for estimating channel parameters between UAVs and UEs. By integrating the XAI approach with the deep CGAN, a data-efficient model suitable for mmWave communication is developed, which achieves comparable results with much fewer records. For evaluation purposes, we utilize ray tracing simulation data, related to different urban characteristics. To our knowledge, such methodology represents a unique contribution to UAV channel modeling, paving the way for user-centric sixth-generation (6G) networks that require efficient, fast, and explainable AI mechanisms for network management.

The rest of this paper is structured as follows: Section II elaborates on the basic concept of XAI methods in greater depth. Section III outlines the proposed XAI-based CGAN channel model. Then, Section IV presents the results, demonstrating the practicality of the proposed technique. Section V concludes the paper.

2. XAI methods

XAI methods represent efforts to provide the users with a straightforward explanation of the black-box ML models' internal functionality or identify the key factors influencing their outputs. This understanding empowers experts to refine and optimize the training procedure of ML-based models, rendering XAI a prominent area of research across various fields. Within the realm of XAI systems, model-agnostic techniques are typically categorized into visualization methods such as surrogate models, knowledge extraction methods (e.g., rule extraction techniques), influence methods including feature importance analysis, and example-based explainable techniques. One notable feature importance analysis method is the SHapley Additive exPlanations (SHAP) method, an additive feature attribution approach, which computes Shapley values (or SHAP values) for each feature within the input dataset [13]. Shapley value for a feature *"i"* is the average marginal contribution of that individual feature to the model prediction across all possible feature subsets $S \subseteq M \setminus \{i\}$, where S is any subset of M, the set of all input features.

All additive feature attribution methods try to provide an explanation model g that explains the output of the original model ($f(x)$). For explanation, simplified inputs, denoted as $\acute{x}$, are typically employed, which can be transformed into the original input space via a mapping function ($x = h_x(\acute{x})$). The $\acute{x}$ vector, with the length of M, constitutes zeros and ones, showing a possible subset of features within x, where $\acute{x}_i = 1$ indicates the presence of the feature in the subset. The additive attribution approach yields an explanation model which satisfies $g(\acute{x}) \approx f(h(\acute{x}))$ and is expressed as $g(\acute{x}) = \phi_0 + \sum_{i=1}^{M} \phi_i \acute{x}_i$, where the $\acute{x}_i = \{0, 1\}^M$ is the simplified input and $\phi_i \in \mathbb{R}$ is the importance value of feature i. The feature importance is determined as follows:

$$\phi_i(f, x) = \sum_{\acute{z} \subseteq \acute{x}} \frac{|\acute{z}|!(M - |\acute{z}| - 1)!}{M!} \left[f_x(\acute{z}) - f_x(\acute{z} \setminus i)\right] \tag{1}$$

In the Equation (1), $\acute{z}$ is the subset vector of $\acute{x}$ ($\acute{z} \subseteq \acute{x}$), meaning the non-zero components are a subset of non-zero elements in $\acute{x}$. The $|\acute{z}|$ is the number of ones in $\acute{z}$ and M is the cardinality of the original input features. $f(\acute{z}) = f(h_x(\acute{z})) = f(z_S)$ since $z_S = h_x(\acute{z})$, where S is the set of non-zero elements' indexes in $\acute{z}$ vector. So, the calculation of Shapley values faces a problem when computing $f(z_S)$ as most models cannot approximate the patterns of missing features. To tackle this limitation, the SHAP methods use the conditional expectation $E\left[f(z)|z_S\right]$ to approximate $f(z_S)$. Additionally, SHAP methods assume features independence and linearity in the model for the sake of simplicity, which means $E\left[f(z)|z_S\right]$ approximates as $f\left(z_S, E\left[z_{\bar{S}}\right]\right)$. This implies that the missing feature can be estimated using the average values of this feature in the provided background samples. It is important to note that, despite this assumption, SHAP methods are capable of capturing feature correlations by considering all possible feature subsets within each coalition.

There are various SHAP explainers inside the SHAP library, such as Kernel SHAP, which is model-agnostic, while Linear SHAP, Tree SHAP, and Deep SHAP are specialized for specific types of ML models. Deep SHAP provides global and local explainability for Deep Learning (DL) models by combining the Shapley values concept with the DeepLIFT method. Functioning as a SHAP method, it assumes the DL model is a linear model with independent input features, so it treats each DL layer as a linear model and backward the computed Shapley values through the network.

3. mmWave Channel Model

In this paper, we define a model to generate the parameters of the bidirectional channel linking a transmitter to a receiver, focusing on key parameters, namely path loss, arrival and departure angles, and propagation time delay. We assume the UAV is endowed with a cellular Base Station (gNB), while UE serves the stationary receiver; however, the transmitter and receiver roles can be interchanged. There are three distinct channel states to characterize the mmWave channel between the transmitter and receiver: LOS, non-LOS, and no-link availability. Note that our main focus is on modeling the channel parameters for non-LOS paths since the basic trigonometry can be used to calculate angles and delay and Friis' Law for path loss parameter in the straight LOS paths [14]. Each link (n) is represented by six parameters, namely the path loss (Pl_n), the azimuth and elevation angles of the receiver (ϕ_n^R, θ_n^R), the azimuth and elevation angles of the transmitter (ϕ_n^T, θ_n^T) and the propagation delay (d_n). The main objective is to develop a data-driven model capable of producing parameters that closely resemble real-world ones. The channel parameters of ray tracing simulation data from [10] are used for training and evaluation purposes. This dataset considers 20 non-LOS paths within each link (channel), so the model must generate 120 parameters for each link (20 paths * 6 parameters), with a maximum loss of 200 dB.

Given that the estimation of channel parameters relies on the channel state (LOS, non-LOS, or no-link), firstly, a two-hidden-layer deep classifier is used, as reference [10], to estimate the probability of UE being in the LOS of the UAV. This model utilizes the link distances $d = [d_x, d_y, d_z]$ and the cell type (terrestrial in our case) and generates the probability of the link state.

3.1. Channel modeling via XAI-GAN

In GANs, the generator (G) attempts to produce more realistic synthetic data from random noise (z), while the task of the discriminator (D) is to differentiate between real and synthetic ones. Through adversarial training, GANs improve in generating better synthetic data with a distribution close to the training data. In CGAN, both the generator and discriminator receive additional conditioning information, to guide the generation process. In this work, we opt for CGAN, conditioned on the link's state, for mmWave A2G UAV channel parameter estimation for the given urban environment. This choice is motivated by CGAN's demonstrated success in capturing complex input data distributions and generating high-quality synthetic data for mmWave channel modeling, compared to CVAE, as evidenced in prior research [12, 11]. However, we seek to enhance the CGAN performance by integrating the XAI methods, leading to XAI-GAN. We specifically employ the Deep SHAP approach due to its compatibility with the deep structure of CGAN, as the reference [15].

To enhance the CGAN channel model, we augment the training procedure of CGAN by integrating the XAI methods. In the original CGAN, the generator's loss, $(D(G(z)))$, is computed based on the discriminator's assessment of the generated synthetic data $G(z)$. In XAI-GAN, after the calculation of the generator's loss, the generated synthetic data $G(z)$, along with the discriminator and its prediction $D(G(z))$ are fed into the Deep SHAP. Its output reveals the synthetic features' influence on the resulting loss. This will allow the generator to learn which features help the discriminator identify the synthetic data and use this knowledge to guide its gradient descent process.

After obtaining the feature importance (SHAP value) of synthetic data on the discriminator output via the Deep SHAP method, we transform it into a matrix, referred as the "explanation matrix". Each element of this matrix falls within the range of [0,1], denoting the impact of the corresponding feature. Values closer to zero indicate minimal impact on prediction, while those approaching one signify greater influence. Following this, both the discriminator loss for generated data and the explanation matrix M_{ex} are fed to the generator as feedback. The matrix M_{ex} and the generator's gradient ∇ are subjected to a Hadamard's product, as in the equation (2), ensuring that the features' significance is considered when updating the generator's weights, causing more control over the training process.

$$\nabla_{new} = \nabla + \alpha M_{ex} \nabla \tag{2}$$

The parameter α serves as a regularizer and the product helps guide the gradient descent more effectively, leading to the generation of synthetic data closer to the real parameters.

4. Experimental Results

In this section, we outline the experiments conducted to evaluate the efficiency of our generative approach. We utilize the ray tracing simulation dataset from [10] for evaluation. This dataset encompasses vectors connecting UAVs to terrestrial or aerial gNBs. We assume the terrestrial cell only, considering the UE instead of terrestrial gNB and UAV with an aerial BS for our analysis. Additionally, using different city blueprints, this dataset captures diverse environmental and building characteristics of various cities. Our evaluation focuses on three key cities: Boston, London, and Beijing. The ray tracing simulations conducted at 28GHz in [10] also involve UAVs positioned at various heights of 30, 60, 90, and 120 meters for each environment.

To assess our channel parameter model, we compare it with two models of literature, namely CGAN [12] and CVAE [10]. The hyperparameters and architecture employed for training these models are detailed in Table 1. It's worth noting that these generative models are conditioned on the predictions of the link state model for the specified link. Hence, the link model is initially trained individually on the local city datasets.

4.1. Performance evaluation metric

At first, the two metrics of Kullback-Leibler (KL) divergence and Wasserstein Distance (WD) are selected to evaluate the efficiency of the XAI-GAN model. These metrics quantify the disparity between the path loss distribution of the original test dataset and the distribution of synthetic path loss generated by various generative models. The comparative results are presented in Table 2. The results demonstrate that the distribution of synthetic path loss produced by the XAI-GAN is much closer to the true distribution compared to other alternatives, in terms of

Table 1
Model summary and hyperparameters for all the evaluated models

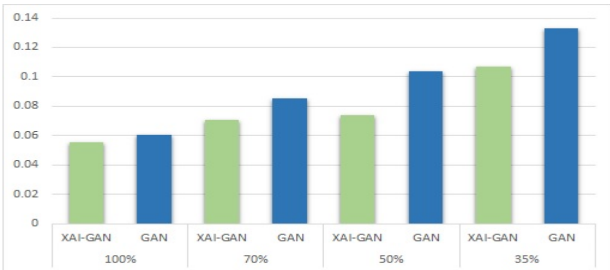
	Link state prediction	XAI-GAN	CGAN	CVAE
Hidden units	[50,25]	gen-[280,560,1120] dsc-[1120,560,280]	gen-[280,560,1120] dsc-[1120,560,280]	enc-[200,80] dec-[80,200]
Optimizer	Adam	Adam	Adam	Adam
Epochs	10	5	5	5
Batch size	100	280	280	280
Learning rate	10^{-3}	10^{-4}	10^{-4}	10^{-4}

Table 2
KL and WD distances between path loss distribution of real data and synthetic data

City	Distance	XAI-GAN	CGAN	CVAE
Boston	**KL**	0.029	0.044	0.135
	WD	9.653	9.717	9.798
London	**KL**	0.055	0.060	0.122
	WD	9.758	9.926	10.217
Beijing	**KL**	0.032	0.048	0.115
	WD	10.637	10.984	10.967

London Data	XAI-GAN	CGAN
100%	0.055	0.060
70%	0.070	0.0855
50%	0.074	0.1038
35%	0.107	0.1328

(a)



(b)

Figure 1: KL distances between London's path loss distribution and synthetic distribution achieved by trained models

both criteria, underscoring the accuracy of the proposed model in representing the channel parameters.

In the second stage, we train XAI-GAN and CGAN channel models on the London channel parameter dataset with 70%, 50%, and 35% proportion of the dataset, respectively. The results for these trained models are shown in Fig 1. For the model trained with 70% of the dataset, the KL distance of the original CGAN is 0.085, while the XAI-GAN distance is 0.070, showing an improved performance of 17%. Similar improvements are observed for the 50% and 35% data subsets. This demonstrates that the XAI-GAN can achieve the same level of accuracy with significantly less training data.

5. Conclusion

Our paper presents a modified model for wireless UAV-based channel parameter generation using CGAN integrated with the XAI method. Our experimental findings demonstrate the effectiveness of the proposed XAI-GAN framework in generating synthetic data with more resemblance to real ones. Integrating the Deep SHAP explainer enhances the gradient descent process of the generator, leading to a more data-efficient model. Experimental results on models trained with different proportions of the dataset illustrate the superiority of XAI-GAN in accurately modeling the link between UE and UAV, even with a 35% reduction in training samples.

Acknowledgments

Work supported by the European Union under the Italian National Recovery and Resilience Plan (PNRR) PE00000001 - program "RESTART", Mission 4 Issue 2 Investment 1.4 “Potenziamento strutture di ricerca e creazione di ”campioni nazionali di R&S” CN00000023 – “Sustainable Mobility Center (CNMS)”, and by the HORIZON-CL4-2021-SPACE-01 project "5G+ evoluTion to mutioRbitAl multibaNd neTwORks" (TRANTOR) No. 101081983

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