A Comprehensive Study on Path Loss Estimation Using Deep Hybrid Learning in 5G Networks

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Abstract — One of the most important factors in radio network design is path loss – a phenomenon that may be measured using a variety of techniques, including deterministic, empirical, machine learning, and deep learning models. Each approach has its own limitations, such as inability to capture non-linear interactions, high computational resource demand, and inability to reflect changes in environmental conditions, among many others. The deep learning model has the capacity to recognize intricate patterns and has been essential in removing those obstacles; therefore, in this study it is used for path loss prediction in 5G communications in the South Asian region. The model makes use of long- and short-term memory (LSTM), gated recurrent unit (GRU), convolutional neural network (CNN), and dense neural network (DNN) approaches to take advantage of all the benefits that each algorithm provides. The performance of the proposed strategy was validated by testing it against multiple state-of-the-art approaches, while relying on the same dataset. An examination of the relevance of characteristics has also been carried out to gain a better understanding of the influence of path loss. A variety of characteristics that are directly related to path loss were evaluated, followed by an examination of how they affect the decision-making process. The results show a possible solution that can help handle this path loss estimation for mmWave communication, especially for 5G networks and beyond.

Keywords — 5G, deep learning, machine learning, mmWave, path loss

1. Introduction

5G networks use higher frequency and smaller cell sizes, rendering the issues of signal degradation, fading, and interference more important [1], [2]. Signal strength is the most important parameter for maintaining a reliable communication link and determines throughput. Path loss refers to the degradation of the electromagnetic signal as it propagates through a channel [3]. Mathematically, it is the difference between the transmitting power and the receiving power of a signal. Knowledge of path loss in a given environment makes it easier to efficiently plan radio networks [4]. Path loss measurement can help optimize power usage according to channel conditions. Additionally, knowledge about the path loss of a channel may greatly improve the quality of service and resource allocation.

There are several methods to measure path loss. The early methods involve empirical models developed based on data observed under real-world scenarios [5]. Several parameters such as distance, frequency, and attenuation factor are taken into account when developing specific formulas. The models capture the average path loss value of a channel in a certain setting. There are several empirical models such as the free space path loss model [6], the Hata model [7], the Okumura model [8], the 3GPP TR 38.901 model [9], and the log distance model [10]. Simplicity is one of the main reasons behind their widespread use.

They are pretty basic models that require some simple parameters, like distance, frequency, and some environmental data that change based on a given setting. Consequently, it is very easy to modify the model according to environmental needs. For example, the Hata model can be adopted in urban, suburban, and rural settings. Its simplicity eliminates the need for computational resources and makes it an economical option. Its ease of use and thorough understanding have led to its adoption as the main foundation of radio network planning [10].

3GPP has developed one such empirical model, known as 3GPP TR 38.901, keeping in mind the nature of 5G communication and its requirements. However, there are several major limitations that led to the adoption of other techniques. One of the major limitations is their rigidity. Although the models capture some of the environmental parameters, they cannot reflect a sudden change of a certain parameter. Also, the models are much more generalized. Consequently, they cannot truly capture the difference in settings that vary from one country to another.

The urban setting prevailing in Europe does not necessarily reflect the conditions that exist in Asia. Therefore, path loss measurements may not be accurate. Additionally, changes in some parameters may cause significant changes in path loss readouts.

In some communication modes, such as vehicular communication, the parameters change rapidly, making the path loss models inconsistent in such scenarios. Also, some of the empirical models require the transmitter and receiver to be in the line-of-sight setting, which reduces their usability in non-line-of-sight environments.

Statistical analysis is another approach that is similar to the empirical method. Instead of relying on curve fitting based on real-world data in the empirical method, the statistical method uses probabilistic and statistical analysis to model the propagation of electromagnetic waves. Many statistical methods such as log distance path loss model and log normal shadowing [11] exist.

One of the major limitations of the method is its inability to model optical phenomena such as diffraction, reflection, and scattering. These phenomena are very common in high-frequency environments, which makes the statistical method ineffective in high-frequency cases.

Another method of measuring path loss relies on deterministic models [12]. These models make use of electromagnetic principles to predict the propagation of signals through the environment based on their interaction with several environmental factors [13]. Instead of the observed values, these models are developed by simulating the real world environment. As a result, they are environment-specific and yield measurements with a higher degree of accuracy.

There are several deterministic models in use. Ray tracing [14] is the most popular deterministic model. It tracks the rays from the transmitter to the receiver and finds out how all the ray components interact with the environment. Several parameters such as diffraction, scattering, and reflections are taken into account based on the shape and materials of a given object. The model is used mainly in urban and indoor environments.

Ray launching [15] follows a similar principle of simulating the multipropagation of rays from the transmitter to the receiver. However, it does not trace each ray, which makes it faster. It is mainly used where there is a trade-off between computational resources and accuracy.

It needs to be borne in mind there several other models, such as the uniform theory of diffraction (UTD) [16] and the finite difference time domain (FDTD) [17] exist. These, however, suffer from some disadvantages. The high computational resource requirement makes them a costly option. Due to the high computational volume, they require more time for processing and do not perform accurately in a complex environment where the parameters change rapidly. The high dependence on environmental factors makes them very sensitive to small-scale variations.

Another deterministic method that solves the problem is the parabolic equation method. Unlike the UTD and FDTD, it allows for wave modeling in one main direction only. The method greatly reduces the computation load, as it ignores the backward waves. However, it finds limited use in the near-field region and, like other methods, it also lacks accuracy when the parameters change abruptly.

The geometry method is based on the same foundation as the deterministic model, i.e. it measures path loss by estimating the interaction of the wave with various environmental factors. However, the geometry-based method introduces a statistical method to simulate multipath effects. It is a hybrid method that utilizes the statistical method while also relying on physical accuracy. However, the need for detailed environment data makes its use complex in larger areas. Also, the computational complexity is very high in this case.

Today, artificial intelligence has gained greater traction in every aspect of engineering [18]. Due to its ability to understand complex patterns and make decisions, it is also relied upon in path loss measurements. Machine learning [19] is one of the subsets of artificial intelligence. Machine learning (ML) makes estimations based on previously observed data [20]. It uses several algorithms to find a common pattern among the various features that may influence path loss and makes decisions based on those determinations.

Several algorithms, such as linear regression [21], support vector regression [22], and decision tree [23] are used. However, machine learning lacks the ability to capture non-linear relationships. Deep learning (DL) networks have become very useful in this regard. It is a subset of machine learning that has been constructed to mimic the operation of a human brain [24]. The inclusion of neurons, layers, and activation functions enables deep learning algorithms to capture non-linear relationship as well [25].

In this paper, a deep hybrid model is proposed to estimate path loss. The model consists of long short-term memory (LSTM), a gated recurrent unit (GRU), a convolution neural network (CNN), and a dense neural network. The model was trained using data tailored for the South Asia region. The model was fed with several parameters, such as distance between transmitter and receiver, time delay, received power, phase, azimuth angle of departure, azimuth angle of arrival, elevation angle of departure, elevation angle of arrival, frequency, season, phase, and RMS delay spread. The model explores the three distinct algorithms to take advantage of all of their functionalities. Along with the estimation, the importance of the features and their influence on estimating path loss have been explored.

Table 1 shows the several methods and their limitations in estimating path loss. It is evident from the table that deep learning algorithms can estimate path loss more accurately compared to the deterministic model, and at a lower cost. But the high data requirement is hurdle affecting its adoption. The proposed hybrid model may offer a potential solution to the problem.

Our contributions are as follows.

1) Combining several deep learning algorithms to develop hybrid models for the estimation of path loss in the South Asia region. Instead of focusing only on one kind of algorithm, we have combined several algorithms like LSTM, GRU, CNN, and DNN to capture both temporal and spatial dependencies while predicting path loss.
2) Conducting a comparative study benchmarking the solution against other commonly used algorithms to validate the performance of the proposed hybrid model.
3) Interpreting the model's decision-making process by studying the impact of each feature utilized in the model.
4) Investigating the model's ability to detect path loss to boost it in real world scenarios.

Tab. 1. Comparison of various path-loss models.

Method	Advantage	Limitation
Empirical	Simple and fast	Poor generalization
Deterministic	Very accurate capture of several physical effects	Computationally demanding
Statistical	Scalable	Fixed distribution
Geometry based	Balance between physical realism and efficiency	Need of detailed environment info
Machine learning	Ability to capture non-linear relationship	Requires large amounts of labeled data
Deep learning	Very high accuracy	Computationally demanding

2. Literature Review

Due to the superior performance of machine learning and deep learning algorithms in recognizing the relationship between path loss and various factors, several researchers have explored different approaches based on these models.

2.1. Machine Learning-based Approaches

Several researchers have used machine learning algorithms to estimate path loss. While evaluating the best models, almost all commonly used algorithms have been tested, but the best-performing solutions varied depending on a specific environment. AdaBoost was found to show superior performance in tropical regions [26], random forests showed better performance in the region of uneven terrain attributes [27], and gradient tree boosting for millimeter wave communication (mmWave) communication was best suited for indoor environments [28].

Several researchers adopted numerous performance enhancement steps during the data preparation and training stages, instead of relying on the algorithm alone. In [29], before moving on to support vector machine-based model, dimensionality reduction techniques – such as principal component analysis – were employed to lower the use of computational resources. In another work, support vector regression was relied upon to reduce complexity and training time with different kernels to find the optimal model [30].

Various machine learning algorithms such as AdaBoost and random forest were employed to find the best model for predicting path loss in aircraft cabins [31]. The data expansion method generating partial data samples using the empirical approach has also been adopted to achieve further prediction accuracy improvements. Instead of relying on one specific algorithm, an ensemble model named voting regression was proposed. It consisted of k-nearest neighbors (KNN), support vector regression (SVR), random forest (RF), AdaBoost, and gradient tree boosting (GTB) algorithms to improve its performance [32].

2.2. Neural Network-based Approaches

Due to their ability to capture complex patterns, deep learning approaches have gained momentum, replacing machine learning algorithms where the availability of data is not a problem. Several researchers have also used deep learning-based approaches to estimate path loss. Artificial neural networks (ANN) are one of the most commonly used solutions. An ANN has been used to build path loss prediction models in corridor environments with varying frequencies [33].

Two types of ANN (multilayer perception (MLP) and radial basis function (RBF)) were used to model path loss of an ultra wide-band channel in a mine environment [34]. The model was designed to focus on the balance between generalization and precision. In [35], an ANN-based model was adopted to predict path loss in a multi-wall, multi-frequency indoor environment. The model is based on MLP and the training of data follows the backpropagation algorithm.

Instead of simply using ANN, some researchers conducting data preprocessing and training stages to increase the level of accuracy. In [36], an ANN-based model was deployed to predict path loss in urban environments. To optimize the ANN model and adapt it to a specific problem, an adaptive differential evolution algorithm named CoDe was used. The authors of [37] used ANN to predict path loss for very high-frequency wireless communication. In the study, extensive analysis has been performed to find the optimal numbers of input parameters, neurons, activation functions, and learning algorithms. MLP combined with ADALINE was used to predict the loss of signal propagation in microcellular urban environments [38].

Just like it was the case with machine learning approaches, rather than depending on one type of algorithm, researchers utilized various algorithms with ANN to build more robust models. The authors of [39] proposed a two-layer RBF neural network-based model. It predicted path loss using hybrid rival penalized competitive learning (RPCL) and recursive least squares (RLS) algorithms. The model offered better performance compared to empirical approaches such as the data model. In [40], field strength was predicted using a combination of an empirical model and an artificial neural network. The research was based on a dense urban environment.

A hybrid model was developed using the Hata model and low complexity ANN to predict path loss in [41]. The model outperformed a high-complexity ANN model by accurately predicting path loss.

Another approach based on neural networks is the backpropagation neural network. In [42], a backpropagation neural network was used to predict the received power in a suburban scenario, while in paper [43], backpropagation neural networks were used to build a model that can be useful in multiple environmental settings (rural, urban, and suburban). In addition to the ANN and backpropagation neural network, other types of networks such as the 3-layer wavelet neural

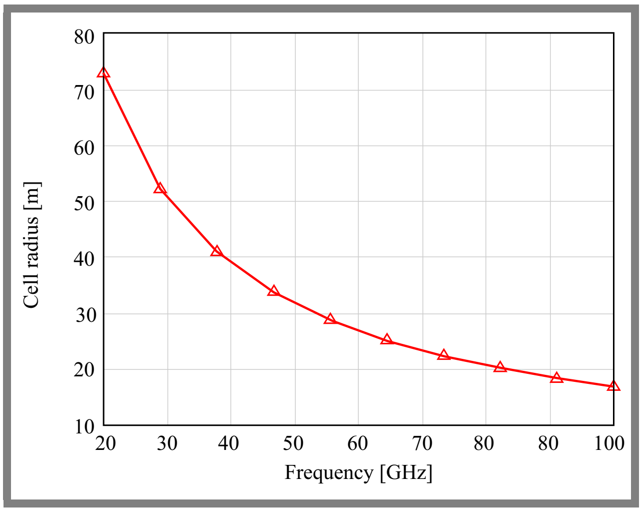

Fig. 1. Impact of using higher frequencies on cell radius.

network have been developed to predict field strength for different frequencies [44].

CNN is another prominent deep learning-based approach. It has been used extensively for model building. In [45], two convolutional neural networks based on group-16 visual geometry (VGG) and residual network (ResNet-50) were tested. ResNet-50 was found to be the best performing solution. Multitask learning was introduced to further enhance the accuracy of the predictions made. The introduction of multitask learning increased the accuracy rate to 2–4%. In [46], a CNN-based model was proposed to predict the path loss exponent of outdoor millimeter wave band channels. In [47], the authors used CNN to build a path loss prediction model for high-traffic scenarios. The environment has various obstacles that greatly impact the communication using high-frequency bands, and it makes it very difficult for conventional methods to accurately estimate path loss.

3. Problem Analysis

5G networks use millimeter wave (mmWave) spectrum (24 to 100 GHz) to facilitate higher capacity and ultra-low latency. The use of higher frequencies allows to support massive device connectivity. However, using higher frequencies comes with its disadvantages too. One of the key challenges is the reduction of cell size. Figure 1 shows the impact of frequency increment on the radius of the cell. As one may notice, at 20 GHz the cell radius is marginally higher than 70 m. As we continue to increase the frequency even further, the cell radius declines sharply. At 100 GHz, the cell radius reduces to less than 20 m. A lower cell radius will result in frequent cell switching events that greatly impact path loss and throughput. When employing the free space path loss model, it can be seen that higher frequency has a significant impact on path loss. The free space path loss (in decibels) can be expressed as:

$$FSLP = 20\log_{10} d + 20\log_{10} f + 20\log_{10} \frac{4\pi}{c}\,, \qquad (1)$$

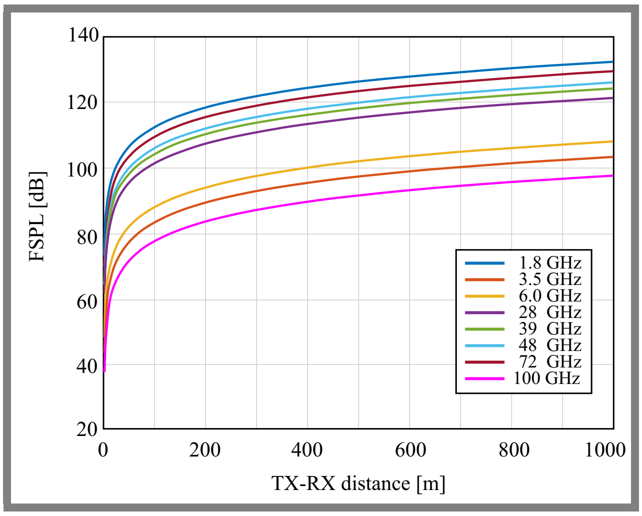

Fig. 2. Impact of using higher frequencies on path loss.

where d is the separation between the transmitter (Tx) and the receiver (Rx), f is the operating frequency, and speed of light is denoted as c. Figure 2 shows the impact of higher frequencies on path loss.

As the number of steps increases, the path loss also increases. At 1000 m separation, using the 1.8 GHz frequency results in a path loss that is closer to 90 dB. Using higher frequencies results in greater path loss. As one may see from the figure, an operating frequency of 100 GHz causes a path loss exceeding 120 dB at 100 m separation. Consequently, path loss estimation is of greater importance in 5G networks, as it allows for efficient radio network planning.

4. Methodology

The proposed hybrid method consists primarily of LSTM, GRU, and CNN layers. While LSTM layers are used to capture temporal dependencies, convolution layers are used for capturing spatial dependencies. GRU layers are used here instead of a stack of LSTM layers to reduce computation requirements. In Fig. 3, the working process is shown in the form of a block diagram. The process involves collection of the data set, preprocessing, designing, training and evaluating the model, and then comparing it with baseline ML-DL algorithms.

The data set has been based on a 5G communication environment in the South Asia region, as described in [48]. The dataset contains multiple data which were obtained through a simulation relying on NYUSIM, but only those variables that are closely related to and can be used to predict path loss are considered in this research. These include the following: transmitter-receiver (T-R) separation distance, time delay, received power, RMS delay spread, and frequency. As far as frequency is concerned, the dataset is mainly focused on the high band and the frequencies used here are 7.125, 24.25, 52.6, and 71 GHz.

The process of preparing raw data trainable for the deep learning model is important, since it is closely related to finding the best outcome from the prediction model. The

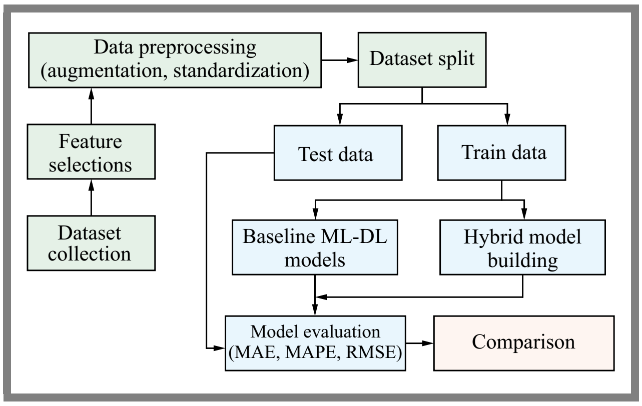

Fig. 3. Block diagram depicting the methodology used.

cleaner the data set, the better outcome can be obtained from the prediction model; thus, it is an important phase before training the model. Two stages are developed:

- Data augmentation is a method through which newer artificial data can be created. Deep learning algorithms require a robust larger dataset to build a general model. Data augmentation helps in that regard to create more samples and increase the size of the dataset. Several methods are used, such as adding noise and transformation. One of such methods is bootstrapping. It creates new data using a method known as "resample with replacement". The primary reasons for choosing bootstrapping for data augmentation are its non-parametric character and flexibility. Bootstrapping not only allows to increase the size of the dataset, but also helps generalize the model, making it more robust to noise.
- Standardization. As several values have an outlier effect and fail to follow normal distribution, we have applied min-max scaler to all variables. This will augment convergence and prevent any bias caused by the outliers.

$$x_{transformed} = \frac{x - x_{min}}{x_{max} - x_{min}} , \tag{2}$$

where x is the value of a feature, x_{min} and x_{max} are the minimum and maximum values of the feature, respectively.

4.1. Proposed Deep Hybrid Model

The deep learning model has to be built in such a way that it is able to take into account every aspect of the dataset and can predict accordingly. To build a solution that fulfills this requirement, a hybrid model turns out to be the best approach, as it combines different deep learning algorithms. In this research, a hybrid model is built by combining LSTM, GRU, CNN, and a dense layer, as shown in Tab. 2. It is well known that LSTM is a resource-intensive model, as it can be expanded and may utilize large datasets to predict better outcomes.

After this layer, GRU is utilized. It is less resource-intensive and more efficient in producing a better outcome, as GRU is used for capturing the temporal dependencies.

However, it is much simpler than LSTM, which results in faster training. After GRU, a dilated convolution layer is used. It offers a unique feature, as it is able to drop the value after a specific range based on the dilation rate. The dilation rate has been essential for increasing the receptive field of the layers. The dilation rate has been varied here to capture both local and global dependencies. Thus, LSTM is used to expand the values. It is then the task of GRU to concise them, with dilated convolution taking over to make the prediction precise.

Lastly, a dense layer is used that will be activated based on the ReLU activation function to predict the final result and for fast convergence. The Adam optimizer has been employed for the model with a learning rate of 0.001.

Tab. 2. Deep hybrid model parameters.

Layers	Units	Parameters	Activation function
LSTM	128	68 608	tanh
LSTM	64	49 408	tanh
GRU	64	24 960	tanh
Conv1D	32	4 128	tanh
Conv1D	32	2 080	tanh
Conv1D	32	2 080	tanh
Conv1D	32	2 080	tanh
Conv1D	32	2 080	tanh
Dense	1	33	ReLU
Total parameters 472 613 (1.80 MB)			
Trainable parameters 157 537 (615.38 KB)			
Non-trainable parameters 0 (0.00 B)			
Optimizer parameters 315 076 (1.20 MB)			

4.2. Baseline ML/DL Models for Comparison

To validate the performance of the proposed deep hybrid model, its outcomes are compared with those achieved by several commonly used baseline ML and DL models. In the following section, a brief analysis of the baseline models is presented.

- Linear regression (LR). The model estimates path loss by assuming a linear relationship between path loss and the input features. The model was chosen for its simplicity and interpretability. The parameters used include fit intercept (set to true) and no regularization.
- Polynomial regression (PR). It is an extension of linear regression. It models non-linear relationships by including polynomial terms of the input features up to degree 2. The model is used to capture the non-linear relationship while maintaining computational efficiency.
- Random forest regression (RFR). It is an ensemble model. It includes 100 decision trees, with a maximum depth of 10 and a minimum of 2 samples per split. RFR is implemented because of its ability to capture non-linear relationships and robustness against overfitting.
- Support vector regression (SVR). The SVR model uses a kernel of radial basis function (RBF) with $C = 10$ and

$\varepsilon = 0.1$. SVR is efficient in handling higher-dimensional data and can model non-linear relationships through kernel transformations.

- Artificial neural network (ANN). The model consists of two hidden dense layers with 64 and 32 neurons, respectively, both using the ReLU activation function. The model also incorporates a dropout layer to reduce overfitting. ANN by far outperforms machine learning-based models in capturing non-linear relationships.
- Long short-term memory (LSTM). LSTM is used to capture temporal dependencies of the features. The model consists of two stacked LSTM layers with 64 and 32 units, respectively, both using the hyperbolic tangent (tanh) activation function. A dropout layer is also added to reduce overfitting. The model helps capture the sequential dependencies that may be overlooked by other approaches.
- Gated recurrent unit (GRU). Like LSTM, GRU also captures temporal dependencies. The model consists of two stacked GRU layers containing 64 and 32 units, respectively, each using the tanh activation function. The dropout layer is also used here to reduce overfitting. Although LSTM shows superior performance in capturing long-term dependencies, GRU can perform better in scenarios with limited data or where the temporal dependencies are moderately long.
- Convolution neural network (CNN). CNN is used to capture spatial dependencies. The model has a stack of six 1D convolutional layers, each with 32 filters, with a kernel size of 2. The dilated convolutional architecture is effective in capturing the spatial characteristics.

5. Result Analysis

5.1. Error Matrix Analysis

The evaluation metrics include mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). MAE measures the average magnitude of errors between the predicted and actual values. It can be expressed as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| , \tag{3}$$

where y_i is the actual value and $\hat{y}_i$ is the predicted value.

MAPE measures the average percentage error. It is sensitive to small actual values. It can be expressed as follows:

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| . \tag{4}$$

RMSE gives more weight to larger errors by squaring them before averaging. It can be formulated in the following way:

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

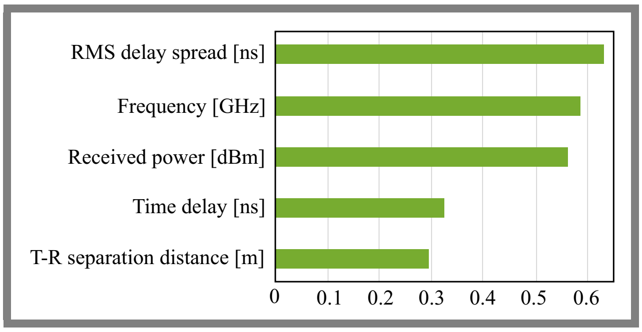

Fig. 4. Comparisons of feature sensitivity.

Tab. 3. Deep hybrid model parameters.

Model	MAE	MAPE	RMSE
LR	17.0053	10.8424	21.9414
RF	16.6703	10.6766	21.6529
SVM	15.0382	9.6501	19.3329
Polynomial	13.8306	8.9102	17.7603
LSTM	5.3798	3.4097	6.9062
ANN	4.8112	2.9737	6.1571
CNN	4.2579	2.6533	5.4366
GRU	4.0791	2.5039	5.1116
Proposed hybrid model	**3.9742**	**2.4512**	**5.0747**

Table 3 presents the performance metrics for all models. From the table, it is evident that the neural network-based model outperforms machine learning-based models, as it is capable of capturing non-linear relationships more effectively by incorporating spatial and temporal dependencies. The proposed deep hybrid model achieves the lowest RMSE and MAE, outperforming all baseline models. The results indicate that the model is able to successfully integrate several algorithms to extract their individual qualities in order to produce the best result.

5.2. Feature Sensitivity Analysis

While building the model, a total of five important variables were considered to estimate path loss. These variables have a direct influence on path loss. Studying sensitivity of the features is important to analyze whether a given model is biased towards one parameter only, which can severely impact its accuracy. The five variables, including RMS delay spread, operating frequency, received power, time delay, and distance between the transmitter and the receiver were taken into account to predict path loss.

After analyzing sensitivity of the features, it is evident from Fig. 4 that the prediction model is more sensitive to RMS delay spread, operating frequency, and power received by user equipment (UE). A minor alteration in these variables will significantly affect prediction values. RMS delay spread is a crucial parameter for determining path loss, as it indicates time dispersion of the signal arrival phase, present due to

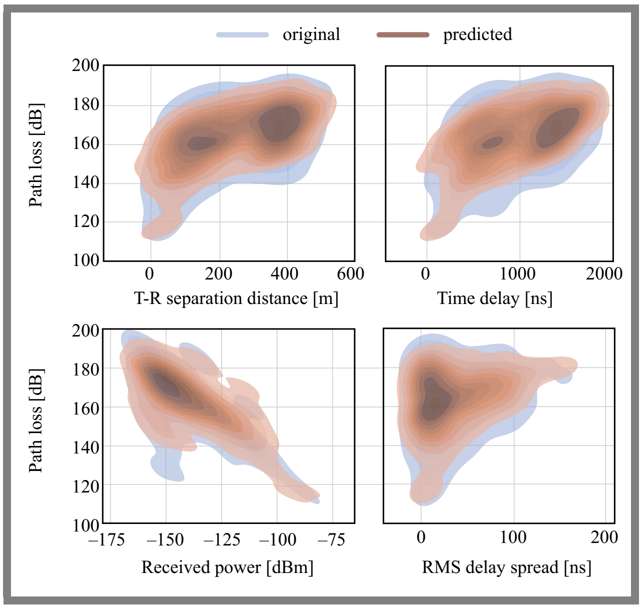

Fig. 5. Distribution of predicted values.

the multipath nature of the system. It identifies how spread out these arrival times are, thus helping manage the signal's integrity, especially in high-speed communication systems.

On the contrary, the prediction model proposed in this research is less sensitive to the T-R separation value – a characteristic that is desired in the practical world, because this separation distance can vary significantly, especially when UE is mobile. If the prediction model relies mostly on this parameter, then path loss prediction will be significantly impacted for high-speed users, and the prediction model will predict an arbitrary value which will eventually lead to a complete failure to operate efficiently in a real-world scenario.

The sensitivity is quantified using partial derivatives, which can be written as:

$$S_{(y,x_i)} = \frac{\partial y}{\partial x_i} , \tag{6}$$

where:
$S_{(y,x_i)}$ is the sensitivity of output y with respect to x. $\frac{\partial y}{\partial x_i}$ represents how y varies in response to small changes in x.

5.3. Analyzing the Distribution of the Prediction Values

It is important to know what value is produced from the deep learning model to make it suitable for real-world scenarios. It will help to better understand the model and tune its attributes to produce the best results. The five important parameters are plotted against predicted and actual path loss values in such a way that the probability density function (PDF) of the actual and predicted path loss is explained. The reason behind this is to see the range of predicted and original values and to detect any outliers or wrongly predicted values.

From Fig. 5 it is clear that the prediction model has captured the scenario clearly, as there is no outlier present in the plots. Moreover, the prediction values are more confined than the actual values, which not only represents the accuracy of the prediction model but also shows that it operates consistently in all the scenarios. As RMS delay spread plays the most crucial role in terms of impact, the distribution of predicted values against a specific parameter is more confined than in the case of actual values. This indicates that deviation from actual data is not significant. Moreover, the model could analyze every aspect of the related parameter and make proper justification before making the prediction.

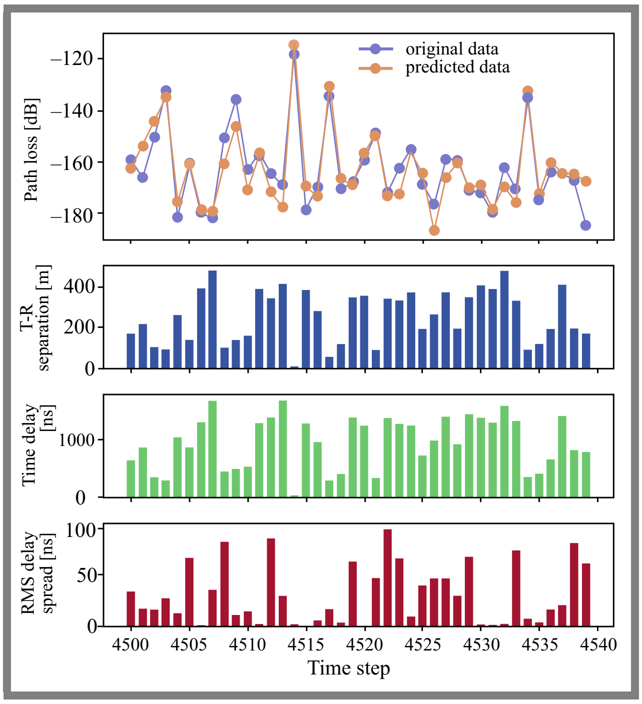

Fig. 6. Comparison of original and predicted data.

5.4. Original and Predicted Data Patterns

Figure 6 illustrates that estimations of the prediction model not only closely align with multiple data points of actual values but also effectively capture the underlying patterns. For example, at time step 4514, both T-R separation and RMS delay spread decrease over time, while the actual path loss increases, and the predicted path loss also reflects the increase. A similar pattern is observed in steps 4504, 4517, and 4534. On the contrary, the model also accurately predicts the opposite scenarios, as seen in time steps 4507, 4526, and 4539. These prediction values indicate that the model successfully recognizes various scenarios and patterns, demonstrating its prediction accuracy.

6. Conclusions

Since path loss is a critical component of high frequency wireless communication, in this research a deep hybrid model was developed to predict path loss for high frequency communication, specifically for 5G and B5G. By combining LSTM, GRU, convolutional layers, and dense layers in the model development phase and utilizing the distinct characteristics of each algorithm, optimal results were achieved.

The approach becomes more robust and versatile when all types of dependencies are combined into one model. The convolutional layer offers spatial domain information, while

LSTM and GRU provide the temporal viewpoint of the features. Numerous simulations have demonstrated how well the suggested model predicts path loss and identifies its variance pattern.

By examining the dependency of the model on various parameters, the study further investigated the significance of the individual characteristics in the decision-making process of the suggested model.

Lastly, this study examines the ability of the hybrid model to predict actual outcomes by examining each pattern that might potentially emerge in a real-world environment. The results clearly demonstrated the model's potential for use in real-world scenarios.

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