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ML Modeling For Path Loss In 5G High-FrequencyBands For Enhanced Network Performance

Naresh. A[1], Arun Sai. G[2], Raju Goud. k[3], Santhi. K[4]
[1,2,3] UG Scholar, Department of ECE, St. Martin's Engineering College, Secunderabad, Telangana, India-500100
[4]Assistant Professor, Department of ECE, St. Martin's Engineering College, Secunderabad, Telangana, India-500100
rajukoyyada408@gmail.com

Abstract:

The evolution of wireless communication has driven the advancement of 5G networks, utilizing high-frequency bands to deliver exceptional data rates and ultra-low latency. Path loss prediction has traditionally relied on empirical models such as Okumura-Hata and COST-231, formulated through extensive field measurements and mathematical calculations. However, these conventional models struggle with simplified assumptions, static parameters, and the inability to accurately capture non-linearities and multipath effects in modern high-frequency environments. This poses a challenge, as precise and adaptive path loss prediction is essential for efficient network planning and deployment in 5G and beyond. Traditional models lack flexibility and fail to represent real-world propagation conditions, necessitating advanced solutions to overcome these limitations. To address this, the proposed system leverages machine learning techniques, incorporating Ridge Regression, Decision Tree Regressor, and a hybrid model combining a Feed-Forward Neural Network (FFNN) with a Decision Tree Regressor. A user-friendly GUI is integrated to facilitate data ingestion, preprocessing, model training, evaluation, and prediction, ensuring a streamlined and efficient workflow for path loss estimation. The proposed system significantly enhances network design, optimizes resource allocation, and improves overall network performance by delivering highly accurate and adaptive predictions tailored to complex propagation scenarios in high-frequency 5G networks. By integrating artificial intelligence with wireless communication, this approach bridges the gap between conventional path loss models and real-world 5G deployment, ensuring efficient, scalable, and high-performance network infrastructure.

Keywords: 5G networks, path loss prediction, machine learning, Ridge Regression, Decision Tree Regressor, Feed-Forward Neural Network, high-frequency propagation, network optimization, adaptive modeling, wireless communication.

1. INTRODUCTION

Over the past decade, the rapid advancement of wireless communication has led to the emergence of fifth-generation (5G) technology, revolutionizing connectivity and network performance. 5G promises ultra-fast data speeds, lower latency, and higher capacity, making it an essential enabler for future digital transformation. With the increasing demand for high-definition content, cloud computing, and real-time applications, 5G plays a crucial role in ensuring seamless data transmission and efficient resource utilization.

Beyond speed improvements, 5G facilitates massive connectivity by integrating a wide range of smart devices, from IoT sensors and wearables to autonomous vehicles and industrial automation systems. This expansion supports the vision of a fully connected world where smart cities, augmented reality, and mission-critical. The conceptual framework for Future IMT (International Mobile Telecommunications) is depicted highlighting essential applications that define next-generation networks. Using a structured layout, the visualization categorizes major 5G-enabled innovations such as ultra-high-speed connectivity, immersive 3D experiences, AI-driven automation, and enhanced communication for smart industries and intelligent infrastructure.

2. LITERATURE SURVEY

The A measurement effort described in [1] that was conducted at 3.7 GHz in a variety of rural Greek locales was utilized to create various machine learning models, which were then contrasted with a few chosen empirical models. However, the comparison was only made using information gathered from a thorough measurement in a rural setting. The results provided an RMSE in the range of 4.2–4.3 dB, demonstrating a higher prediction accuracy than those empirical models.

In a previous study [2], an innovative approach was proposed for developing path loss models using convolutional neural networks (CNN), specifically through meta-learning, referred to as the CNN model with meta-learning. This approach was compared to existing CNN and FI models. It is important to note that the application of this method was limited to the smart factory environment and the specific frequency of 28 GHz.

The most popular artificial neural network (ANN) multilayer perception (MLP) neural network was utilized in [3] to reliably predict path loss. It was built by combining the data from the transmitting antenna and that of the receiver (Rx), including 3D locations and environmental characteristics. To assess the model's performance, a comparison was made between the actual measured outcomes and the predicted results, excluding considerations for losses from the base station (BS). Notably, the inclusion of environmental variables led to enhancements in the precision and reliability of the prediction models.

Utilizing a dataset of field measurements at 28 GHz in a suburban environment, Cheng et al. [4] introduced an innovative path loss modelling technique based on convolutional neural networks (CNN). In their research, they proposed two key components: the enhanced local area multi-scanning method (E-LAMS) and a unique CNN architecture incorporating four subnetworks with shared features between convolution layers. Nonetheless, it is worth noting that further improvements are required to enhance the performance of this model, particularly in line-of-sight scenarios. The study's results indicate that the proposed CNN-based approach outperforms existing empirical models.

In [5], KNN, SVR, RF, and AdaBoost were employed as four machine learning techniques to simulate the radio coverage offered by a flying base station in the urban city of Tripoli. The chosen algorithms were trained on a dataset produced by a ray tracing method. Even though only a line-of-sight (LOS) scenario was used in the investigation, the performance of each model was contrasted. The most accurate predictions came from the tree-based ensemble models, with AdaBoost achieving the lowest MAPE value of 2.72%.

A deep learning model, such as the LSTM, was used to develop a way of predicting fluctuations in path loss [6]. The training and validation data were taken from measurements of path loss in an urban environment. The model was compared to a conventional approach that predicts using the most recent observed median path loss value, utilizing 100 fast-fading data points as input data. In the validation analysis, the measurement campaign was restricted to an urban environment, and the error analysis was limited to the root mean square error. They outperformed the traditional method by more than 1 dB, achieving RMSE prediction accuracy of nearly 2 dB.

The authors in [7] examined two machine learning models, using tabular data and images as two different forms of input to perform path loss predictions in metropolitan locations. They looked at occasions where CNN received just one image and not the other two. By simply creating three duplicates of the same channel, they were able to change the monochrome images into coloured ones while still using the same CNN architecture. With an MAE value of 3.07 dB as opposed to the 3.15 dB of the conventional bimodal approaches, the proposed methodology outperformed existing fusion methods in terms of results.

Similarly, a deep learning technique was utilized in [8] to explain the process of path loss based on the path profile in urban propagation situations. Even still, the LoS and NLoS scenarios' measuring campaigns were only applicable to urban settings. Simulation findings demonstrated that the suggested model outperformed traditional models, and the explainable model's accuracy reached 72%.

In [9], image texture techniques were used to enhance the DL model for path loss prediction. Thus, the algorithm produced a new set of features that showed the specified area's built-up profile. However, further experimental data are needed to verify and rate the effectiveness of the suggested model. The model-aided approach provides an improvement of about 1 dB.

In a separate study [10], a methodology involving a 3D-CNN and a 3D-LAMS algorithm was applied to sample and extract three-dimensional spatial data between the transmitter (Tx) and receiver (Rx) for creating a 3D image representation. The measurement campaign is expected to extend its scope beyond urban environments to explore additional factors influencing path loss. Through multiple trial runs with varying dataset sizes, the proposed path loss prediction model demonstrated its optimal performance.

To compare the similarities and differences between the CNN model and the NN model, Kuno et al. [11] devised a CNN model. They made use of the training and verification data supplied during the IEICE's propagation competition. As a result, the CNN model's estimation accuracy declined near the main roadway and the plaza.

Three machine learning models were used in [12] for radio channel modeling in urban vehicle environments. However, the inquiry was only able to simulate LOS and NLOS conditions utilizing the ray tracing-generated data set. Among the chosen models, RF performed best with a low RMSE of 1.80 ns, while the MLP model had the highest RMSE at 11 ns.

In [13], data from online sources such as OpenStreetMap and various Geographical Information Systems were collected to construct a machine learning model aimed at predicting cellular coverage in metropolitan regions. This model demonstrated the capability to promptly estimate path loss, even in the absence of training data from the physical measurement campaign. Also, numerous feature engineering strategies were investigated in [14] to enhance the machine learning algorithms' predictive performance. They found that, especially for small datasets, more basic models can be just as effective as more complex ones.

In [15], the author employed the image reflection technique to create a dataset that could be used to test any straightforward machine learning model for indoor prediction. The outcome of the comparative analysis demonstrates that the ANN model outperformed the linear model and provided the dataset with the lowest MSE and MAE values.

A novel path loss model capable of estimating path loss was proposed in [16]. The proposed model is grounded in multidimensional Gaussian process regression (GPR), which predicts local shadow fading to give channels spatial consistency in propagation in indoor environments. To test and validate the suggested model, though, more varied environments must be used.

In [17], the authors conducted path loss prediction at 7 GHz within an urban environment by employing a model-assisted deep learning approach. Their proposed model utilizes a distinct set of input features, encompassing both fundamental and engineered attributes. The numerical results demonstrate that the deep learning model outperforms the chosen empirical models in terms of prediction performance. The proposed approach must be enhanced in the context of an environment with additional obstacles because it is still a hybrid model.

In similar work by [18], a viable alternative to improve path loss prediction with the use of the random forest model was proposed. The test carried out in their work showed that the use of the random forest technique with attributes such as geographical coordinates, distance, azimuth, and antenna gain presented better results than other considered models [19].

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Although additional features need to be considered to train and test the model to improve its performance.

Utilizing machine learning methods, Aldossari et al. [20] presented innovative approaches to improve path loss models, addressing the challenge associated with complex channel characteristics and time-consuming measurements. In their study, they successfully reduced the measurement workload necessary for wireless channel modeling through the application of regression techniques.

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3. PROPOSED METHODOLOGY

This research represents a comprehensive approach to predicting path loss in 5G high-frequency bands using machine learning. By integrating data preprocessing, multiple regression models, evaluation metrics, and user-friendly visualization within a single application, it addresses the challenges of traditional propagation models and provides a scalable, adaptable, and accessible solution for modern network planning and optimization.

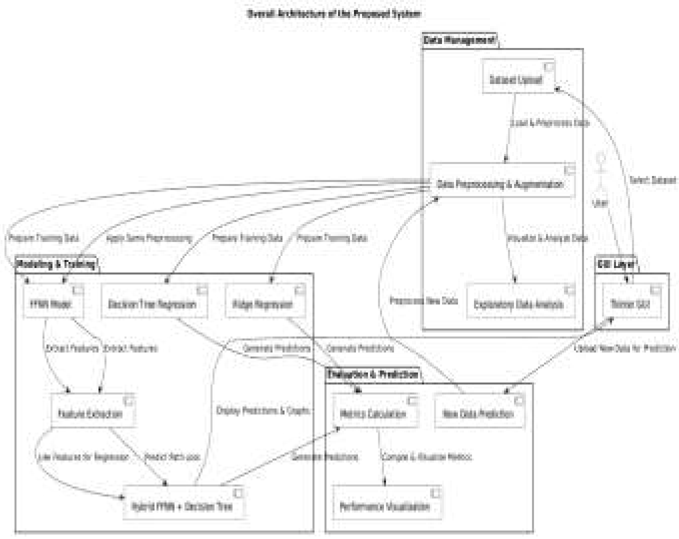

Figure 1: Proposed System

Key Components and Workflow

a. Data Acquisition and Preprocessing

•Dataset Upload: The application begins with a module that allows users to select and load a CSV file containing simulation data. This data typically includes parameters such as seasonal variation, simulation run numbers, physical distances, time delays, received power, phase, angles of departure and arrival, path loss, RMS delay spread, season encoding, and frequency.

•Data Cleaning and Transformation: Once the dataset is loaded, the project applies several preprocessing steps:

•Label Encoding: Categorical features like seasonal variation are converted into numeric values using label encoding.

•Data Augmentation: Resampling techniques are used to balance the dataset, increasing the number of samples to improve model robustness.

•Train-Test Split: The data is divided into training and testing sets to evaluate the model's performance.

•Feature Scaling and Normalization: Standardization is applied to ensure that the various features contribute equally to the model's learning process.

•Exploratory Data Analysis (EDA): Visualization techniques such as histograms, density plots, and heatmaps help in understanding the distribution and correlations among the features.

b. Machine Learning Model Development

•Multiple Modeling Techniques: The project incorporates different machine learning approaches for regression:

•Ridge Regression: A linear model that incorporates L2 regularization to prevent overfitting and manage multicollinearity.

•Decision Tree Regression: A non-linear model that splits the data based on feature thresholds to capture more complex relationships.

•Hybrid FFNN + Decision Tree Model: A feed-forward neural network (FFNN) is used to extract higher-level features from the dataset. These features are then fed into a decision tree regressor for the final prediction. This hybrid approach leverages deep learning for robust feature extraction while retaining the interpretability and efficiency of decision trees.

•Model Training and Persistence: Each model is trained on the preprocessed training data. Once trained, models are saved (using joblib for classical ML models and Keras for the FFNN) so that they can be reloaded for future predictions without retraining, enhancing efficiency.

c. Prediction on New Data

•Prediction Module: Users can upload a new dataset for prediction. The same preprocessing steps (e.g., label encoding and scaling) are applied to ensure consistency with the training data. The pre-trained FFNN model predicts the path loss on the new data, and these predictions are further refined using feature extraction and decision tree regression.

•Visualization of Predictions: The final predictions are displayed within the GUI and plotted against sample indices, providing a clear visual representation of the model's output.

d. User Interface and Integration

•Tkinter GUI: The project features a robust Tkinter-based GUI that ties all the components together. The GUI includes:

•Buttons and Controls: Dedicated buttons for uploading datasets, preprocessing data, training various models, generating performance graphs, and making predictions.

•Text Log Window: A text widget displays logs, outputs, and metrics, making it easier for users to follow the workflow and understand the intermediate steps.

•Visual Feedback: The integration of matplotlib and seaborn ensures that all visualizations (e.g., histograms, scatter plots, and bar graphs) are easily accessible and interpretable.

•Modular Architecture: The code is structured in modular functions, each handling a specific part of the process (data upload, preprocessing, model training, evaluation, and prediction). This modular design improves code maintainability and allows for easier updates or additions to the system.

Applications:

- 5G Network Optimization – Machine learning models can predict and compensate for path loss in high- frequency bands, improving signal coverage, reducing dead zones, and optimizing base station placement.
- Beamforming and Antenna Tuning – By understanding path loss variations, the system can assist in dynamically adjusting beamforming techniques and tuning antenna parameters for better signal reception.
- Smart Urban Planning – ML-based path loss models help in designing efficient 5G infrastructure in dense urban areas, ensuring optimal signal propagation despite obstacles like buildings and vegetation.
- Autonomous Network Management – Predictive models enable self-healing and self-optimizing networks, allowing telecom operators to adjust power levels, bandwidth allocation, and handover mechanisms dynamically.
- Enhanced IoT and Smart City Connectivity – Reliable path loss prediction ensures better connectivity for IoT devices, autonomous vehicles, smart traffic systems, and industrial automation in 5G-powered environments.

4. EXPERIMENTAL ANALYSIS

Fig. 2 illustrates how the application displays key information from the dataset (for example, a preview of the first few rows) in the text widget. This immediate feedback helps users verify that the correct dataset has been selected.

Figure 2:GUI of proposed ML modelling for pathloss estimation system after uploading the dataset.

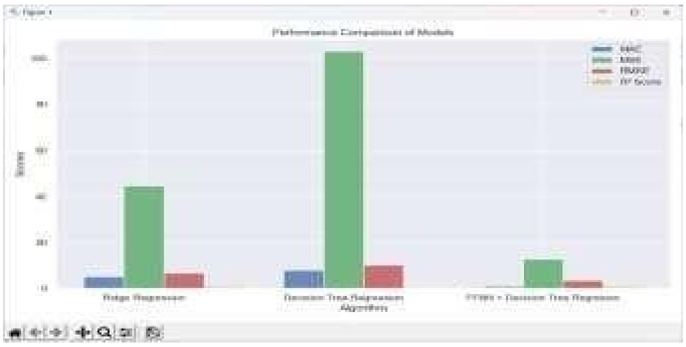

Figure3: Performance comparison of existing ridge regressor, decision tree regressor and proposed hybrid FFNN +DTR models.

Figure 4: Sample predictions on test data.

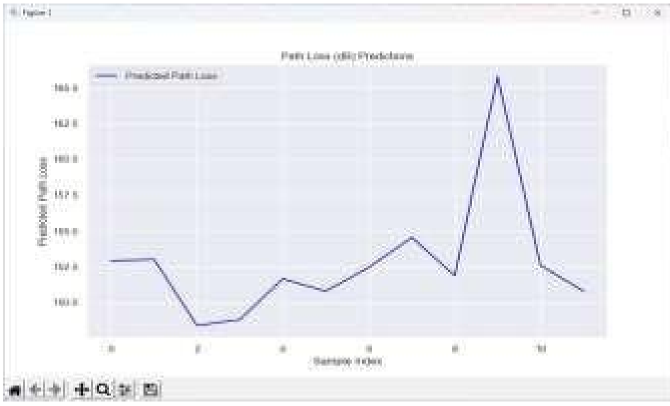

Figure 5: Pathloss prediction graph obtained using proposed hybrid FFNN with DTR model

Figure 3 offers a comparative bar chart (or similar visualization) that juxtaposes the performance metrics (such as MAE, MSE, RMSE, and R²) across the three models. It clearly demonstrates how the hybrid model performs relative to the traditional regression approaches, emphasizing its improved accuracy and robustness.

Figure 4 displays sample predictions generated on a new test dataset. The GUI shows how the predicted path loss values are integrated into the dataset, providing users with tangible results that can be further analyzed or exported for operational use.

Figure 5 presents a time-series or index-based line graph depicting the path loss predictions generated by the hybrid model. The graph provides a clear visual summary of how the model predicts path loss over a series of samples, aiding in the identification of trends and potential anomalies.

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5. CONCLUSION

The proposed system presents a transformative, machine learning–based solution for predicting path loss in 5G high-frequency networks, effectively addressing the shortcomings of traditional empirical models. By integrating multiple regression techniques—namely Ridge Regression, Decision Tree Regression, and a hybrid approach combining a Feed-Forward Neural Network with a Decision Tree Regressor—the system harnesses the strengths of both linear and non-linear modeling. This multifaceted approach allows for a more nuanced understanding of the complex propagation phenomena encountered in modern wireless environments, including non-linearities and multipath effects that traditional methods struggle to capture. The system is designed with a user-friendly graphical interface that streamlines the workflow from data ingestion and preprocessing to model training, performance evaluation, and prediction on new datasets. This integration not only simplifies the process for network engineers and researchers but also facilitates real-time decision-making in network planning and optimization. The dynamic nature of the model—coupled with its ability to adapt to varying environmental conditions and frequencies—ensures improved accuracy and robustness in predicting signal attenuation. Consequently, the system enables more efficient resource allocation and optimized base station deployment, which are critical for maintaining high-quality network performance. Overall, this innovative solution bridges the gap between theoretical advances in machine learning and practical applications in telecommunications, paving the way for smarter, data-driven network management strategies that meet the ever-evolving demands of 5G and future wireless technologies.

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