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Deep Neural Network Based on Long Short-Term Memory for Predictive Learning of Wireless Path Loss Datasets

[1]Ikechi Risi, and [2]Konyeha, C. C

[1] Department of Physics, Rivers State University, Port Harcourt, Rivers State, Nigeria.

[2]Department of Electrical/ Electronic Engineering, Benson Idahosa University

ikechi.risi@ust.edu.ng, ckonyeha@biu.edu.ng

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Abstract: This paper proposes and evaluates a deep learning approach using Long Short-Term Memory (LSTM) networks for the predictive modeling of wireless path loss. We developed the deep LSTM network architecture trained on measured signal path loss datasets. The model takes relevant environmental and geometrical features as input and predicts the path loss value. We compare the performance of the LSTM model under three prediction optimisation algorithms using standard evaluation metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The algorithms include the stochastic gradient descent (SGDM), Root mean square propagation (RMSP) , and Adaptive moment estimation (ADAM). Results demonstrate that the deep LSTM network trained with the RMSP algorithm achieves superior predictive accuracy, effectively capturing complex propagation phenomena and environmental dependencies. The findings imply that an LSTM-based deep learning method trained with the RMSP algorithm offers a robust and potentially adaptive solution for accurate path loss prediction in various wireless environments.

Keywords: Path Loss Prediction, Deep Learning, Long Short-Term Memory (LSTM), Wireless Communication, Radio Propagation, Machine Learning Algorithms.

1. Introduction

The performance of wireless communication systems is fundamentally governed by how radio signals propagate from transmitter to receiver [1-3]. Path loss, a measure of signal attenuation as it travels through the environment, is a primary factor influencing coverage, data rates, and overall system capacity. Numerous empirical and semi-empirical path loss models exist, such as the Free Space Path Loss (FSPL), Okumura-Hata, and COST 231 models [2], which are based on theoretical principles and measurements under specific conditions. However, these models often rely on simplified assumptions and may not accurately reflect the intricate propagation mechanisms present in diverse and evolving environments, including urban canyons, indoor spaces, and dynamic scenarios with moving objects [4-11].

With the advent of machine learning, there is an opportunity to enhance path loss predictions by leveraging large datasets gathered from real-world measurements. The advent of Big Data and advancements in machine learning have opened new avenues for developing more accurate and adaptive path loss prediction models [13-15]. Machine learning techniques can learn complex, non-linear relationships from large datasets of measured path loss values, along with relevant environmental features, to provide more precise predictions [13, 16-17]. Among the various machine learning architectures, deep neural networks, particularly Recurrent Neural Networks (RNNs) and their advanced variants like LSTMs, have shown significant promise in handling sequential data and capturing long-term dependencies [18, 19]. This paper focuses on the potential of LSTMs for predictive learning of path loss datasets.

Thus, the motivation behind this research stems from two primary factors. The first is the the limitations of existing path loss models in complex environments and their reliance on ideal conditions. The second is the extensive growth of data generated from advanced wireless communication systems, which can be better harnessed through machine learning techniques to derive more accurate and robust predictions.

2. Theoretical Framework

2.1 Path Loss Models

Path loss models can be categorized into empirical, deterministic, and statistical models [5-8]. Empirical models derive equations based on measured data, while deterministic models simulate physical phenomena causing signal degradation. Statistical models, on the other hand, leverage historical data to predict outcomes based on underlying statistical properties.

2.2 Long Short-Term Memory (LSTM)

LSTM networks are a type of recurrent neural network (RNN) specifically designed to learn from sequences of data while mitigating issues like vanishing and exploding gradients [12,14]. LSTMs utilize memory cells and gating mechanisms to preserve information over long time intervals, making them particularly well-suited for tasks involving sequential data, such as time-series predictions in path loss forecasting.

2.3 Review of related works

Accurate prediction of path loss is crucial for network planning, resource allocation, and optimization. While conventional models, such as the Hata model and the Okumura model, have provided basic frameworks, they often fall short in dynamic environments characterized by multipath propagation, shadowing, and varying geographical features. Smith et al. [5], elucidate the limitations of these conventional methods, particularly their inability to incorporate variable terrains and urban environments.

In recent years, machine learning, particularly deep learning, has emerged as a powerful alternative for modeling complex relationships in data. With the rise of machine learning, several studies have sought to enhance path loss predictions through the application of algorithms beyond traditional statistical methods. Early efforts utilized simple regression models and decision trees, as reported by Zhao et al. [17]. However, models often struggled with generalization across different conditions. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have shown promise in handling sequential data and capturing temporal dependencies in recent time. Given their ability to model time-series data, LSTMs have gained traction in the field of wireless communication for predicting different datasets. For instance, Buzzini et al. [12] gathered extensive measurement data in a metropolitan area to train their LSTM model, significantly improving the model's performance in that particular geographical context.

Kumari et al. [4] utilized LSTMs to predict path loss in urban environments, achieving significant accuracy improvements over both traditional models and simple feedforward neural networks. Chakraborty et al. [15] compared LSTM to Convolutional Neural Networks (CNNs) and hybrid models. Their results indicated that LSTM networks excelled in capturing temporal dependencies resulting from dynamic environments. Tahsin et al. [16] integrated geographical information system (GIS) data into LSTM frameworks to enhance the predictive accuracy of path loss models, bridging the gap between spatial and temporal aspects.

These previous works indicate a growing inclination towards utilizing LSTM networks for path loss prediction, with promising results in terms of accuracy and adaptability [20, 21]. However, some of these key challenges remain [21]. Researchers have noted issues regarding overfitting, the need for extensive training data, and computational burden.

In this contribution, we propose and evaluate a deep learning approach using LSTM networks for the predictive modeling of wireless path loss under three prediction optimization algorithms. The algorithms include the stochastic gradient descent (SGDM), Root mean square propagation (RMSP), and Adaptive moment estimation (ADAM). The method takes relevant environmental and geometrical features as input and predicts the path loss value, demonstrating its superior performance on a specific dataset, analyzing its capabilities.

3. Methodology

Here, present the measured signal path loss data collection method and the proposed deep LSTM network architecture. The model takes relevant environmental and geometrical features as input and predicts the path loss value. The methods applied to investigate the performance of the LSTM model under three prediction optimisation algorithms using standard evaluation metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are also shown. The algorithms include the stochastic gradient descent (SGDM), Root mean square propagation (RMSP), and Adaptive moment estimation (ADAM)

3.1 Dataset Collection

In this paper, we employed a field drive test-based method for collecting path loss data. This drive testing involves comprehensive measurements of signal strength and service quality parameters at the receiver terminal within the coverage area of the assessed base stations (BS). Consequently, the drive test system offers valuable insights into the performance of cellular networks.

The tools utilized in the field drive test system include a Global Positioning System (GPS), mobile phone software, two LTE mobile phones, a scanner, MapInfo software, data cards, a laptop, a power inverter, direct test cables, and an extension board. All these components were integrated and housed within a vehicle for the drive test. The MapInfo software is specifically designed to visualize drive test location maps and generate route data.

Using the field drive test system tools, we acquired live signal data from a typical Long Term Evolution (LTE) transceiver base station antenna site, all operating at a frequency of 2600 MHz with a bandwidth of 10 MHz. These transceiver base station antennas, referred to as NodeBs, are sectorized. The LTE network under investigation belongs to one of the major telecom service providers offering GSM, WCDMA, HSPA, and LTE services across Uyo town, Akwa Ibom State, Nigeria.

Measurements were conducted using field test tools equipped with TEMS application software, which is specifically designed for radio spectrum analysis. TEMS is a robust and professional-grade testing software for radio frequency cellular communication networks. It can scan, collect, and display a wide range of network data in real-world conditions. Additionally, it provides users with the opportunity to assess and analyze network performance, as well as to identify and diagnose existing network issues efficiently.

3.2 Data Preprocessing

Data preprocessing steps are critical to ensure the quality of input for the LSTM model:

1. **Normalization**: Scaling features to a standard range to facilitate faster convergence.
2. **Segmentation**: Dividing data into sequences to create input-output pairs appropriate for LSTM training.
3. **Handling Missing Data**: Implementing techniques such as interpolation to address gaps in the datasets.

3.3 LSTM Network Architecture

The LSTM model for path loss prediction includes the following components as displayed in Fig. 1:

- **Input Layer**: A fully connected layer to accept processed input features.
- **LSTM Layers**: Stacked LSTM layers to capture temporal dependencies in the data.
- **Dense Layer**: A fully connected layer that interprets the output from LSTM. This layer captures the two hidden layers and the dropout layer.
- **Output Layer**: A regression layer providing the predicted path loss value.

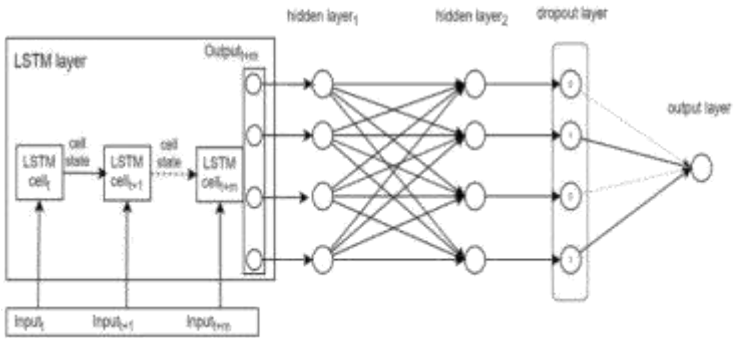

Fig. 1: The LSTM Architecture comprising of the input, dense, and output layers.
This Fig. reveals the data information flow through the LSTM layer with input **x** and output **y** with t time steps.

3.4 The LSTM Training Algorithms

The choice of optimization algorithm plays a crucial role in the training of LSTM networks. The following algorithms are investigated in this paper:

(a) Stochastic Gradient Descent with Momentum Algorithm

SGDM is an iterative approach to finding the minimum of a function, frequently employed in machine learning. SGD with Momentum is a powerful optimization technique for training deep learning models as it helps to smooth the optimization path, reducing oscillations and speeding [22].

(b) Root Mean Square Propagation

Stochastic gradient descent with momentum uses a single learning rate for all the parameters. Other optimization algorithms seek to improve network training by using learning rates that differ by parameter and can automatically adapt to the loss function being optimized. Root mean square propagation (RMSProp) is one such algorithm [23]. It keeps a moving average of the element-wise squares of the parameter gradients. The RMSProp algorithm uses this moving average to normalize the updates of each parameter individually. Using RMSProp effectively decreases the learning rates of parameters with large gradients and increases the learning rates of parameters with small gradients. ε is a small constant added to avoid division by zero.

(c) Adaptive Moment Estimation

Adaptive moment estimation (Adam) [24] uses a parameter update that is similar to RMSProp, but with an added momentum term. It keeps an element-wise moving average. The full Adam update also includes a mechanism to correct a bias that appears at the beginning of training.

3.5 Training and Testing

The model is trained using Mean Squared Error (RMSE) as the loss function, and the datasets are split into training and testing sets. Early stopping is implemented to avoid overfitting.

3.5 General Model Evaluation:

- **Testing:** Evaluate the trained model's performance on the unseen test set using the RMSE, Mean Absolute Error (MAE), and R-squared as performance metrics.
- **Comparison:** We compare the performance of the LSTM model under three prediction optimisation algorithms, which are SGDM, RMSP and ADAM.
- **Visualization:** Visualize predicted path loss against measured path loss, and plot prediction errors across different regions or scenarios to understand the model's strengths and weaknesses.

4. Results and Discussion

The results and discussion of the proposed LSTM network performance for the adaptive learning of the path loss data under three optimisation algorithms (SGDM, RMSP and ADAM) during training and testing with path loss data are shown in this section. The program coding and evaluation of the proposed learning approach using three performance metric were implemented with MATLAB 2024b computation software.
Shown in the graphs of Figs 2-4 are the predictive fitting performance updates achieved by the LSTM network trained with the path loss data under three prediction optimisation algorithms using the RMSE metric. While the (a) parts of Figs 2-4 (a) reveals the predictive fitting performance updates achieved by the LSTM network trained with the path loss data under three prediction optimisation algorithms, the (b) part displayed attained RMSE values during path loss data training. The overall precision performance attained by LSTM with the RMSP, SGDM and ADAM training and testing using RMSE, MAPE and Max.MAPE are shown in Figs.5-6 and Table 1. The results clearly demonstrate that the deep LSTM network trained with RMSP algorithm achieves superior predictive accuracy, effectively capturing complex propagation phenomena and environmental dependencies. The findings imply that LSTM-based deep learning method trained with RMSP algorithm offers a robust and potentially adaptive solution for accurate path loss prediction in various wireless environments in the studied enviroments

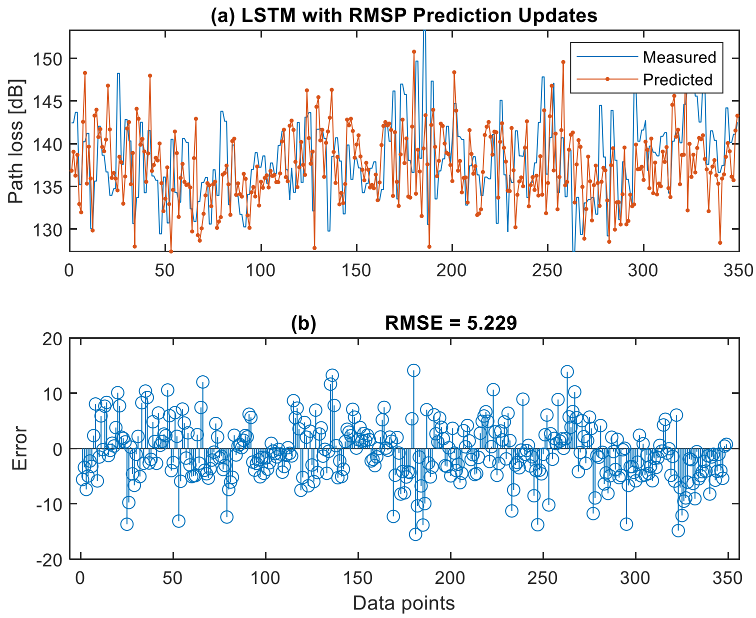

Fig. 2: Proposed LSTM with RMSP prediction performance during path loss data training

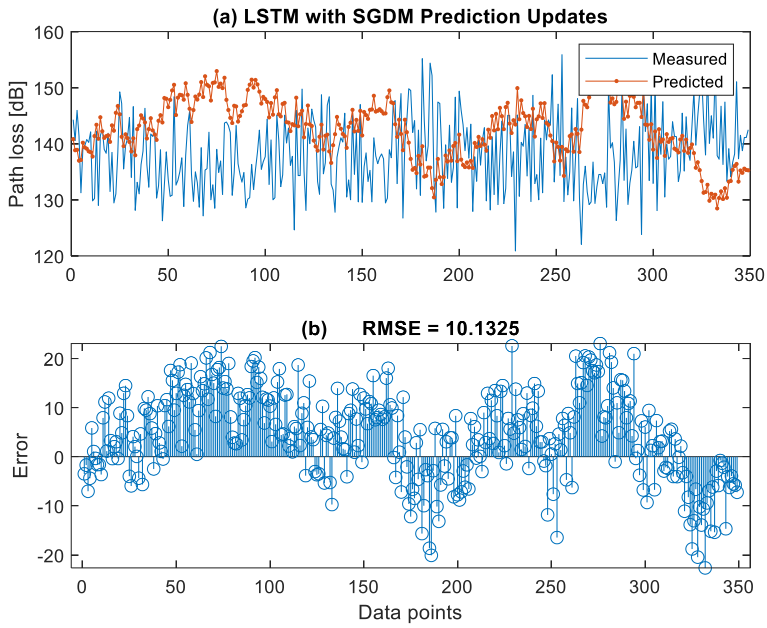

Fig. 3: Proposed LSTM with SGDM prediction performance during path loss data training

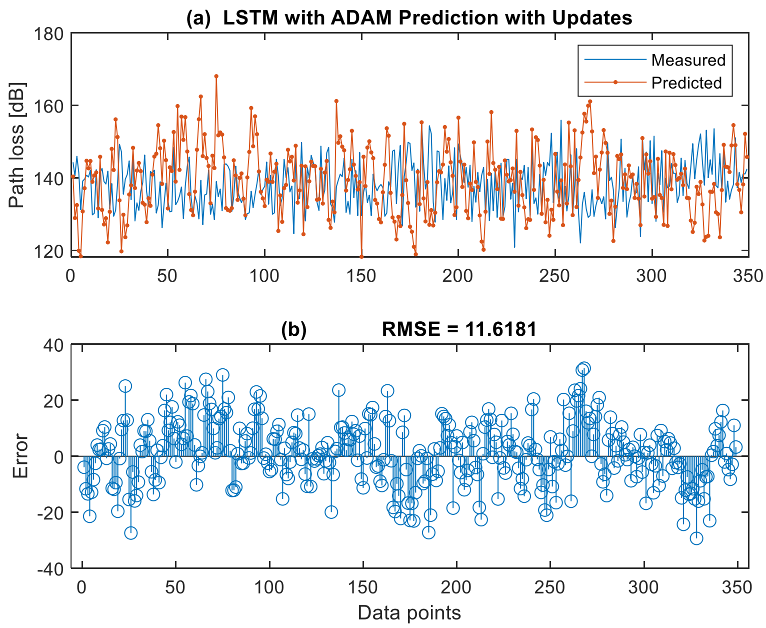

Fig. 4: Proposed LSTM with ADAM prediction performance during path loss data training

Fig. 5: Performance Comparison of LSTM with RMSP, SGDM and ADAM during path loss data training

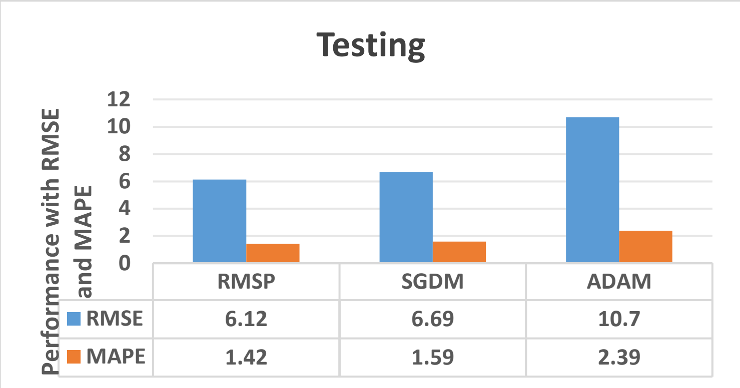

Fig. 6: Performance comparison of LSTM with RMSP, SGDM and ADAM during pathloss data testing

Table1: LSTM Algorithm Performance during Predictive Pathloss Data Training and Testing

LSTM Algorithm	**Training**		
	RMSE	MAPE	Max.Mape
RMSP	5.22	1.18	10.90
SGDM	10.13	2.40	18.66
ADAM	11.61	2.66	
	Testing		
	RMSE	MAPE	Max.Mape
RMSP	6.12	1.42	10.90
SGDM	6.69	1.59	15.16
ADAM	10.70	2.39	26.03

5. Conclusion

This paper presented a novel approach to path loss prediction using LSTM networks, effectively harnessing the power of deep learning to address complexities in wireless communication environments. The performance of the LSTM model was deeply investigated under three prediction optimisation algorithms using standard evaluation metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The algorithms include the stochastic gradient descent (SGDM), Root mean square propagation (RMSP), and Adaptive moment estimation (ADAM). The algorithms include the stochastic gradient descent (SGDM), Root mean square propagation (RMSP), and Adaptive moment estimation (ADAM). Results demonstrate that the deep LSTM network trained with RMSP algorithm achieves superior predictive accuracy, thus suggesting it can make means to significant contribution to network planning and optimization.

Future work may involve exploring hybrid models integrating LSTM with other machine learning techniques, employing transfer learning to leverage datasets across different environments, and real-time implementation in mobile applications for dynamic network management.

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