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A Hybrid Exponential-LSTM Approach For Improved Signal Loss Prediction In Urban Macro Environments

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Abstract:
In this paper, an improved hybrid model is proposed for signal loss prediction in Urban Macro (UMa) environments. The model combines the strengths of Long Short-Term Memory (LSTM) networks and exponential functions (EXP) to address limitations in both approaches. The exponential function captures the general trend of signal loss in UMa environments, while the LSTM network learns complex underlying temporal patterns in the data. The proposed hybrid model is evaluated using real-world data collected from drive tests in Port Harcourt, Nigeria. The results show significant improvements over the standalone EXP and LSTM models, achieving a 48% reduction in Mean Squared Error (MSE) compared to the EXP model and a 73% reduction compared to the LSTM model on unseen testing data. This underscores the strength and superiority of the hybrid approach over conventional signal loss models in UMa environments.

Key word: *LSTM, Signal, Prediction, Machine Learning, Wireless, Communication*

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I. Introduction

In wireless communication, the signal strength received at the receiving antenna is a weakened version of the original transmitted signal. This weakening, known as path loss, is broadly caused by two factors: signal spreading and obstacle attenuation [1]. As the signal travels from the transmitter, it expands over a larger area, resulting in a decrease in its strength—a phenomenon that follows the inverse square law. Additionally, as the signal encounters obstacles such as walls, foliage, hydrometeor or people, its strength is further reduced [2]. An adequate knowledge of these losses is required for effective network planning that would result in reasonable quality of service (QoS) and low latency.

To quantify these losses, network planners and engineers employ path loss models. These models are classified into deterministic, empirical [3], and machine learning [4] categories. Propagation models help predict the received signal strength (RSS) at a receiver location, which is essential for tasks such as cell tower placement, power control, and link budget calculation. However, an accurate path loss model is required for precise network planning to ensure that cell towers are positioned to cover a large area with minimal signal loss reaching the receiving antenna [5].

The prediction of path loss is particularly challenging in urban macro (UMa) environments due to the complex interplay of various factors, including building density, height variations, and street canyons, which cause significant signal diffraction, reflection, and scattering [6]. Traditional models often fall short in these settings, necessitating the development of more sophisticated approaches.

In recent years, hybrid models that combine different methodologies have shown promise in improving prediction accuracy. These models leverage the strengths of both theoretical and data-driven techniques, thus capturing the nuances of signal propagation in diverse environments. For instance, combining deterministic models with machine learning techniques can address the limitations inherent in each approach when used in isolation [7].

Among machine learning techniques, Long-Short-Term Memory (LSTM) networks have gained popularity due to their ability to learn long-term dependencies and temporal patterns in sequential data [8, 9]. LSTMs are particularly effective in scenarios where the signal propagation characteristics exhibit temporal variations. On the other hand, exponential functions have been widely used to model the general decay of signal strength with distance, providing a robust theoretical foundation [10].

Empirical Received Signal Strength (RSS) models are derived from channel measurements over distance in the location of interest [5]. They are generally given by

$$RSS(dB) = 10nlog_{10}\left(\frac{d}{d_o}\right) + C, \quad (1)$$

where n is the path-loss exponent, which quantifies how much the signal power decreases as the distance between the transmitter and receiver increases, d is the distance between the transmitting antenna and the receiver, d_o is the reference distance. Many empirical models have been derived from this general form, such as:

1. *Free space loss (FSL) model*: This model mathematically represents the attenuation of electromagnetic wave power over distance in a line-of-sight scenario without obstacles [14]. The formula in decibel form is

$$RSS^{FSL}(dB) = 20log_{10}(d) + 20log_{10}(f) - 147.55, \quad (2)$$

where f is the frequency in Hertz. The Free Space Loss (FSL) model provides a theoretical framework but can underestimate real-world signal loss due to its neglect of environmental factors.

2. *ITU-R model*: developed by the International Telecommunication Union Radiocommunication Sector (ITU-R), is a standardized method for predicting signal weakening (path loss) in various environments like urban, suburban, and rural areas [1]. It is given by

$$RSS^{ITU-R}(dB) = 20\, log_{10}(f) + Nlog_{10}(d) + L_f - 28, \quad (3)$$

where N is the distance power loss coefficient, L_f is the floor penetration loss factor. While the ITU-R model provides useful approximations for different environments, it is essential to note that its accuracy may vary due to simplifications.

3. *Walfisch-Ikegami (RSS^{WI}) model*: This is developed by combining the signal loss due to line-of-sight (LoS) and non-line-of-sight (NLoS) conditions [15]. The loss model in decibel is given by

$$RSS^{WI}(dB) = FSL + L_{rts} + L_{msd}, \quad (4)$$

where L_{rts} is the roof-top-to-street diffraction and scatter loss, and L_{msd} is the multi-screen diffraction loss. However, the model performs poorly where the transmitter antenna heights is close to or below rooftop levels [16].

4. ***Cost231 Hata Model*** [16]***:*** is developed to predict signal loss in a microcellular environment. It is an extension of the original Hata model. It is expressed as

$$RSS^{Cost}(dB) = A + B\log_{10}(f) + C\log_{10}(d) + [F(h_t, terrain) + g(h_r)], \quad (5)$$

where f is frequency (MHz), d represents distance between transmitter and receiver (km), h_t is transmitter antenna height (m), h_r receiver antenna height (m). $A, B, C, F,$ and G are constants that depend on several factors. A Depends on the environment (urban, suburban, etc.) and frequency. B is usually a constant close to 4, C depends on the environment and terrain type, $F((h_t\,), terrain)$ is the correction factor for antenna height and terrain roughness, and $g(h_r)$ is the correction factor for receiver antenna height (relevant in urban areas).

A significant limitation of the COST231 Hata model is its potential inaccuracy in complex environments, such as dense urban areas with irregular building shapes.

The use of machine learning (ML) techniques for predicting signal loss has garnered significant attention in recent years. Various ML algorithms have been applied to predict and optimize wireless signal degradation, with notable improvements in accuracy and performance metrics.

For instance, [17] demonstrates the combination of Particle Swarm Optimization (PSO) with exponential and polynomial functions to predict signal loss in agricultural fields. The study argues that hybridizing these models improves key performance metrics such as Mean Absolute Error (MAE) and R^2.

In [18], Support Vector Regression (SVR) is compared with selected empirical models and a Multilayer Perceptron Artificial Neural Network (MLP-ANN) for signal loss prediction in urban outdoor environments at a carrier frequency of 853.71 MHz. Various kernels were evaluated for SVR, with the Laplacian kernel yielding the most accurate predictions. The work presented in [19] employs Feed-Forward Neural Networks (FFNN) for predicting received signal strength loss at a frequency of 1800 MHz using the Levenberg-Marquardt algorithm. By varying the number of neurons between 1 and 50, the study concluded that the optimal configuration was a FFNN with a tangent activation function and 48 hidden neurons, achieving an MAE of 4.21.

Although Long Short-Term Memory (LSTM) networks have been highly effective in numerous prediction and modeling tasks, their application to wireless signal degradation remains underexplored. In [20], LSTM is combined with XGBoost for storm prediction in western France, demonstrating excellent performance.

Similarly, LSTM has shown high accuracy in predicting future stock market values [21]. Additionally, [9] highlights the use of an LSTM combined with a climate model (LSTM-CM) for drought prediction, where it outperforms other models in the study.

Despite these successes in other domains, there is a notable gap in literature regarding the use of LSTM for predicting signal degradation in wireless communication, highlighting the need for further research in this area.

LSTM workflow:

Information flows through the LSTM cell, which has a special internal state that can hold information for long periods. It makes use of three gates to maintain the internal state:

- Forget Gate (f_t): Decides what information to forget from the previous cell state by analyzing the previous cell state (C_{t-1}) and current input (X_t). Outputs values between 0 and 1, where 0 means forget and 1 means keep.
- Input Gate (i_t): Determines what new information to store in the cell state by analyzing the current input (X_t) and previous cell state (C_{t-1}). Generates a candidate value ($C_{t'}$) to add to the cell state, controlling what information is added.
- Output Gate (o_t): Determines what information from the cell state to use as the output. Analyzes the current cell state (C_t) and current input (X_t), outputting values between 0 and 1 to control the contribution of each element to the final output.

Proposed hybrid model:

This paper proposes an improved hybrid path loss model for UMa environments, combining the strengths of an exponential function, which captures the general signal decay with distance, and an LSTM network, which learns complex temporal patterns, to achieve superior prediction accuracy. Previous studies, such as [11, 12, 13] have demonstrated the potential of hybrid approaches in enhancing the reliability of path loss predictions. For example, the authors of [11] combined support vector regression with genetic and tabu search algorithm for RSS prediction, claiming that their results significantly outperform the five models used for comparison.

By integrating these methodologies, we aim to develop a model that not only improves prediction accuracy but also enhances the adaptability of wireless networks in dynamic urban settings. The contributions of this research are as follows:

1. Enhanced Prediction Accuracy: By combining the strengths of EXP and LSTM networks, the proposed model significantly improves the accuracy of signal loss predictions in urban macro (UMa) environments.
2. Improved Network Planning: The research aids in more precise network planning, enabling better placement of cell towers, which enhances overall network performance and user experience.
3. Hybrid Model Framework: This study contributes an improved framework that integrates theoretical and machine learning approaches, providing a foundation for future research and development in path loss modeling for various environments.

The remainder of this paper is organized as follows: Section 2, brief survey of related works is presented, while Section 3 details the methodology of employed in this paper, including data preprocessing, model training, and the development of the Hybrid EXP-LSTM model. Simulation results are presented and discussed in Section 4, and conclusion on the presented work is finally drawn in Section 5.

II. Methodology

This work follows a stepwise approach as shown in the block diagram Figure 1. The procedure can be implemented for signal attenuation modelling in any other research field. The approach is explained as follows:

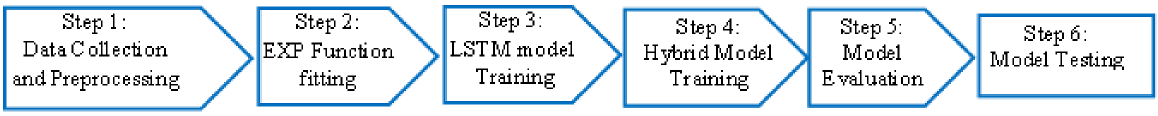


Figure. 1. Flowchart of the proposed path loss model

The data collection process involved conducting drive tests along six predefined routes to gather the Received Signal Strength (RSS) dataset. The data was acquired using a TEMS W995 phone connected to TEMS Investigation software, alongside a Global Positioning System (GPS) and MapInfo Pro on a laptop. The entire setup was carefully placed within a vehicle Figure 2a that maintained an average speed of 40 km/h to minimize Doppler effects during the acquisition process.

For training the proposed model, average datasets from four distinct routes as depicted in Figure. 3a were utilized, while the testing dataset consisted of average data from the remaining two routes shown in Figure 3b. All preprocessing and computational tasks were conducted using MATLAB R2021a.

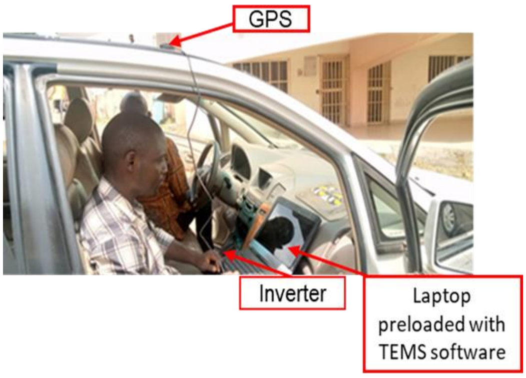


Figure 2a. Preparation for data collection campaign

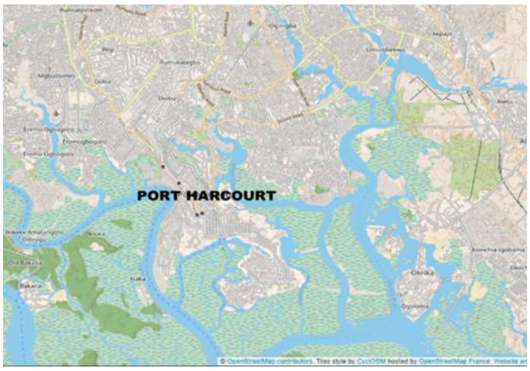


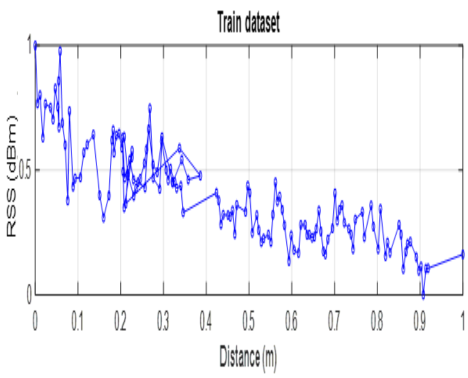
Figure 2b. Location of study area

Data normalization:

Data normalization is a critical preprocessing step in machine learning, ensuring that features contribute equally to training and thereby enhancing model performance. While various normalization techniques exist, we opt for the Min-Max scaling method expressed in (6) when training LSTM models due to its promotion of gradient stability, a crucial aspect for deep learning architectures like LSTMs. This technique scales each feature to a range between 0 and 1, facilitating consistent and effective training.

$$X_{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}}, \qquad (6)$$

Where $X_{max} \neq X_{min}$ and X_i represent the data points, X_{min} is the minimum value in the dataset, and X_{max} is the maximum value in the dataset.



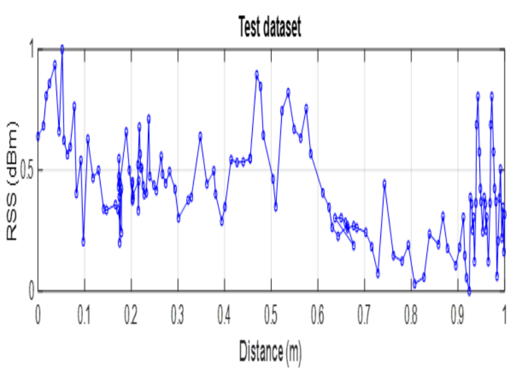


Figure 3a. Average RSS versus distance for training
Figure 3b. Average RSS versus distance for testing

Fitting exponential function:

Exponential (EXP) fitting function was utilized to obtain an estimation of the path loss model., and to determine the correlation factor between RSS and distance.

Exponential functions are mostly used when the rate of change of a function is proportional to the initial amount of the function. Urban Macrocells (UMa) are characterized by closely spaced tall buildings, and the rate of change of signal loss in such environments often exhibits exponential decay. The two-term exponential model (7) is used to model the signal loss.

$$RSS(dBm) = a_1 e^{a_2 d} + a_3 e^{a_4 d}, \tag{7}$$

where d is the distance between the transmitter and the receiver; a_1 and a_3 are the scaling factors that determine the vertical stretch of the exponential curve while a_2 and a_4 are the growth rates of the exponentials. A large value of a_2 and a_4 results in steeper curve.

Figure 5 shows the plot of RSS versus distance, and the exponential function is fitted. The correlation coefficient of 0.8634 was obtained after fitting the exponential curve which indicate a strong positive correlation between signal loss and distance. However, the fitted exponential function reveals that the relationship between signal loss and distance is not strictly linear but follows an exponential curve. This fitting underscores the importance of considering the exponential nature of signal loss in a UMa with respect to distance in wireless communication. A more specific exponential function in term of RSS and distance could be expressed for the location under study as

$$RSS(dBm) = 0.7161 e^{-1.507d} + 0.174 e^{-34.8d}, \tag{8}$$

LSTM architecture and model training:

Hochreiter and Schmidhuber [8] proposed LSTM to address the vanishing gradient problem or decaying error backflow in the traditional recurrent neural network (RNNs). This is achieved through special gates that control the flow of information into, out of, and within the cell. These gates include: input gate, forget gate, and output gate.

Figure 4 presents a schematic LSTM memory block and detailed expression for each components are described in (9(a-d)) and (10(a,b).

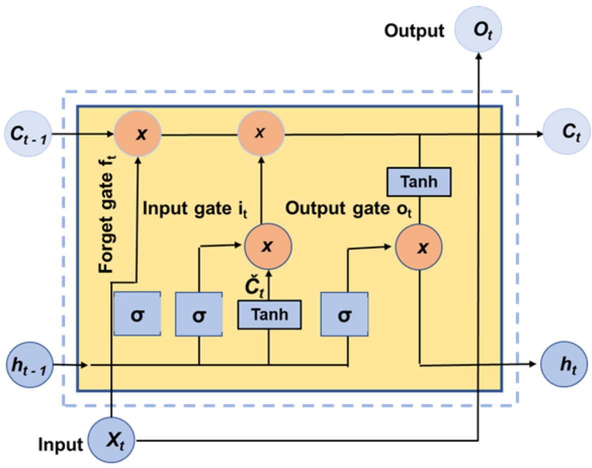


Figure 4. ***Long Short-term Memory Model***

The mathematical formulation of an LSTM cell can be represented as follows

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right), \tag{9a}$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \tag{9b}$$
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o), \tag{9c}$$
$$\hat{y}_t = W_y h_t + b_y, \tag{9d}$$

The cell state (c_t) and the hidden state (h_t) are updated using the following

$$c_t = f_t c_{t-1} + i_t \tanh\left(W_c[\![x_t, h_{t-1}]\!]\right. \tag{10a}$$
$$h_t = o_t\, tanh(c_t) \tag{10b}$$

where W_f, W_i, W_o, W_c are weight matrices, the sigmoid activation function (σ), tanh is the hyperbolic tangent activation function, and y_t is the predicted signal loss.

Hybrid EXP-LSTM for signal loss prediction

The preprocessed data, as discussed in the data collection preprocessing section 3.1, is first fitted with an exponential function. The output is then fed as the input sequence (X_t) to the LSTM network. This addresses the LSTM's sensitivity to data, which can lead to poor performance due to insufficient or noisy data. The LSTM network processes this sequence and learns the underlying relationships between these measurements. The target output (y_t) is the corresponding signal loss value. Performance is quantified using three metrics: mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE).

Loss function and optimization

The difference between the predicted signal loss (y_t) and the actual measured value (y_{truth}) is quantified using the Root Mean Squared Error (RMSE) loss function. The LSTM model is trained by minimizing this loss function for fifty epochs using the Adam optimizer. We chose Adaptive Moment (ADAM) estimation after comparing its performance with that of the Stochastic Gradient Descent (SGD) optimizer across different numbers of layers (1 to 5). The results are presented in Table 1 and Figure 6. Based on Figure 6, the Adam optimizer appears more stable than SGD, with both curves intersecting around the layer 3. Therefore, we opted to train the model using Adam with a layer configuration of 3 in this paper.

Table 1: MSE Performance evaluation of Adam, SGDM on testing data for 5 layers

Layers	**Adam**	**SGD**
1	0.043	0.055
2	0.042	0.063
3	0.043	0.042
4	0.045	0.037
5	0.045	0.034

III. Result And Discussion

This section analyzes the performance of the proposed hybrid EXP-LSTM model for signal loss prediction in Urban Macro (UMa) environments. The model combines the strengths of Long Short-Term Memory (LSTM) networks and exponential functions (EXP) to address inherent data sensitivity issues in LSTMs. The training and testing datasets are presented in Figures 3a and 3b, respectively. We evaluated the performance of the EXP model, LSTM model, and the proposed hybrid EXP-LSTM model using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) (Tables 2 and 3).

Figure 5 visualizes the fitted exponential function on the training data. The MSE of 0.0308 indicates a good fit. On the testing dataset, the MSE increases to 0.0325, representing a commendable 5.5% error increase despite encountering new data. This highlights the EXP function's robustness in capturing exponential trends.

The LSTM model outperforms the EXP model on the training data as shown in Table 2 due to its ability to learn more complex underlying patterns in the training data (even though both models use the same data). However, on the testing data of Table 3, the LSTM model's MSE value of 0.0379 suggests underprediction compared to the MSE value of 0.0325 for the EXP model. This indicates limitations in the LSTM's generalization to unseen data.

Figure 7 displays the proposed hybrid EXP-LSTM model plot. As evident from Table 3, the hybrid model significantly outperforms both the EXP and LSTM models on the testing data. It achieves a 48% reduction in MSE compared to the EXP model and a 73% reduction compared to the LSTM model. This demonstrates the effectiveness of combining the strengths of both approaches.

The hybrid EXP-LSTM model was trained using 50 epochs to achieve a minimum RMSE (fitness function). Figure 8 illustrates that the RMSE stabilizes around epoch 20, indicating successful convergence.

The results validate the effectiveness of the proposed hybrid EXP-LSTM model. It leverages the EXP function's robustness to capture the general trend while capitalizing on the LSTM's ability to learn complex temporal patterns. This combination leads to superior performance in signal loss prediction, particularly for unseen data in UMa environments.

Table 2. Performance evaluation of EXP, LSTM and EXP-LSTM model on training data

	MSE (dB)	RMSE (dB)	MAE (dB)
Exponential Model	0.0308	0.1755	0.1335
LSTM model	0.0037	0.0612	0.0310

Table 3. Performance evaluation of EXP, LSTM and EXP-LSTM model on testing data

	MSE (dB)	RMSE (dB)	MAE (dB)
Exponential Model	0.0325	0.1803	0.1399
LSTM model	0.0379	0.1946	0.1572
Hybrid Model	0.0219	0.1479	0.1141

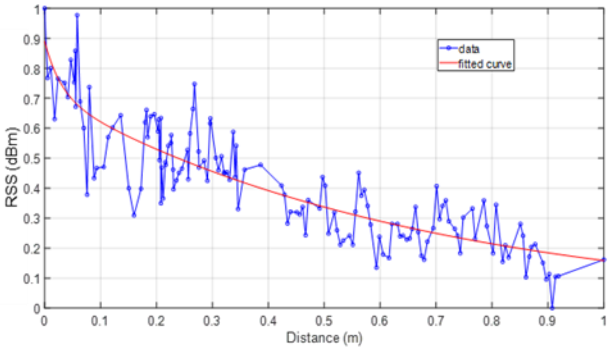


Figure. 5. Curve fitting of exponential function

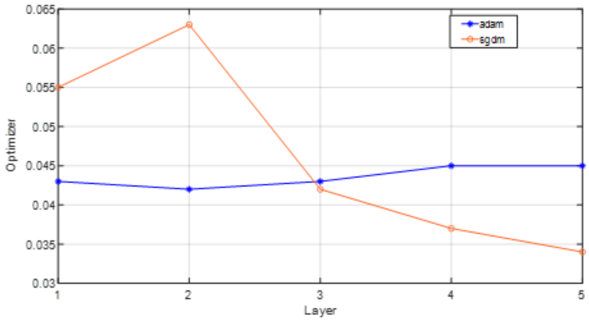


Figure 6. MSE evaluation plot of Adam, SGDM on testing data for five layers

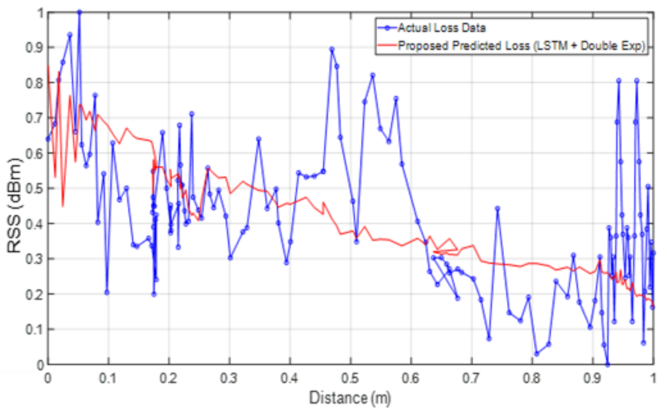


Figure 7. Hybrid EXP-LSTM fitted on test data

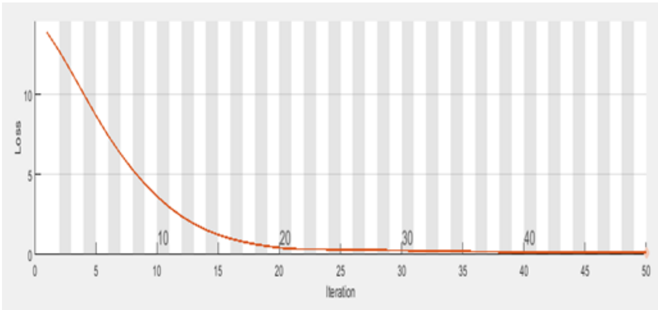


Figure 8. Loss function plot

Figure 9 showcases the error plot for the hybrid EXP-LSTM model, revealing the distribution of prediction errors across varying distances. This plot provides valuable insights into both the model's predictive accuracy and its ability to generalize signal loss predictions in Urban Macro (UMa) environments. With an RMSE value of **0.19811**, the plot reflects the average error between predicted and actual signal loss measurements. This low RMSE indicates that the hybrid EXP-LSTM model performs effectively, minimizing prediction errors, particularly when tested on unseen data. Notably, the RMSE value is significantly lower compared to the standalone EXP and LSTM models, underscoring the hybrid model's superior ability to capture the complex relationship between signal loss and distance, enhancing prediction precision and reliability.

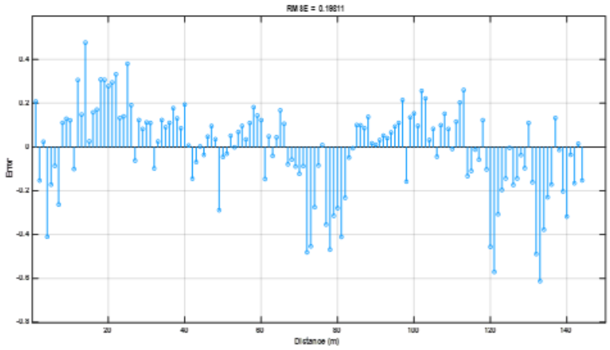


Figure 9. Error plot

IV. Conclusion

This paper presented a hybrid EXP-LSTM model for signal loss prediction in Urban Macro (UMa) environments. The model leverages the complementary strengths of exponential functions and LSTM networks. The EXP function captures the general exponential decay of signal strength with distance, while the LSTM network learns complex temporal relationships within the data. By combining these approaches, the hybrid EXP-LSTM model achieves superior performance compared to standalone models. It effectively captures general trends and adapt to unseen data, making it a valuable tool for network planning and optimization in UMa environments. Future work could explore the application of this hybrid approach to different signal loss prediction tasks and investigate the impact of varying LSTM network architectures on performance.

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