Rain Attenuation Prediction Modeling for Microwave and Millimeter Wave Band Using LSTM

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***Abstract*—This study introduces a Long-Short Term Memory (LSTM) network prediction model that can accurately forecast rain attenuation in tropical regions, where weather-related interference is substantial because of long periods of wet seasons. The International Telecommunication Union-Radiocommunication (ITU-R) rain attenuation prediction models and Crane model were used to acquire historical attenuation data in dB, which reveals rain attenuation up to 31.61 dB and 28.65 dB, respectively. This data was obtained by utilizing local rainfall data and an 11GHz microwave link profile from Addis Ababa, Ethiopia. The proposed model uses this data as input and achieves great accuracy in predicting rain-induced signal degradation, with an MSE of $\mathbf{3.3644 * 10^{-4}}$ and RMSE of 0.018. This indicates the model's usefulness in anticipating rain-induced signal degradation, which is critical for frequency bands above 7 GHz.**

Key Words-Rain Attenuation Prediction, Microwave, Millimeter wave, Long Short-Term Memory Network (LSTM).

I. INTRODUCTION

The microwave and mmWave frequency bands are essential for data transmission but are sensitive to environmental factors like rain, which can scatter, absorb, or diffract the waves, leading to signal power loss known as rain attenuation. This affects the clarity and reliability of the terrestrial line-of-sight link [1] as well as earth-space satellite communication links [2]. While in temperate regions, frequencies up to 10 GHz are viable, in tropical areas, rain interference can occur at frequencies as low as 7 GHz due to larger raindrops.

The study of rain attenuation has been conducted for several decades, and different authors have proposed several models. The research work in [3] presents a thorough examination of computational intelligence techniques for rain attenuation analysis and prediction. It introduces a machine learning model that employs regression analysis to estimate the regression coefficients κ and α across different frequencies, which are typically difficult to compute. This model, requiring only frequency in GHz and rain rate in mm/hr as inputs, achieves a remarkable accuracy of 97%. The paper referenced in [4] critiques conventional empirical, statistical, and fade slope models for their reliance on statistical rain measurements and lack of generalizability. It proposes a deep learning architecture that integrates satellite and radar imagery data along with link power measurements to accurately predict both near- and long-term rain fade events. The study shows the superior performance of the model compared to existing machine learning algorithms and highlights radar data's efficacy for short-term predictions and satellite data's suitability for long-term forecasts. In another research work in [5], a Long-Short Term Memory (LSTM) network method, a deep learning algorithm suitable for time-series data, was proposed to predict rain attenuation events in satellite communications. To address the lack of a rainfall database, the authors generated a synthetic rain attenuation database following ITU-R guidelines. The LSTM model trained on this data achieved an accuracy of 91.88%, surpassing the best external model's accuracy of 87.99%. This approach holds potential for improving satellite network performance through rain attenuation prediction. Due to the variable and stochastic nature of rain, finding one model is a big challenge. However, by considering the gaps and limitations of previous research work, a better approach can be made[6].

We organize the rest of this paper as follows: Section II describes materials and methods with graphical illustrations; Section III presents existing rain attenuation models; Section IV explains the proposed prediction model; Section V presents results and discussion; and finally, Section VI concludes the paper.

II. DATA AND METHODOLOGY

This study focuses on developing a deep learning method of predicting rain attenuation using local data to accurately predict the attenuation of a microwave link due to rain. This section presents the data and methodology one by as follow:

A. Data

The National Metrology Agency of Ethiopia (NMAE) provided us with rainfall rate data for Addis Ababa city, which were recorded at 15-minute intervals from 2015 to 2022. Figure 1 provides the visual representation of this data. The rain rate in Addis Ababa reaches a maximum of 112.8 mm/hr during the rainy season, which can cause significant signal power loss on communication link in the region and long-term rainfall data can help to determine the behavior of rain rate thereby allowing microwave link designers to properly estimate this loss while defining the fade margin of the microwave link.

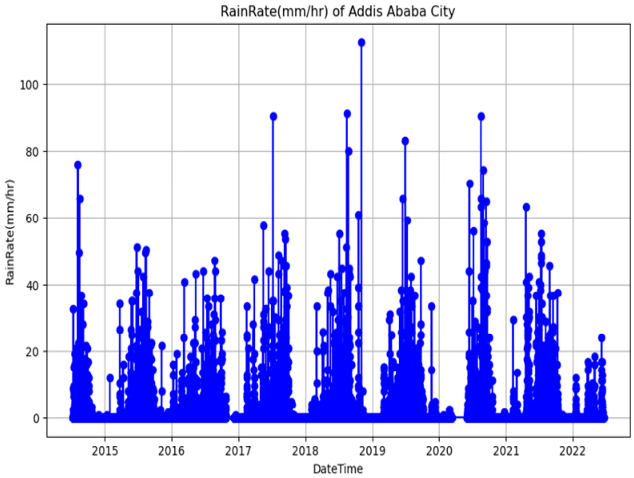

Figure 1. 15-minute distribution of rain rate in Addis Ababa for 8 years

The terrestrial Line-of-Sight like was taken between Addis Ababa at an azimuthal angle of 203.920 with an altitude of 2401m above sea level and Furi at an azimuthal angle of 23.920 with altitude of 2842m above sea level. The link is vertically polarized at operating frequency of 11GHz. Table 1 presents the link parameters. The link is vertically polarized, and both the receiving station (Addis Ababa) and the transmitting station (Furi). Figure 2 presents a graphical representation of the LoS elevation and surface elevation.

Table 1. Link parameters for terrestrial LoS microwave link

Parameters	AddisAbaba(Rx)	Furi(Tx)
Elevation(m)	2842	2401
Latitude	08.52582°N	09.01067°N
Longitude	38.41125°E	38.44504°E
Antenna gain (dBi)	42	42
Antenna height (m)	10	10
Frequency (GHz)	11	
True azimuth (°)	23.92	203.93
Vertical angle (°)	-1.59	1.48
Link length (km)	16.42	
Tx line loss (dB/100)	4.53	4.53
Tx line loss (dB)	0.91	0.91
Circuit branching loss	6.8(dB)	6.8(dB)
Tx power (dBm)	30	30
Free space loss (dB)	139.6	139.6
Rx threshold level(dBm)	-76.2	-76.2
Atmospheric absorption loss	0.35(dB)	0.35(dB)
Effective frequency spacing	21.7(MHz)	21.7(MHz)

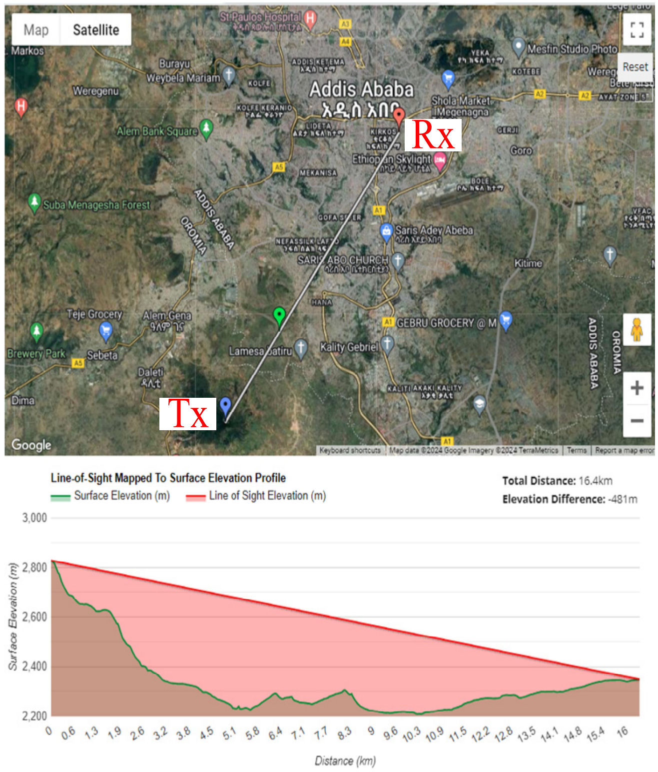

Figure 2. Surface elevation vs LoS elevation of the link

B. Methodology

Although conventional rain attenuation prediction models such as the ITU-R models provide a solid foundation for understanding rain attenuation, they are quite complex and have some limitations in handling the variable nature of rain using their statistical method. Conversely, when properly trained with local data, AI-based models can accurately predict future events. However, in many countries, obtaining properly recorded local data, especially rain attenuation data, is a major challenge for advancing prediction models using AI. This study employs ITU-R rain attenuation estimation models to produce historical rain attenuation data in dB by utilizing local rain rate data and the microwave link information. Matlab function rainpl for ITU-R rain attenuation prediction model and cranepl function for the global crane model are used in developing historical rain attenuation in dB. The generated data compiled with the rain rate data to form a compete dataset for the proposed LSTM model.

III. EXISTING RAIN ATTENUATION PREDICTION MODELS

A. The ITU-R Rain Attenuation Model

Obtaining historical rain attenuation data in dB from countries such as Ethiopia has posed a significant challenge for the design of data-driven models, such as deep learning ones. However, the International Telecommunication Union-Radio Communication Sector (ITU-R) provides a method to calculate rain attenuation for different regions based on locally measured rainfall data for different frequency bands. The ITU-R recommendation in [1, 2, 7, 8] provides mathematical formulations for determining the rain attenuation for prediction. Recommendation ITU-R P.838 gives a way to use the power law equation to figure out the exact attenuation for predicting rain attenuation in a terrestrial microwave link, which is shown in equation 1 below:

$$\gamma_R \left(\mathrm{dB}/_{\mathrm{km}}\right) \;=\; kR_{0.01}{}^{\alpha} \qquad (1)$$

where values for the coefficients κ and α. The values for the coefficients k and α in equation 1 are determined as functions of frequency, f (GHz), in the range from 1 to 1 000 GHz, from the following equations:

$$log_{10}\, k = \sum_{j=1}^{4} \left(a_j \, exp\left[-\left(\frac{log_{10} f - b_j}{c_j} \right)^2 \right] \right) + m_k \, log_{10} f + c_k \qquad (2)$$

$$\alpha = \sum_{j=1}^{5} \left(a_j \, exp\left[-\left(\frac{log_{10} f - b_j}{c_j} \right)^2 \right] \right) + m_k \, log_{10} f + c_k \qquad (3)$$

where:

f: frequency (GHz)

κ: either k_H or k_V (horizontal or vertical polarization)

α: either a_H, or a_V (horizontal or vertical polarization)

The coefficients a_{j}, b_{j}, c_{j}, m_{k}, c_{k}, m_a, and c_a in equations 2 and 3 are used for calculating specific attenuation, and they are given in tables in this recommendation. These equations are dependent on the frequency and rainfall rate. The regression coefficients (κ and α) can be calculated from the values given in equations 2 and 3 as follows:

$$k \;=\frac{[k_H + k_v + (k_H - k_v)\cos^2\theta \cos 2\tau]}{2} \qquad (4)$$

$$\alpha = \frac{[k_H a_H + k_v a_v + (k_H a_H - k_v a_v)\cos^2\theta \cos 2\tau]}{2k} \qquad (5)$$

where θ is the path elevation angle and τ is the polarization tilt angle relative to the horizontal polarization (45 for circular polarization). The ITU-R P.530 in [1] defines the total path attenuation over a microwave link can be determined as the multiplication of the specific attenuation and the effective path length as;

$$A_{0.01}(\mathrm{dB}) = \;\gamma_R(\mathrm{dB/km}) d_{eff}(\mathrm{km}) \qquad (6)$$

where $A_{0.01}$(dB) represents the total path attenuation due to rain over the entire link, γ_{R}(dB/km) represents the specific attenuation and d_{eff}(km) is the effective path length. Using those ITU-R model, it is possible to calculate rain attenuation data from local rainfall data and the microwave link profile. This study uses rainpl Matlab function, which utilizes the ITU-R rainfall attenuation model to estimate the path loss of signals propagating through rainfall conditions in a specified region[8], especially for links operating in short distance. The microwave links of shorter path length are assumed to experience similar rainfall over the period. The rainpl function, with the parameters (range, freq, rainrate, elev, tau, pct) returns rain attenuation value in dB, where range represents the path length in km, freq represents the frequency, elev represents the elevation, tao represents the polarization tilt and pct represents the percentage of time. Using this function, historical rain attenuation data in dB has been generated.

B. The Crane Rain Attenuation Model

The Crane rain attenuation model is a widely-used method for calculating the attenuation of signals caused by rainfall. It was developed for Earth-space and terrestrial propagation paths and is particularly useful for predicting attenuation statistics for single paths. This model was proposed by R.K Crane in 1980[9]. Crane's attenuation model relies on empirical observations of rain distribution, the vertical extent of rain, the length of the signal path immersed in rain, and frequency-dependent coefficients[10].

$$A_{0.01}(\mathrm{dB}) = \gamma \left(\frac{e^{y\sigma}-1}{y} - \frac{b^a e^{z\sigma}}{z} t \frac{b^a \epsilon e^{zD}}{z} \right) \text{for } \sigma < D < 22.5 \quad (7)$$

$$A_{0.01}(\mathrm{dB}) \;= \gamma \left(\frac{e^{yD}-1}{y} \right) \;\text{ for } 0 < D < \sigma \qquad (8)$$

where $A_{0.01}$(dB) is path attenuation due to rain, D is propagation distance (km) and γ=specific attenuation identical to that calculated in rainpl. The coefficients k and α are determined by the frequency, polarization state, and elevation angle of the signal path. These coefficients, provided by both the Crane Electromagnetic Wave Propagation through Rain model[11] and the ITU-R P.838-3 Specific Attenuation model for rain prediction methods, remain consistent and apply across the frequency range of 1 GHz to 1000 GHz. The specific attenuation model is applicable for frequencies spanning from 1 to 1000 GHz, with rainfall-specific attenuation calculated according to the ITU rainfall model specified in ITU-R P.838-3.

For comparison purposes, this study utilizes both the ITU-R model and the crane model to calculate the rain attenuation using the local rain rate data and the microwave link information. Figure 3 presents the result as a fitting curve graph.

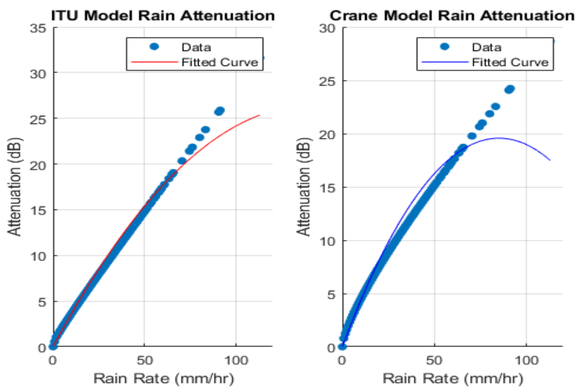

Figure 3. Curve fitting graph of generated ITU-R rain attenuation data and Crane model rain attenuation data in dB

C. Rain Attenuation Prediction Using AI Models

The integration of AI techniques in the prediction of rain attenuation for satellite and terrestrial communication links has been limited, primarily due to the complex and non-linear nature of rainfall patterns and the scarcity of localized attenuation data. Traditional approaches have relied on statistical, empirical, or physical models to estimate the impact of rain on signal propagation. However, these methods often fall short of capturing the dynamic variability of rain events. In contrast, AI models such as in [5, 12-16], particularly those employing deep learning architectures like Long Short-Term

Memory (LSTM) networks, offer a promising alternative due to their ability to learn from historical data and predict future events with remarkable accuracy and precision. This study introduces an LSTM-based model designed to predict rain attenuation, leveraging the strengths of AI to overcome the limitations of conventional methods. Despite the absence of locally measured rain attenuation data in dB for Ethiopia, this research circumvents this challenge by synthesizing historical data through established models recommended by the International Telecommunication Union (ITU-R) and the Crane model. These models provide a foundation for generating eight years of historical rain attenuation data, which, when combined with local rain rate measurements, can train the LSTM network to forecast rain attenuation with a high degree of reliability[17, 18]. The LSTM based rain attenuation prediction model studied here represents a significant advancement in the field, offering a more nuanced understanding of rain’s impact on communication links. It stands as a testament to the potential of machine learning in enhancing predictive capabilities and ensuring more robust and reliable communication systems in the face of adverse weather conditions.

IV. LSTM BASED RAIN ATTENUATION PREDICTION

In 1997, Sepp Hochreiter and Jürgen Schmidhuber introduced Long Short-Term Memory (LSTM), a type of recurrent neural network (RNN) designed to overcome issues like exploding and vanishing gradients. LSTM incorporates constant error carousel (CEC) units and comprises cells, input gates, and output gates in its architecture. Unlike traditional RNNs, LSTM effectively retains information over extended periods, making it ideal for handling long-term dependencies. Its chaining structure deviates from single-layer neural networks, contributing to its effectiveness in managing long-term dependencies and finding diverse applications beyond standard RNNs.

In contrast to traditional Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks incorporate an additional component termed memory. This memory consists of several crucial elements: a forget gate (f), which operates as a neural network with sigmoid activation; a candidate layer (C), composed of a neural network employing tanH activation; an input gate (I), implemented as a neural network with sigmoid activation; an output gate (O), structured similarly with sigmoid activation; the hidden state (h); and the memory cell (C). Each of these components plays a distinct role in the LSTM architecture, enabling it to effectively retain and manipulate information over extended sequences, thus addressing the limitations of traditional RNNs in managing long-term dependencies. LSTM model can be explained in the following four steps as follow;

Step 1: To predict future sequences, it is necessary to utilize the cell state to retain pertinent information from past inputs, ensuring accurate predictions. Then the incoming data can be linked to previous patterns in the time-series data. This process can be formulated as forget gate equation as;

$$f_t = \sigma\left(W_f \times [h_{t-1}, x_t] + b_f\right) \tag{9}$$

Step 2: Determining crucial information for storage involves two stages. The first input gate layer, employing a sigmoid layer, decides which values to update. Subsequently, a tanH layer generates a vector for new candidate values, termed which is combined with the input gate's decision to update the state. This phenomenon can be formulated as candidate gate equations as;

$$\left.\begin{array}{l} i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \\ \overline{C_t} = \tanh\,(W_c \times [h_{t-1}, x_t] + b_c) \end{array}\right\} \tag{10}$$

Step 3: Updating the old cell state to the new cell state, involves multiplying the old state by the forget gate discarding unnecessary elements. Then, the product of the input gate and the candidate gate creates the new candidate value, adjusted by the update decisions. This can be given as the cell state information given as;

$$C_t = f_t \times C_{t-1} + i_t \times \overline{C_t}) \tag{11}$$

Step 4: Determining the output state involves filtering the cell state. The first sigmoid layer decides which part of the cell state's output to produce, followed by applying the tanH function to the cell state and multiplying it by the sigmoid gate's output. This process enables the generation of output based on the decision-making mechanism and it can be formulated as;

$$\left.\begin{array}{l} O_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \\ h_t = O_t \times \tanh(C_t) \end{array}\right\} \tag{12}$$

The LSTM cell architecture with formulas can be visualized in figure 5.

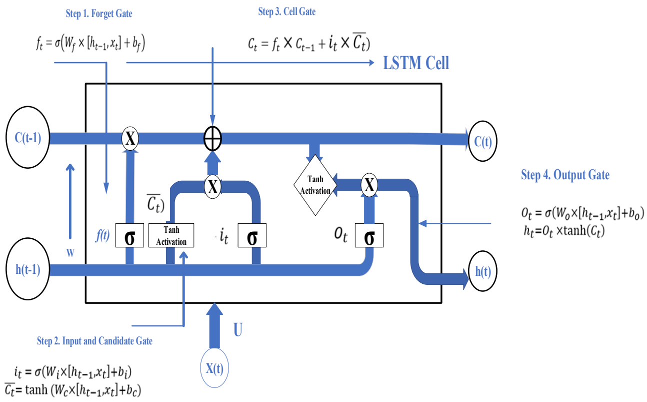

Figure 4. LSTM cell architecture with formulas

The diagram in Figure 4 provides a comprehensive overview of how LSTM networks process and retain information over time, which is essential for tasks that involve sequential data. The gates within the LSTM—input, forget, and output—work in harmony to regulate the flow of information. They decide what to keep, what to discard, and what to pass on as output at each step in the sequence. The LSTM cell takes the current input, X(t), and the previous hidden state, h(t-1), and applies a series of transformations through these gates. The forget gate uses these inputs to determine which parts of the cell state, C(t-1), are no longer needed and can be forgotten. The input gate decides which new information is relevant and should be added to the cell state. The cell state is then updated by combining the old state (what’s not forgotten) and the new information (what’s relevant). Finally, the output gate uses the updated cell state to generate the final output, h(t), which is then passed on to the next step in the sequence or used as the final prediction.

V. RESULT AND DISCUSSION

The proposed LSTM model has been trained with the historical rain rate data and synthesized historical rain attenuation data. The dataset is visualized as in figure 5.

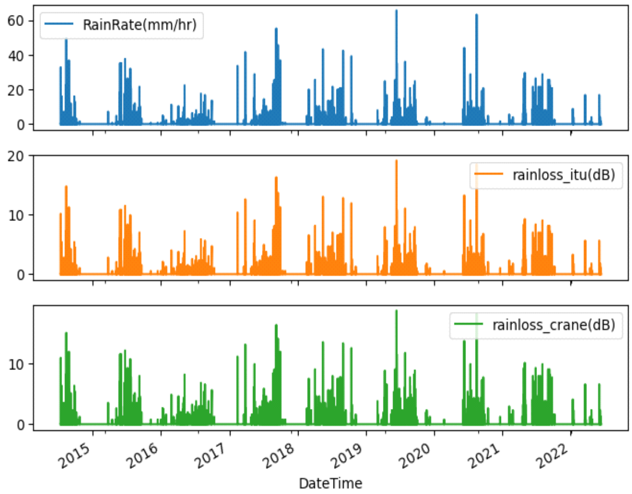

Figure 5. Training dataset visualization

The dataset is split into training, validation, and test with a ratio of 80:10:10 respectively.

The created neural network model is a sequential architecture with an LSTM layer containing 128 units followed by a dense layer with 1 output unit. The total number of trainable parameters is 67,713, and the model's size is approximately 264.50 KB. Its purpose is to predict rain attenuation based on rainfall data, leveraging temporal dependencies captured by the LSTM. The dense layer produces the final prediction, and the model aims to optimize its performance during training. Non-trainable parameters are absent in this architecture. It is summarized in Table 2 below;

Table 2. Summary of the LSTM Model

Model: sequential

Layer (type)	Output shape	Param #
lstm(LSTM)	(None, 128)	67,584
dense(Dense)	(None, 1)	129

Total params: 67,713 (264.50 KB)

Trainable params: 67,713 (264.50 KB)

Non-trainable params: 0 (0.00 KB)

The LSTM network will process 32 samples at a time during training, and defines 20 epochs, indicating the complete dataset will be run through the network 20 times. The model. fit function trains the model using these parameters, with the addition of early stopping, a mechanism that halts training if the model's performance on the validation set doesn't improve, effectively preventing overfitting and ensuring the model generalizes well to new data. The graph in Figure 6 shows the validation and training loss of the model training.

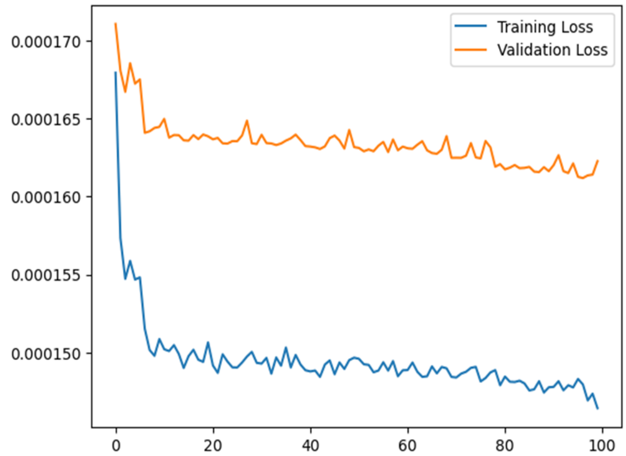

Figure 6. Training and validation loss of LSTM model

The output indicates that the LSTM model has been evaluated on the test dataset, and the loss value (mean squared error) is reported as approximately $3.3644 * 10^{-4}$. The root mean square error (RMSE), which is a standard measure of the difference between predicted and observed values, has been calculated from this loss value. The RMSE for the test set is reported as 0.018, which is a low error value indicating that the model's predictions are very close to the actual data points. This suggests that the LSTM model performs well in predicting rain attenuation from the given dataset.

Prediction of the model is made by one line of code as prediction = model.predict(X_test). The output indicates that the LSTM model has made predictions on the X_test dataset. The process completed in 811 steps, taking 16 seconds, with an average time of 19 milliseconds per step. This suggests that the model efficiently processed the test data and generated predictions for each sample.

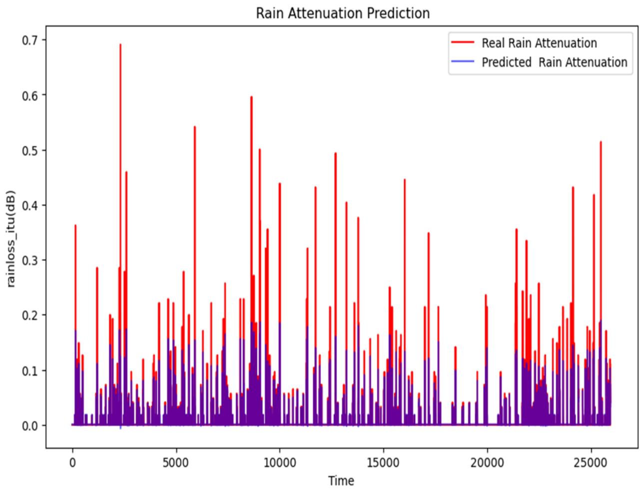

Figure 7. Prediction of Rain Attenuation(rainloss_itu(dB))

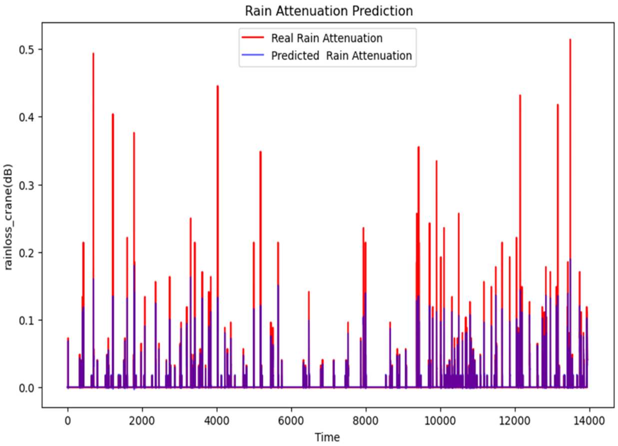

Figure 8. Prediction of Rain Attenuation(rainloss_crane(dB))

The prediction graphs in Figure 7 and Figure 8 show that the predicted rain attenuation is generally lower than the real rain attenuation. This could mean that the model used to make the predictions is underestimating the amount of rain attenuation. Even though the prediction seems to underestimate the actual rain attenuation (red line higher than purple line), there can still be positive aspects to consider:

General Trend Matches: The overall rise and fall of the predicted line (purple) seems to follow the real data (red line). This suggests the prediction captures the general pattern of rain attenuation over time.

Potential Baseline for Improvement: Even if underestimating, the prediction provides a baseline. Engineers can use this as a starting point to account for rain attenuation and then add a buffer to account for potential underestimation.

Future Refinement: This comparison helps identify any shortcomings in the prediction model. By analyzing the deviations between prediction and reality, the model can be refined to improve accuracy in future iterations.

It's important to note the usefulness depends on the specific application. If a highly precise prediction is crucial, then underestimation might be a significant issue. However, for applications where a general idea of attenuation changes is sufficient, these positive aspects might be valuable.

VI. CONCLUSION

This study introduces an LSTM prediction model for rain attenuation prediction on 11 GHz microwave link located between Furi station (Tx) and Addis Ababa station (Rx), in Addis Ababa, Ethiopia. Using rain rate data from NMAE and microwave link profile data from Addis Ababa University, the study generated historical rain attenuation data in dB by utilizing two Matlab function, "rainpl" and "cranerainpl", the former employing ITU-R rain attenuation model, and the later employing the Global Crane attenuation. The LSTM model was trained and tested with the rain rate and generated attenuation data. The model predicts rain attenuation with MSE of $3.3644 * 10^{-4}$ and RMSE of 0.018. This accuracy suggests that AI-based models, when adequately trained with historical data, can effectively forecast future weather-related events. The proposed model's advantage lies in its ability to function solely on locally recorded data, with the option to integrate with statistical models like ITU-R for additional data if necessary. Its quick prediction capabilities make it suitable for real-time applications across various scenarios.

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