Empowering Clean Air and Advanced 5G Communications with Deep Learning and IoT-Based Monitoring

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***Abstract*—This paper presents a novel approach to modeling the attenuation of millimeter wave (mmWave) signals, using deep learning techniques using IoT sensor data from the University of Mosul. This paper aims to significantly improve prediction accuracy under various environmental conditions, such as water vapor, oxygen, and rain. The research shows that combining Convolutional Neural Networks (CNN) with Recurrent Neural Networks (RNN) leads to a significant improvement in predicting signal attenuation that outperforms traditional models. The paper also discusses the integration of IoT with 5G using deep learning to analyze pollutant data to provide essential tools for the development of smart cities. These deep learning models excel at capturing complex nonlinear environmental interactions, covering more reliable mmWave signal attenuation predictions. The results show that dust could have a good side for spectral efficiency because of the ability to increase the frequency reuse factor in cellular systems. This insight paves the way for future research to explore the effect of dust on spectral efficiency, expanding the focus beyond the mere attenuation and visibility.**

***Keywords*—deep learning, mmWave, dust scatter, frequency reuse, 5G**

I. Introduction

Fundamental adjustments in network design and wireless communication technologies are required to keep up with the growth of mobile data traffic. The 5G network was developed to introduce new spectrum bands, such as those in the mmWave frequency range, and greatly improve energy consumption, capacity, latency, and network speeds [1, 2].

Numerous prior studies have tracked the developments in precoding methods in various channel environments and hybrid beamforming for millimeter-wave massive MIMO communication within the framework of hybrid beam-forming systems. Furthermore, they contrasted the spectrum effectiveness of various precoding methods at the base station using various antenna array sizes [3].

Many scenarios have been studied, including the role of passive components and their design problems, modeling-related issues in CMOS technology, and the effects of contemporary VLSI technologies on the propagation of millimeter wave frequencies [4]. Beamforming and multi-user MIMO at mmWave frequencies were explored as ways to increase the system rate [3]. It was suggested in [5] that larger microcells could be created by stacking multiple micromolar networks on top of each other. In current 5G specifications, this model system architecture is used [6–15].

Dwivedi *et al.* [6] have taken into account the effects of climate weather on the signals of the 5G system. He gave a presentation on a modeling study on the effects of diffraction and storms on the functionality of point-to-point (PPT) wireless communication connections in Riyadh, Saudi Arabia. The findings demonstrated that the increase in free space loss at higher frequencies is caused by dust storms. At frequencies of 14 and 22 GHz, the study was conducted. On the other hand, in [7], we do not take air absorption losses or diffraction into account when assessing the impact of a dust storm. Many articles tried to explain this in 5G [16–25].

A version of the Mie model based on the propagating millimeter wave has been provided in [20] to simulate the impact of a particle dust storm and examine its attenuation. During the same time, the effects of precipitation and diffraction events on wireless PPT communication systems were studied. The results of [9] showed that the diffraction loss increased in the higher frequency bands and that the attenuation of the rain was more pronounced, as shown in Fig. 1.

IoT-Based Air Quality Monitoring: Deploy a network of IoT devices equipped with air quality sensors to collect real-time data on various pollutants, such as PM10, ozone (O_3), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). Utilize IoT connectivity technologies, such as LoRa-WAN,

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NB-IoT, or cellular networks, to transmit the collected data to a central server.

Fig. 2 shows the attenuation as a function of frequency for oxygen, water vapor, light rain, and heavy rain to show the impact of environment and dust on the electromagnetic signals. Fig. 3 demonstrates the scattering and absorption of electromagnetic waves when the signal hits the dust particles.

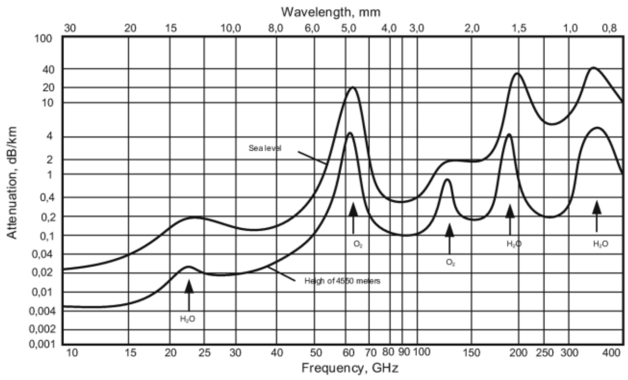

Fig. 1. Attenuation vs. frequency range for mmWave for A. sea level and B. attenuation at 4 Km attitude [10].

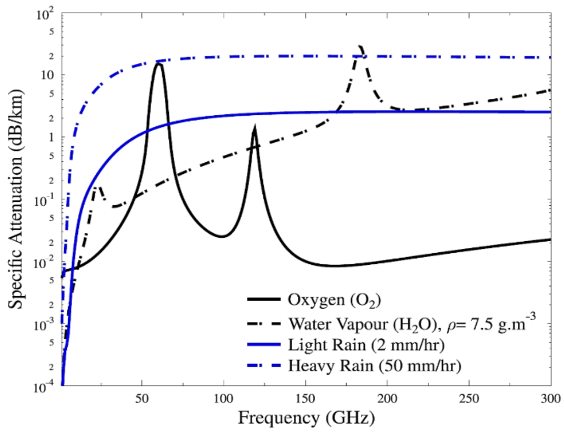

Fig. 2. Specific Attenuation for O_2, water vapor H_2O, light rain, and heavy rain [11].

The purpose of this paper is to provide a new method for modeling the attenuation of mmWave signals using deep learning techniques under a dust environment via the IoT sensor that we collect using Blynk computers distributed over the University of Mosul. We also integrate the 5G with the dust scattering properties.

The rest of this paper is organized as follows, in Section II we discussed the long-range link budget of the mmWave signal and the impact of dust on the signal. In Section III the data is collected and processed. In Section IV metric models are discussed. In Section V the deep learning for prediction is discussed. In Section VI, the proposed model is discussed. Then the results are discussed in Section VII.

II. System Models

A. The Imperial Model

The COST 231 model takes into account several factors, including the size of the dust particles, the concentration of dust, and the frequency of the mobile signal. Another model is the ITU-R P.833 model, which was developed by the International Telecommunication Union (ITU).

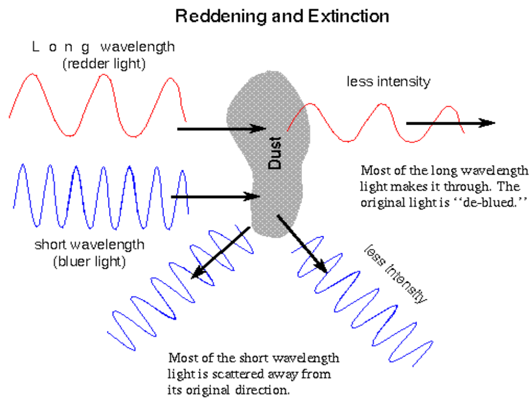

Fig. 3. The scattering of signal on the dust particle [12].

The ITU-R P.833 model is similar to the COST 231 model, but it also takes into account the effects of the terrain and the vegetation.

$$Pr = Pt + Gt + Gr - PL - AL, \tag{1}$$

where Pt and Pr are transmitted and receive signal power in dBm. Gt and Gr are transmitted and receiver antenna gain in dBi, PL refers to the propagation path loss, AL is the atmospheric loss in dB. The propagation path loss can be stated as :

$$PL(f,d) = 32.3 + 20\, log_{10}(f) + 10\, k\, log_{10}\left(\frac{d}{d_0}\right) + X_{\sigma}, \tag{2}$$

where f denotes the carrier frequency in GHz, d is the transmitter and receiver separation distance, the reference distance d_o is 1 m, and k represents the path loss exponent. X_σ represents the zero mean Gaussian random variables with a standard deviation of 1.

Dust particles usually have an important impact on mobile signals, especially mmWave signals. Sometimes, the attenuation may drop from 9 to 11 dB below the signal strength. This may cause a significant drop in the data efficiency of the mobile signal.

However, as mobile communications have wide frequency bands, and as different frequencies may be impacted differently over the same size particle of dust, the humidity, the concentrations, and the vegetation may also impact the behavior of dust particles on the signal attenuation.

B. The Wireless Model for 5G System

As fifth-generation systems (5G) use different frequency bands, signal performance is evaluated using a parameter called the bit error rate (BER), which is the rate of error bits in frames or packets. The relationship between the signal-to-noise ratio (SNR) and BER can be formulated using the following equation.

$$\text{BER} = Q\left(\sqrt{2 \times \text{SNR}}\right), \tag{3}$$

where $Q(.)$ is the Q function, SNR is the signal-to-noise ratio, N_0 is the spectral density of the power of the noise. The quality of the signal strength when transmitted in a dust environment will be impacted by dust attenuation. The received signal strength indicator (RSSI) is a known metric for the quality of signal L.

$$\text{RSSI} = \frac{\text{Received signal power}}{\text{Noise+interference}}. \tag{4}$$

RSSI and SINR usually tell us about the quality of a signal from the transmitter to the receiver. Equation 4 models the impact of dust on the mmWave communications signal. The IoT is increasingly famous for wide-spread devices such as sensors and their ability to integrate with different machine learning methods to enhance the performance of the system.

C. Attenuation due to Dust

Dust particles can cause signal attenuation and scattering. This must be modeled based on particle size, density, and composition.

Attenuation of electromagnetic waves caused by dust. Modeling such attenuation is not an easy task, as it depends on many parameters such as the concentration of dust particles, the composition, and the path length through the dust, which can also be considered as the visibility grade through the dust V, the frequency f. Therefore, modeling such attenuation using deep learning will be a helpful tool for predicting the amount of attenuation expected for the signal.

D. Scattering as a Result of Dust

The scattering of electromagnetic waves by dust involves complex interactions crucial to understanding phenomena in astrophysics and atmospheric science. In the following, we discuss the three scattering models.

Frequency dependence: The impact of dust varies with frequency. Since mmWave frequencies are particularly sensitive to atmospheric conditions, this dependency needs to be thoroughly understood.

Fig. 4 has two parts: the attenuation and scattering properties of the signal when entering dust storms with different particle sizes: 10 μm, 50 μm, and 100μm. For attenuation, the larger the particle sizes, the more attenuation the signal will get. On the other hand, the smaller the scattering, the more scattering the signal will get in the storm. This different behavior of the signal in the dust storm affects the mobile communication signal in a good and bad way. It will have more attenuation and need more power to reach the mobile. However, in a good way, we can use a smaller cell in the cellular system so we can reuse the frequency and that can increase the spectrum efficiency.

While our model evaluates the impact of water vapor, oxygen, and rain on mmWave signal attenuation separately, we recognize the potential for complex interaction between these factors. This can be modeled with a multivariate analysis where the factor changes dynamically over time.

E. Dust to Help Frequency Reuse

As the IoT needs to be reused at the same frequency to reduce cost, we need to know the reuse factor as a function of the air clarity of the environment. The model formulates the Min signal-to-interference ratio as [15]:

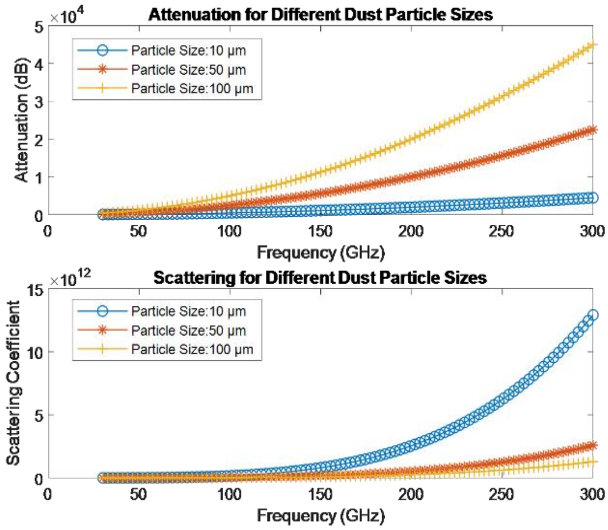

Fig. 4. Impact of dust on attenuation and scattering.

$$\text{Min} - \text{SNIR} = \frac{(x^2+y^2)^{-\frac{k}{2}}}{\text{SFR}(x,y)}, \tag{5}$$

where SFR is the interference factor due to reuse. Fig. 5 shows the frequency of reuse in cellular systems after a particular distance. It is better to reuse the frequency. However, the interference will be higher. Here, the impact of dust can help in that sense, where the scattering and attenuation yield the ability to reduce the distance between each reuse cell.

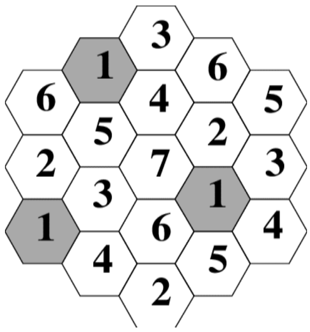

Fig. 5. The shape of frequency reuse of wireless cellular.

Fig. 6 shows the SIR as a function of the frequency reuse factor in the case of a dust storm and without a dust storm in the environment. Without losing generality, the bars show that with dust the SIR provides better results than without dust, as the dust works as a scattering environment that we can use to reduce the distance between two consecutive reuse frequencies. We will test the spectrum efficiency for dust later.

Fig. 6 suggests that dust scattering could enhance spectral efficiency by enabling more frequency reuse in cellular systems as dust typically degrades signal quality and visibility, and it has positive effects on spectral efficiency that may only occur under certain conditions.

These conditions could be under certain particle sizes or concentrations.

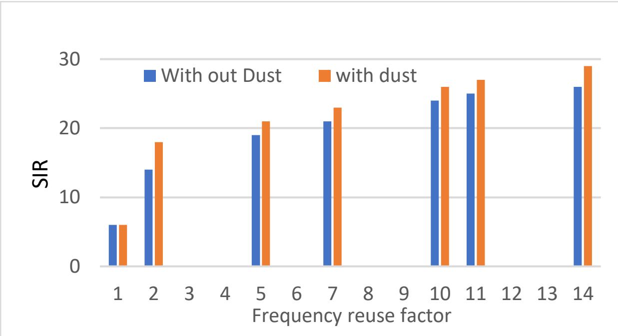

Fig. 6. The SIR as a function of the frequency reuse factor with and without dust.

III. Dataset Collections

At the University of Mosul, we used the Blynk device to gather data from different types of sensors as in Fig. 7. Then we gathered the data to be used to predict the attenuation.

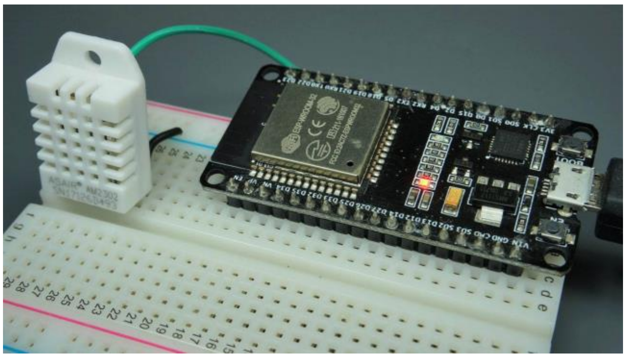

Fig. 7. The Blynk server connects the hardware to the different IoT sensors.

Effective data reprocessing is crucial to ensure the accuracy and efficiency of deep learning models. As shown in Figs. 7 and 8, we collect data from the University of Mosul sites using the Blynk server to create a robust dataset for our proposed models.

A. *Data Collection and Cleaning*

The Data are gathered from multiple sensors distributed throughout the University of Mosul, which are equipped with IoT devices. To improve the generalization of our deep learning models, the data have been collected from various environmental conditions, which represent various temporal and seasonal variations to allow our model to work under extreme or unseen circumstances. Some environmental parameters that this device can measure are air quality pollutants such as PM10, ozone O_3, and nitrogen dioxide, as well as temperature and humidity. The collected data was sent to the central computer to be saved on a seamless connectivity platform such as Blynk.

To address missing data and noise, some steps of preparation have been taken to filter the noise and remove the outliers. Also, some interpolation methods were used to fill in the missing data in the data frame.

B. *Feature Extraction Methods*

Of the raw data, only cleaned data can be extracted to be used as input for our machine-learning models. Some of the important features are as follows. Level of PM10, O_3, NO_2, and SO_2. Temperature degrees, humidity, and wind speed are other features that impact visibility in the dust environment. Some temporal features are also important for different areas like the desert the day and night, and types of seasons.

C. *Data Split*

Data are divided into training and testing to ensure an unbiased evaluation. This will ensure to tuning of the hyperparameters and prevent overfitting. Also, that will ensure robustness.

D. *Integration with Blynk Server*

Using Blynk computers and distributed sensors along the sensors at the University of Mosul provides comprehensive data for our results, as shown in Fig. 8.

Fig. 8. Shows the University of Mosul and the location of red dots on the map to take the data set. The GIS layout is taken from the GIS department at the University of Mosul.

The Blynk server is in charge of all the connections between the hardware and the smartphone. You can run a Blynk server or use Blynk Cloud locally. Due to its architecture, it is open source and can handle thousands of devices.

The Blynk libraries enable the connection for most of the known hardware platforms to help process all the sent and received commands.

E. *Metric Models*

Matrices such as root mean square error (RMSE), mean absolute error (MAE), and R squared (R^2) are used to evaluate the performance of the deep learning model used [18–23].

$$\text{RMSE} = \sqrt{\frac{\{\sum_{i=1}^{N}(x-\{\widehat{x_i}\})^2\}}{N}}, \tag{6}$$

where, x and $\widehat{x_i}$ are the real and predicted data. N is the total amount of data.

$$\text{MAE} = \frac{\sum_{i=1}^{N}(x-\{\widehat{x_i}\})}{N}, \tag{7}$$

$$R^2 = \frac{\sum_{i=1}^{N}(\hat{x_i}-\bar{x})^2}{\sum_{i=1}^{N}(x_i-\bar{x})^2}, \quad (8)$$

where $\bar{x}$ is the average of the data.

IV. Deep-Learning for Prediction

Deep Learning for Air Quality Analysis: Develop deep learning models, such as convolution neural networks (CNN) or recurrent neural networks (RNNs), to analyze the air quality data collected. Train models on historical data to identify patterns, trends, and correlations between different pollutants and environmental factors. Extract relevant features from the collected data, such as pollutant concentrations, temperature, humidity, wind speed, and wind direction. Apply feature transformation techniques, such as scaling, normalization, or dimensionality reduction, to improve the performance of deep learning models [24–29].

Selection and training of deep learning models. Select a suitable deep learning model architecture, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), based on the specific air quality analysis task. Train the deep learning model on the preprocessed and feature-engineered data. Utilize appropriate loss functions and optimization algorithms to minimize the error and improve model performance [30, 31].

To address the computational demands of deep learning models, we implement some sort of dimensionality reduction techniques to ensure our model stays efficient yet without losing accuracy and to optimize the hyperparameters.

V. The proposed Model

In this paper, the hybrid of CNN and RNN is proposed to obtain the advanced part of both methods. However, the share of each side can be different, which may provide different results. Therefore, a cross-validation technique is used, as shown in Table 1, to find the joint factor between the two techniques.

In Table 1, for $\lambda = 0.001$ the training error is 2.5, and the testing error is 2.4 so the minimum is 2.4 in the testing stage. Next for $\lambda = 0.01$ the training error is 2.31 and for testing is 2.33 so the minimum error occurs in the training stage. The process continues for $\lambda = 0.1$, 1, and 10. Observing minimum error across all evaluated λ shows that $\lambda = 0.1$ provides the smallest minimum error, making it the optimal value.

$$\text{proposed} = \text{CNN} + \lambda\, \text{RNN}. \quad (9)$$

TABLE I. The Cross-Validation Parameter

λ	training	Testing	MIN-MIN
0.001	2.5	**2.4**	2.4
0.01	**2.31**	2.33	2.31
0.1	2.23	**2.22**	**2.22**
1	**2.51**	2.57	2.51
10	**2.63**	2.64	2.63

By using the cross-validation parameter in Table I, we have implemented several a regularization technique to reduce the risk of overfitting, helping the model to learn more generalized patterns. This technique will improve the models' ability to perform better on unseen data.

VI. Results and Discussions

Our proposed method of integration of CNN and RNN to model mmWave propagation in a dust environment provides the potential to improve predicted performance.

To ensure a smooth decision-making process, we employed some feature importance techniques to identify the key environmental factors that lead to predictions, which leads to better models in terms of transparency and actionability.

TABLE II. The Performance of Different Models

	RMSE	MAE	R^2
CNN	0.83	1.4	1.21
Proposed	0.73	1.33	1.34
ARIMA	0.97	2.33	0.86

Table II shows that the proposed method provides high performance in predicting the reuse factor and increasing the data rate of the cellular systems.

From Table II, we can see that the CNN model provides better results than the ARIMA model. However, our proposed joint RNN-CNN model provides better results than both models alone by about %10 in RMSE, %5.2 in MAE, and %9.7 in R^2 than CNN.

The impact of scattering and attenuation of dust storms can be a positive side for frequency reuse, and hence for data rate in the network system.

Our model provides significant theoretical insights and improvement in predicting signal attenuation under different environmental conditions, yet real-world validation helps us identify any relation between the simulation and the actual results and refine the model according to that.

This research highlights the potential for integrating IoT with 5G services to enhance signal attenuation predicting environmental monitoring, even if that may face some challenges such as scalability and network congestions.

VII. Conclusion

This study demonstrates the effectiveness of integrating of deep learning with IoT to improve the predictions of mmWave signal attenuation under various environmental conditions. The main findings and contributions are focused on the integration of machine learning with IoT for improved 5G communication and air quality monitoring. IoT-based platform applications are utilized to predict dust particle monitoring to predict the frequency of 5G communications reuse. The model is based on deep learning techniques such as CNN and RNN and our proposed mode, which provides better performance results for real-time and practical scenarios. The paper shows that dust could have a good side for spectral efficiency as a result of the ability to increase the reuse factor in cellular systems. These results will open the door to further research in modeling dust on spectral efficiency instead of focusing on attenuation and visibility.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Raghad H. Alshekh has collected the environmental data at the University of Mosul. Farhad E. Mahmood finds the impact of the environment on the communication system (mmWave). Farah N. Qassabbashi has determined all the calculations and computations in the paper.

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