A Machine Learning-Assisted Framework for Determination of Performance Degradation Causes and Selection of Channel Switching Strategy in Vehicular Networks

Final Report

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DISCLAIMER

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16. Abstract

As all three major US mobile carriers have launched their own 5G networks and are working hard to expand their coverage nationwide, 5G has come into everyone's daily life. 5G networks use millimeter-wave (mm-Wave) for higher speeds, while 4G long-term evolution (LTE) networks favor lower-band spectrum for better coverage. Vehicle-to-vehicle (V2V) communication enables wireless communication between cars and exchanges their speed, location, and acceleration information. 5G mm-Wave and 4G LTE bands are used in V2V sidelink transmissions. These two wireless channels are affected by different weather conditions, such as rain, snow, dust, and sand. Compared with 4G networks, 5G networks are designed to accommodate the increasing number of devices with higher transfer speed, lower latency, and improved security. However, our study shows that severe weather degrades the 5G performance more significantly than 4G. In this paper, we use NS-3 as a simulator to study the effect of harsh weather of dust or sand on the propagating loss of 5G mm-Wave and 4G LTE signal. We investigate their performance degradation and use a time-series machine learning technique, long short-term memory (LSTM), to predict future signal strength for 5G and 4G. Our simulation results show that LSTM performs well in forecasting signal strength, and we plan to design a system that can dynamically choose the better wireless channel in the future.

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EXECUTIVE SUMMARY[1]

In this study, we propose to formulate and construct a machine learning based model to detect and determine the most likely cause of performance degradation in vehicular communication and develop an integrated framework which will select the best available channel switching strategy according to the learned cause of performance drop. In the intelligent transportation system (ITS), it is very important to keep vehicular communications stable and reliable. In recent years, researchers have proposed schemes that combine ad-hoc direct communication and cellular network infrastructure to provide seamless connectivity and adequate Quality of Service (QoS) for all types of vehicular applications. However, performance degradation may occur anytime due to various factors, such as weather impact, jamming, or other types of interference. Different types of performance drop will be best addressed by different channel switching strategies, but the selection of best channel switching strategy must be adaptive in a timely manner. We aim to address this issue by developing machine learning based models for determination of performance degradation cause and supporting dynamic selection of channel switching strategy based on the current circumstances.

We extend ns3-Millicar model by adding weather impacts to path loss functions. The code and results of our simulation and implementation details are published on GitHub (https://github.com/ericliujian/ns3-mmwave-weather), our simulation results show that multivariate LSTM model is good for predicting future RSSI value of vehicles.

[1] Note that the content of this report has been published as two conference papers in 2022 IEEE International Conference on Wireless for Space and Extreme Environments (WiSEE) and another two journal papers under review. Citation: J. Liu et al., "Investigation of 5G and 4G V2V Communication Channel Performance Under Severe Weather," 2022 IEEE International Conference on Wireless for Space and Extreme Environments (WiSEE), Winnipeg, MB, Canada, 2022, pp. 12-17, doi: 10.1109/WiSEE49342.2022.9926867.
E. Abuhdima et al., "The Effect of Dust and Sand on the Propagating EM Millimeter Plane Wave," 2022 IEEE International Conference on Wireless for Space and Extreme Environments (WiSEE), Winnipeg, MB, Canada, 2022, pp. 1-5, doi: 10.1109/WiSEE49342.2022.9926914.

CHAPTER 1

Introduction and Background

As early as 2016, 3GPP (3rd Generation Partnership Project) group started to develop protocols for the next generation of mobile communication (5G) to provide wireless service with extreme availability, low latency, and reliability requirements. To meet all these requirements, 5G networks in the USA are designed to operate in high frequency (mm-Wave), usually in the range of 24 GHz to 100 GHz [1]. Since the popularity of Tesla, the automotive industry is currently transitioning towards automated driving, and vehicles can communicate with each other in theory. Several V2V use cases have already been proposed within the 3rd Generation Partnership Project (3GPP) Release 15, such as vehicle platooning, extended sensors, advanced and remote driving, or cooperative collision avoidance [2].

When 5G millimeter-wave radiation passes through severe weather environments such as dust and sand, it suffers from frequency-dependent absorptive and dispersive phenomena, causing distortions in amplitude and phase [3]. It engenders a great need to study how severe weather will affect 5G mm-Wave and 4G LTE wireless transmissions.

Previous work [4] displayed the impact of dust and sand on microwave connection and cellular mobile-covered signals by calculating the attenuation factor in dB/km. The attenuation was calculated using different parameters such as frequency, visibility, height, particle size, and dielectric constant.

It usually comes across two methods to study the signal communication in vehicle-to-vehicle (V2V) scenarios. One way is to build a real vehicle-to-vehicle experiment test bed and set up 5G and 4G devices on the vehicles, but it requires a considerable budget and too much effort. Another limitation is that it is quite impossible to get the dust/sand environment we want to study. Another feasible way is to use a simulator to study weather impacts on wireless communication. Millicar[5], a mmWave-based V2X network simulator based on NS-3, is suitable for our research. We extend Millicar and use it to study V2V sidelink communications.

Our work considers the effect of severe weather impacts (dust/sand) on the propagation of 5G mm-Wave and 4G LTE signals. It mainly focuses on particle size, visibility, and humidity. The researchers in [6] investigated the combined rain and snow effect on mm-Wave using International Telecommunication Union (ITU) fading prediction methods. Our research differs from theirs by using the Mie scattering method, and we investigate the weather impacts of 4G LTE communication channel as additional work. Additionally, our work investigates the difference between the weather impacts on 5G and 4G transmission deterioration. Our next plan is to select a better transmission technology in case of deterioration of the weather conditions.

Received Signal Strength Indicator (RSSI) is a well-known measure to evaluate the performance of communication channels. The researchers in [7] evaluated the performance of the 5G sub-bands, 10, 17, 30, and 60 GHz, based on RSSI simulation results. An efficient handover management method is proposed for LTE communication by measuring and forecasting the RSSI of the local Access Points (APs) in [8]. Finally, the LSTM machine learning method is implemented to forecast the future RSSI values for 5G and 4G technologies.

The remainder of this report is organized into six sections. Chapter 2 and 3 overviews several essential topics in this research. The simulation results and discussions are presented in chapter 4 and 5. In the last chapter, we conclude the report and propose suggestions for future extensions.

CHAPTER 2

Method

In this section, we will introduce three crucial concepts in our research. This report's primary mathematical starting point is the attenuation model for weather impacts. Received Signal Strength Indicator is one novel metric we introduced in our model to study wireless transmission between transmitter and receiver in a V2V sidelink scenario. LSTM is the machine learning model we used to forecast future RSSI values.

2.1 Attenuation Model

The Mie scattering theory is one of the methods used to handle a perfect analytical solution to Maxwell's equations during dusty/sandy lossy medium. This solution is valid to apply at different possible ratios of particle diameter and wavelength of propagating wave and is especially used at higher frequency bands. The Mie model computes the attenuation factor of the propagating wave in dB/km. The concentration of dust, particle radius, operating frequency, humidity, and complex permittivity is considered when the attenuation factor is computed in this research. The total attenuation factors during dusty/sandy lossy medium α are defined by [9], [10] in dB and presented in (1)

$$\alpha_{(\mathrm{dB})} = \frac{\mathrm{a_e f d}}{\mathrm{v}}\left[\mathrm{C_1} + \mathrm{C_2 a_e^2 f^2} + \mathrm{C_3 a_e^3 f^3}\right] \quad (1)$$

where d is the length of propagation wave, a_e is the equivalent particle radius in meters, v is the visibility in km, f is the frequency in GHz, C_1, C_2 and C_3 are defined in (2), ε_1 and ε_2 are defined in (3), where H is the air relative humidity in percentage unit.

$$C_1 = \frac{6\epsilon_2}{(\epsilon_1+2)^2+\epsilon_2^2}$$

$$C_2 = \epsilon_2\left[\frac{6[7\epsilon_1^2+7\epsilon_2^2+4\epsilon_1-20]}{[(\epsilon_1+2)^2+\epsilon_2^2]^2}+\frac{1}{15}+\frac{5}{3[(2\epsilon_1+3)^2+4\epsilon_2^2]}\right] \quad (2)$$

$$C_3 = \frac{4}{3}\left[\frac{(\epsilon_1-1)^2(\epsilon_2+2)+[2(\epsilon_1-1)(\epsilon_1+2)-9]+\epsilon_2^4}{[(\epsilon_1+2)^2+\epsilon_2^2]^2}\right]$$

$$\begin{aligned}\varepsilon_1 &= \varepsilon' + 0.04\,H - 7.78\times10^{-4}\,H^2 + 5.56\times10^{-6}\,H^3\\ \varepsilon_2 &= \varepsilon'' + 0.02\,H - 3.71\times10^{-4}\,H^2 + 2.76\times10^{-6}\,H^3\end{aligned} \quad (3)$$

2.2 Received Signal Strength Indicator

Received Signal Strength Indicator (RSSI) measures how well a client can hear a signal. RSSI is a practical measure for determining if the transmitted signal strength is enough to get a good wireless connection. This paper uses RSSI measurement to evaluate the performance of the 4G and 5G wireless communication channels. The RSSI values are obtained from NS3 simulations.

2.3 LSTM model

LSTM is short for long short-term memory, is a neural network architecture commonly employed in artificial intelligence and deep learning networks. LSTM is a particular implementation of recurrent neural networks, which are particularly effective in tasks involving sequential or time-dependent data, such as speech recognition, natural language processing, and time series analysis. Since they can keep a memory of previous inputs, LSTMs are considered particularly efficient for time series prediction [11].

In this work, we use LSTM to predict future RSSI values in case of severe weather for 5G mm-Wave and 4G LTE channels. We plan to use predicted RSSI values to determine signal degradation and design an auto channel switching strategy.

CHAPTER 3

Propagation During Dusty Region

It is known that the desert is the source of the dust and sand in different regions of the world. The average power of the transmitting plane wave is attenuated when the planewave is traveling during transmission media. This transmission media could be a wireless or wired channel. This attenuation is defined as the path loss of transmission channel, so it is dependent on the operating frequency and the path length of the propagating plane wave. Another important factor that affects the attenuation is weather factors. This research studies the effect of dust and sand on the transmission parameters of millimeter plane wave. During dust and sand, the dielectric constant is computed as a complex value. In 2009, research was conducted to compute the real value of the complex dielectric constant during dusty/sandy weather. It was found that the average complex permittivity is 6.3485 – *j**0.0929 and the average density of collected samples is equal to 2.5764 g/m^3 [3]. Another research discussed the effect of humidity on complex permittivity, so the dielectric constant ε' and the dielectric loss factor ε'' can be written as Equation (3). The polarization forms of the propagating millimeter plane wave are discussed in coming sections.

3.1 Linear Polarization

Mathematically speaking, a wave is linearly polarized when its electric field varies with time only along a single axis. In other words, the wave is linearly polarized when its electric field varies with more than one axis as long as there is no phase differences. When the variation of the electromagnetic millimeter wave moves up/down around z−axis, the wave would be linearly polarized along z axis with distance d. In this case, the electric field component is considered in the x direction and magnetic field in y direction as shown below.

$$\tilde{E} = E_O\left[\widehat{a_x} + \widehat{a_y}\right]e^{-\alpha}e^{-jk_o \cdot d}$$

3.2 Circular Polarization

In terms of circular polarization, the electric field is composed from two plane waves that have equal magnitude and different phase by exactly 90° or one-quarter wavelength. The electric field expression can be written as

$$\tilde{E} = E_O\left[\widehat{a_x} + j\widehat{a_y}\right]e^{-\alpha}e^{-jk_o \cdot d}$$

It is assumed that the wave is propagating the distance *d* in *z* direction.

3.3 Elliptical Polarization

In this case, the elliptical polarization is created by two perpendicular waves of different amplitude and different phase as shown.

$$\tilde{E} = \left[E_1\widehat{a_x} + E_2 e^{j\theta}\widehat{a_y}\right]e^{-\alpha}e^{-jk_o \cdot d}$$

where θ is the phase difference, E_1 and E_2 are the amplitude of the electric field in x and y directions, respectively. This is a clockwise elliptical polarization.

CHAPTER 4

Simulation of V2V Channel Performance

We conduct a series of simulations to investigate different weather impacts on 5G and 4G signal strength. In step one, we study weather impacts on received packets for 5G mm-Wave and 4G LTE signals. In the second step, we use RSSI to measure the receiver's power in a wireless radio signal. In the last step, we propose an LSTM model to predict future RSSI of 5G and 4G signals depending on weather conditions.

4.1 Simulation Setup

There are several 5G mm-Wave simulation tools available for public use online, such as NYUSIM [12], 5G toolbox [13] in Matlab, Simu5G [14] and NS-3 mm-Wave [15]. NYUSIM and the 5G toolbox do not meet our requirements since we cannot directly add path loss functions of weather impacts. Simu5G only supports network controlled D2D (device to device) transmissions, and V2V sidelink communication is not supported yet. The only simulator that fits our research is Millicar [5] model based on the NS3 mm-Wave module. NS3 mm-Wave is used to simulate the 5G cellular network operating at mmWaves, and Millicar supports the latest 3GPP channel model for the V2V channel. We extend Millicar by adding weather impacts to path loss functions and a new LTE-enabled vehicle net device. There are several differences between 5G mm-Wave and 4G LTE V2V channels [16]; we only consider the frequency, bandwidth, and numerology to simplify the problem. Our new modified NS3 model can automatically generate ns3 simulation results according to different weather parameters: particle size, visibility, and humidity.

In our simulation scenario, two cars drive in the same direction at the same speed. The two vehicles exchange packets through 5G mm-Wave and 4G LTE channels through sidelink channels. They are driving towards a harsh weather environment that consists of dust or sand, and the weather condition will affect the transmission of both 5G and 4G wireless channels. We want to use our NS3 module to simulate weather impacts on the communication channels between two vehicles.

4.2 Evaluation of Packet Loss for 5G and 4G

This subsection studies how particle size, visibility, and humidity impact 5G and 4G packet loss. We extend our previous work's [17] study on the impacts of dust and sand on received packets among connected vehicles to a 4G LTE channel. As discussed in Section III-A, the total attenuation factors α can be added to 4G LTE path loss function as well. The simulation parameters are shown in Table 1.

Parameters	Value Range
Particle Size (m)	0.000-0.0008
Visibility (km)	0-3
Humidity (%)	0-100
Frequency (GHz)	2.1, 28
Speed (m/s)	20
Inter Packet Interval (microseconds)	30
V2V Scenario	Highway
Vehicle States	Line-of-Sight

Table 1. Simulation Parameters

Fig. 1 shows that when particle size is less than 0.0002 m, 5G mm-Wave and 4G LTE have similar performance, but after 0.0002 m, 4G LTE has better results. As 5G mm-Wave can transmit more packets than 4G LTE, in the case of both 100% received packets, 5G mm-Wave is a better choice. When the particle size is larger than 0.0007 m, there will be no transmitted packets for both channels.

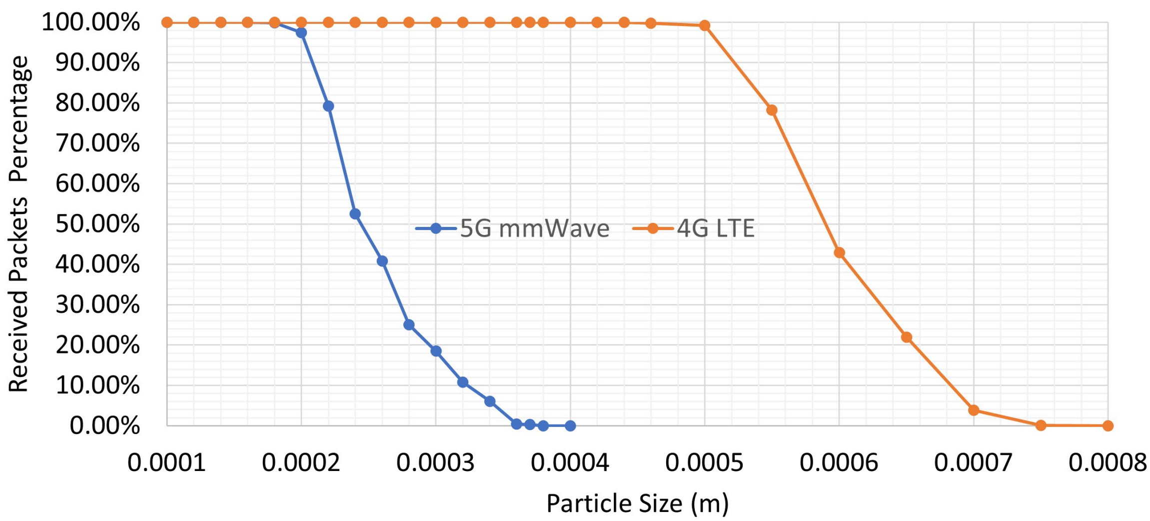

Figure 2. Effect of Particle Size on Received Packets Percentage

Waves with a higher frequency have a shorter wavelength, so 5G mm-Wave's wavelength is smaller than 4G LTE, which matches the fact that smaller particle sizes will start to affect the packet transitions of 5G first.

Fig. 2 indicates that 4G LTE is a better choice against 5G mm-Wave when visibility is less than 2 m, while both 5G mm-Wave and 4G LTE always have 100% of received packets. when visibility is larger than 2 m. Similarly, in the case of both 100% received packets, 5G mm-Wave is preferred.

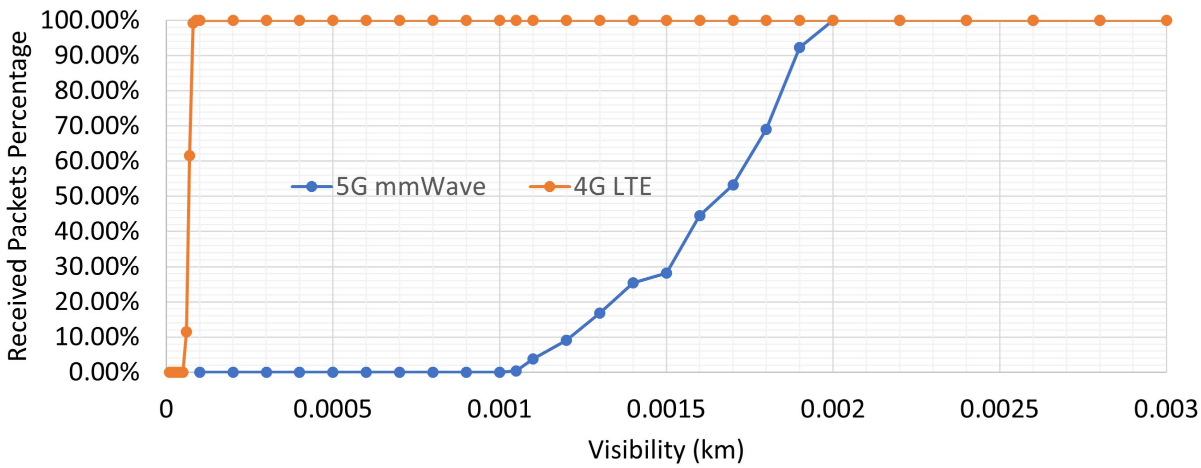

Figure 2. Effect of Visibility on Received Packets Percentage

Fig. 3 shows how humidity affects 5G and 4G packet loss. The simulation is conducted under particle size of 0.00023 m and visibility of 0.00018 km. It shows that 4G LTE tends to have better results after 20% humidity, while 5G mm-Wave is preferred if humidity is lower than 20%.

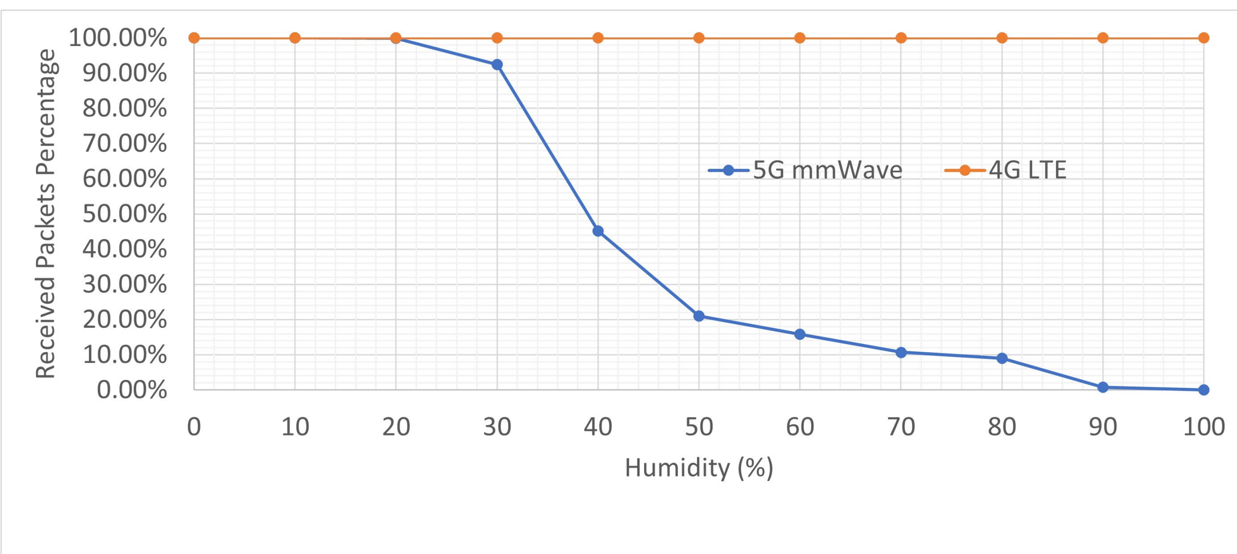

Figure 3. Effect of Humidity on Received Packets Percentage

Fig. 4 plots the path loss on received packets percentage to see the correlation between these two parameters. It clearly shows that as the path loss increase, the received packets percentage of 5G and 4G both tend to decline, but 4G LTE declined much more rapidly.

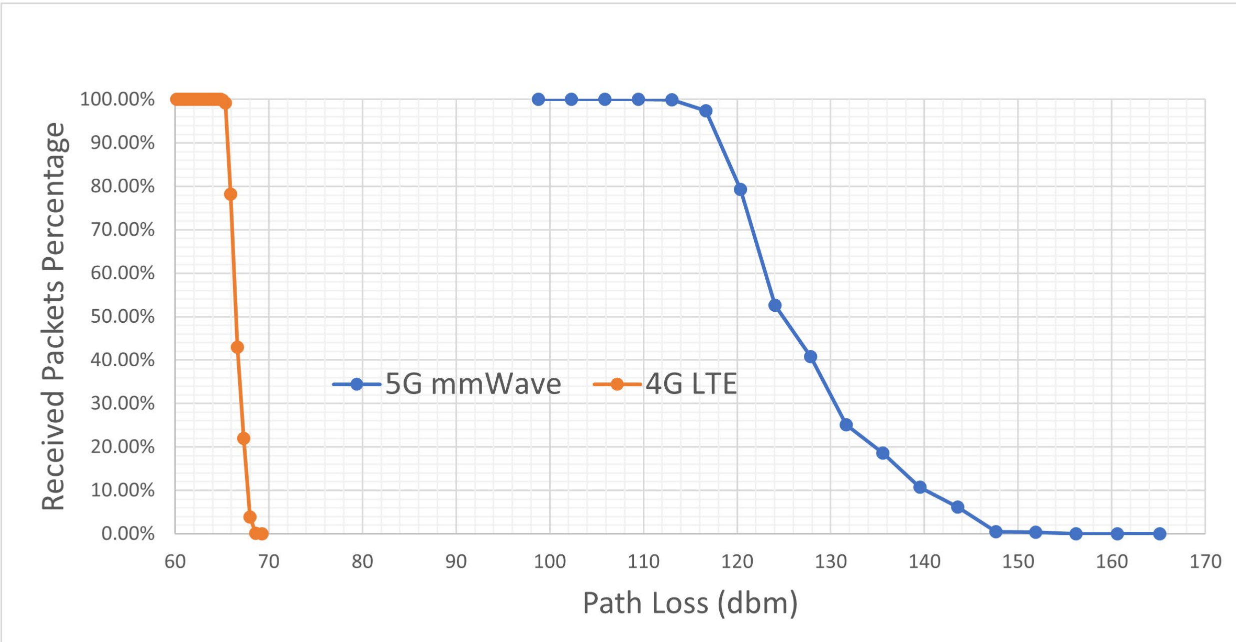

Figure 4. Effect of Path Loss on Received Packets Percentage

4.3 Evaluation of RSSI for 5G and 4G

Our final implementation goal is to design a system that can dynamically measure 5G mm-Wave and 4G LTE signal performance; received packet metrics cannot fulfill this requirement. As we introduced in Section II, we propose using the received signal strength indicator (RSSI) to measure wireless performance. We use the same two-vehicle scenario example and assign the leading car as the transmitter and the following car as the receiver. The leading car simultaneously sends 5G mm-Wave and 4G LTE signals to the back car. Our simulation is to study how different natural weather conditions will affect 4G and 5G transmission.

In order to study natural weather influences on mm-Wave and LTE transmissions, we want to use some actual weather in the USA, and we collect weather(humidity/visibility) data from Climate Data Online (CDO) [18]. Our chosen dataset contains Local Climate logical Data (LCD) for BLANDING MUNICIPAL AIRPORT, UT, US, from 01/01/2021 to 12/31/2021. The weather data for the LCD Weather was collected at 20-minute intervals throughout the year for a specific location. However, due to some unrecorded weather instances, we performed data cleaning to ensure the reliability of the dataset. Ultimately, we utilized a total of 23,528 weather samples for our analysis. While the collected data includes information on humidity and visibility, it does not include particle size information. To address this, we explored external sources and found particle size information online for PM2.5 and PM10 [19]. However, these particle sizes did not align with

the range of dust and sand particles examined in our previous research [17], which spanned from 90 µm to 600 µm. To overcome this limitation, we randomly generated particle sizes between 280 µm to 320 µm, which ensured a controlled range for all weather conditions and maintained consistency.
In Chapter 2.1, we described our basic approach, utilizing the humidity, visibility, and particle size information as inputs for simulations conducted with our newly designed NS3-weather model. We resulted in a total of 23,528 simulation runs. For specific details regarding the time window associated with each weather condition, please refer to Table 2.

Input Parameters	Time Interval (Minutes)
Humidity	20
Visibility	20
Particle Size	20

Table 2. Input Parameter Time Window

We extend our model by auto-generated simulation data according to different weather impacts: particle size, visibility, and humidity. We assign the leading car to transmitter power (TxPower) as 15 dBm. The following car's received power (RxPower) is outputted from our NS3 model. It can be seen from Fig. 5 and Fig. 6 that our model can successfully auto-generated RSSI values for both 5G mm-Wave and 4G LTE channels on our two-vehicle examples. We use LSTM to forecast future RxPower and see how it behaves in the following subsection.

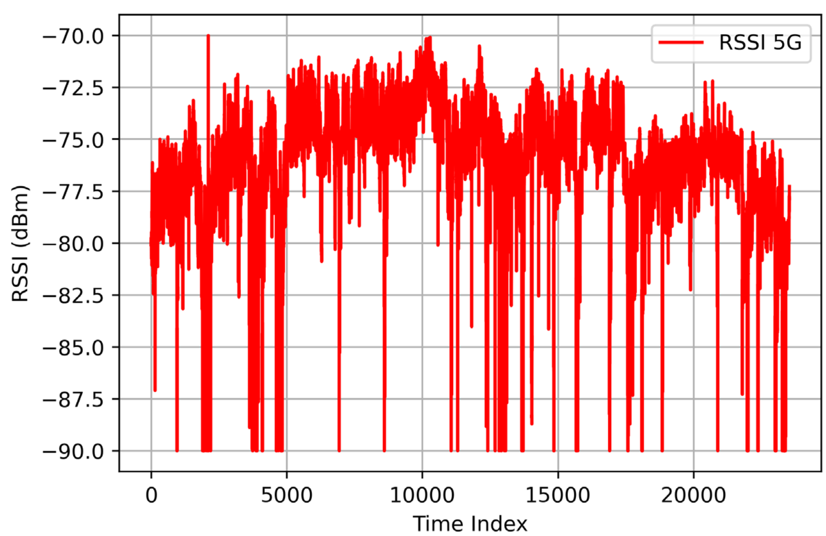

Figure 5. RxPower Values of 5G mm-Wave

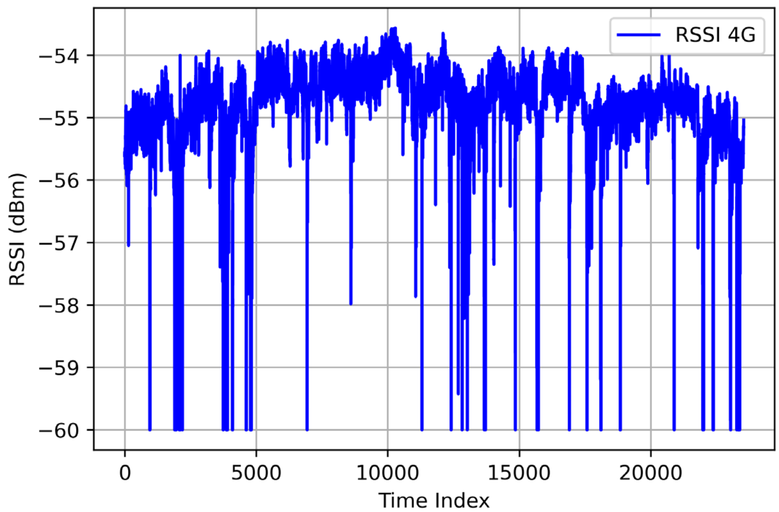

Figure 6. RxPower Values of 4G LTE

4.4 LSTM-based RSSI Prediction

Long short-term memory (LSTM) is an artificial neural network used mainly for time-dependence series [20]. LSTM is well suited for predicting time series data. This paper proposes an LSTM model to predict future RSSI values of 5G and 4G channels.

1) Univariate RSSI Forecasting: The first model proposed is the univariate LSTM model. It receives a single series of observations and learns from past observations to predict future values in the sequence. We used RSSI values from our NS-3 simulation to predict the future 5G mm-Wave and 4G LTE RSSIs separately. To evaluate the model's performance, we selected the first 90% of the RSSI dataset for training and the remaining 10% for testing. The model includes an input layer, one LSTM layer with 100 LSTM units, and a Dropout layer with a value of 0.3. The Dropout, as its name implies, is responsible for randomly dropping neurons and units to avoid over-fitting in the neural network training process. The last layer is a fully connected dense layer that aims to output the estimated values. The proposed model evaluation is carried out through training and validation loss calculations. Python 3.9.12 and TensorFlow 2.9.0 are employed to implement the deep LSTM model. The model is run for 40 epochs with batches size equal to 1024. Fig. 7 and Fig. 8 shows good estimation of future RSSI based on this model.

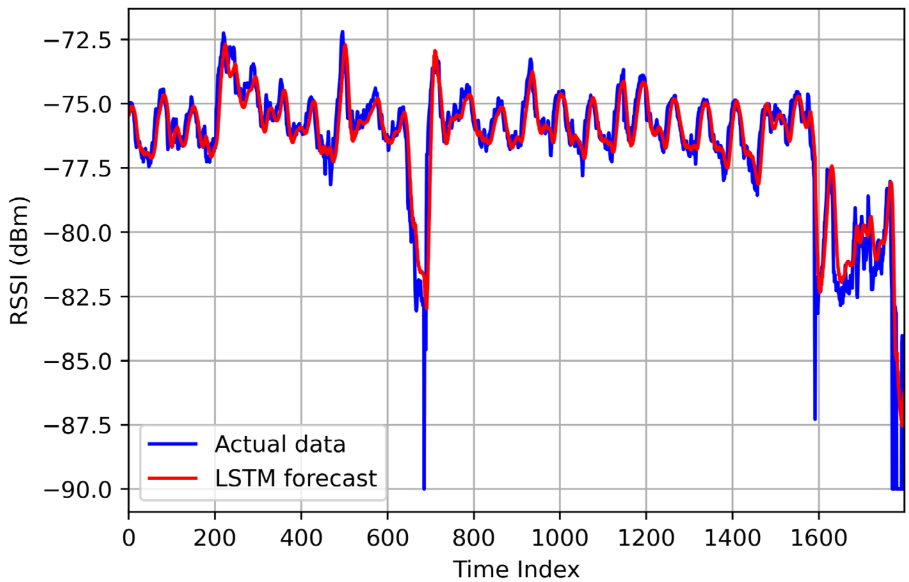

Figure 7. Univariate LSTM based on RSSI for 5G mm-Wave

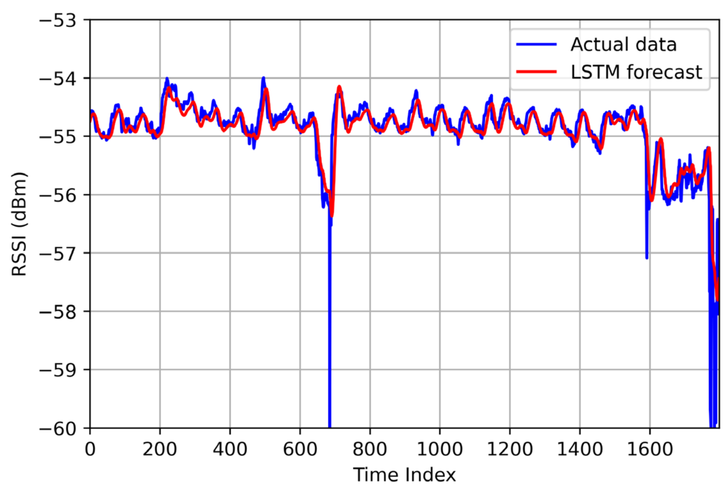

Figure 8. Univariate LSTM based on RSSI for 4G LTE

2) Multivariate Forecasting RSSI: The second approach is the multivariate model that uses RSSI, humidity, visibility, and particle size as the model inputs to predict the future RSSI values. Fig. 9 and Fig. 10 are the forecasting results based on multivariate LSTM. The multivariate LSTM version showed a better performance than the univariate model. Because the RSSI value changes as a function of these parameters. In other words, the future RSSI value depends not only on its current value but also on the current values of humidity, visibility, and particle sizes. The two approaches' prediction performances are shown in Table II. We can see that the multivariate model shows us a lower RMSE and a better performance. The prediction of

future RSSI can be used to build a channel switch mechanism for 5G mm-Wave and 4G LTE in terms of the changing weather conditions.

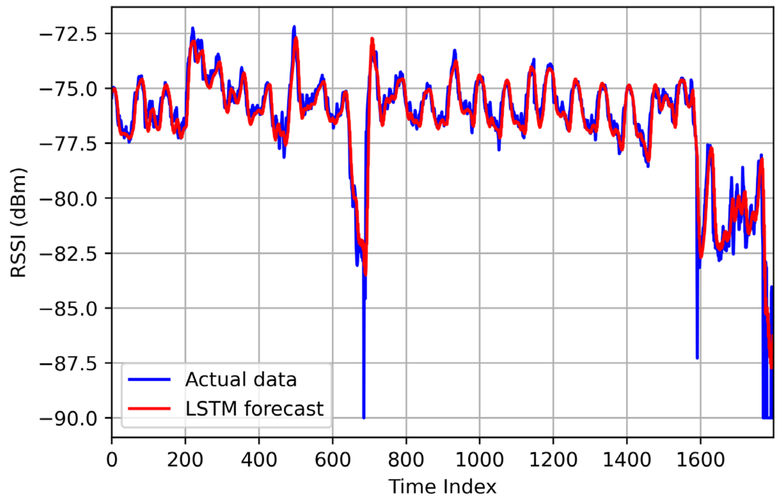

Figure 9. Multivariate LSTM for 5G mm-Wave

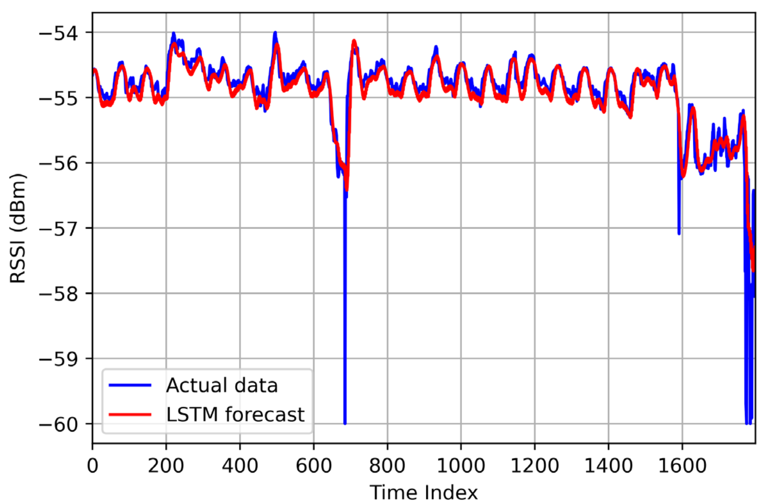

Figure 10. Multivariate LSTM for 4G LTE

Methods	Root Mean Square Error on Test Set
Univariate LSTM for 5G	0.058
Univariate LSTM for 4G	0.050
Multivariate LSTM for 5G	0.048
Multivariate LSTM for 4G	0.044

Table 3. LSTM Prediction Performance

CHAPTER 5

Simulation of Propagating Polarization

In this simulation, the ML6352 is considered to operate at 75.3 GHz and 15dBm output power [17]. According to incident electric filed that is defined and the transmitted power (15 dBm), the computed amplitude E_o is 3.5v by using Maxwell's equations. Also, the measured dielectric constant ε is 6.3485 − j0.0929 with average particle size, a_e= 94.43 *µm* [21]. First, the effect of dust and sand on the propagating attenuation factor is investigated. Fig. 11 shows that the amplitude of the attenuation factor is decreased when the visibility is increased. The amplitude of the attenuation factor is 13.47, 65.23 and 109.235 at 0, 60 and 100 percent humidity, respectively. The effect of dust and sand on the attenuation factor is more evident when the visibility is less than 10m. The attenuation factor increases when the frequency is increased as shown in Fig. 11 and Fig. 12. Also, the skin depth defined by (8) shows that the penetration of the propagating millimeter wave in a dusty/sandy medium varies when the dust and humidity are changed as shown in Fig. 13. The distance that the millimeter wave travels in a dust/sandy medium with (visibility = 10m) to reduce its maximum value by 36.8 percent is 742.223m, 153.3m and 91.54m when the humidity is 0, 60 and 100 percent respectively as shown in Fig. 13. This result helps to know the minimum propagation length to avoid fading or loss of data during disconnected channels. The magnitude of the propagating electric field that is presented by decreases when the visibility decreases. The amplitude of the electric field loses 50 percent of its maximum value when the visibility 4m, 20m and 34m with 0, 60 and 100 percent humidity respectively, as shown in Fig. 13. The propagating electric field is 2.635-*volt*, 0.935 *volt* and 0.388 *volt* when the humidity is 0, 60 and 100 percent respectively.

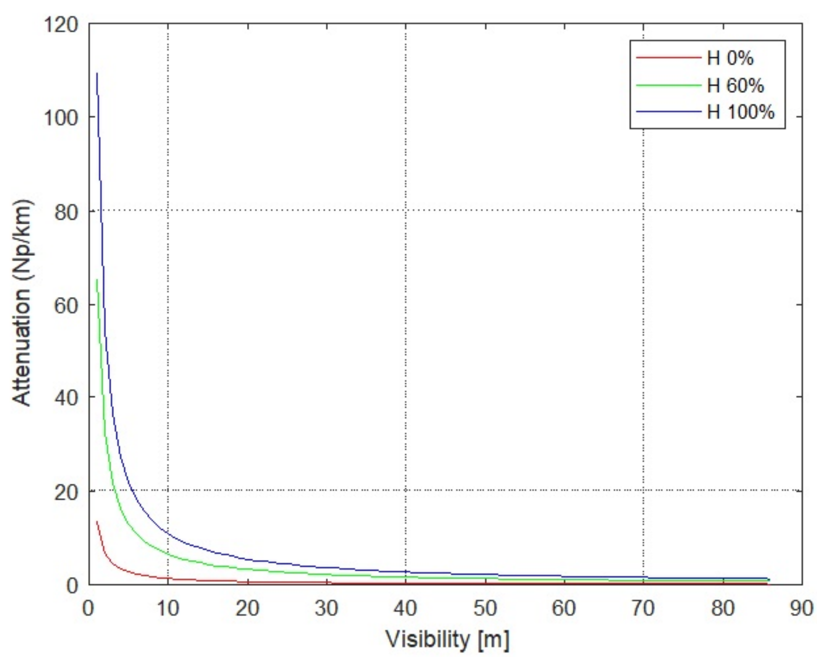

Figure 11. Attenuation factor at f = 73.5GHz

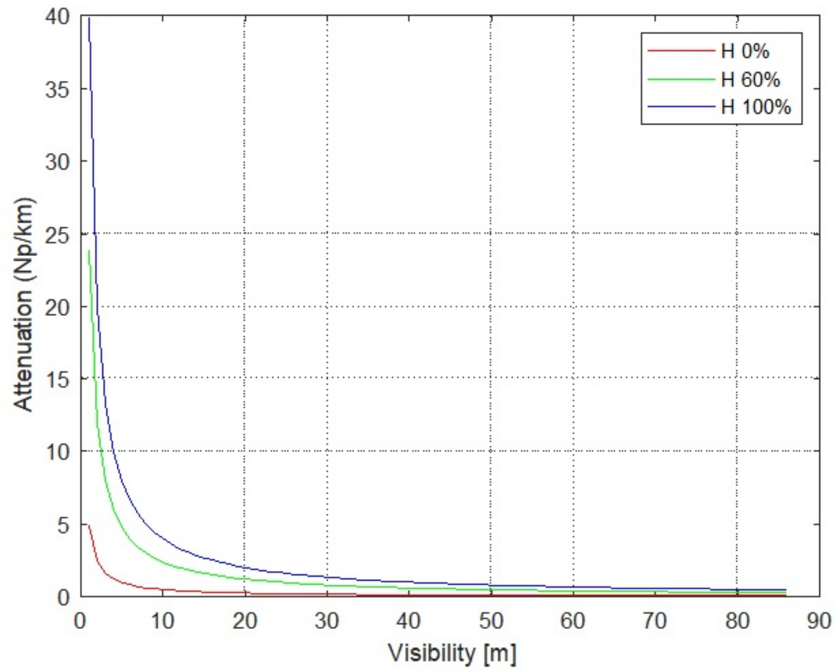

Figure 12. Attenuation factor at f = 28GHz

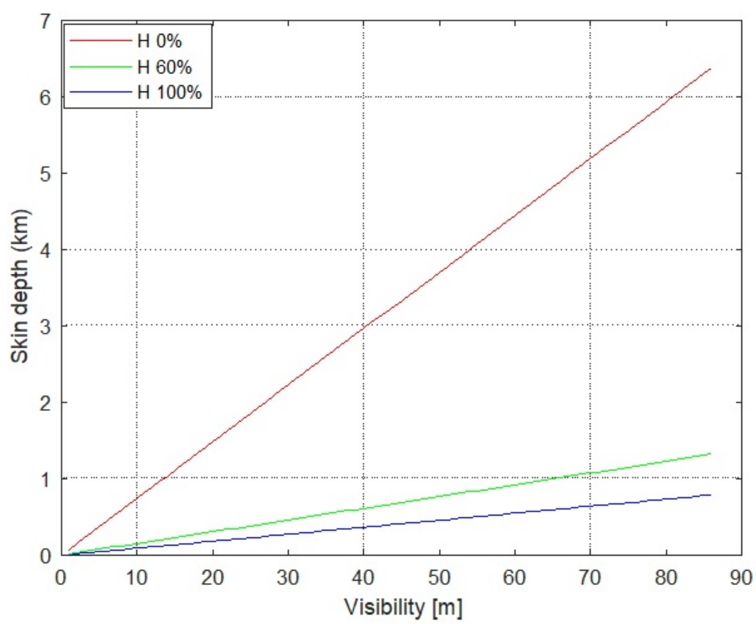

Figure 13. Traveling millimeter wave in lossy medium

Fig. 14 and Fig. 15 show the pattern of propagating millimeter electrical field with different values of visibility. The amplitude of linear polarized electric field is 2.4volt when visibility is 8m, 37m and 64m with 0, 60 and 100 percent humidity respectively. In the case of circular polarized electric field, the amplitude is 8.147 × 10−10*volt* when the humidity is 0, 60 and 100 percent, respectively, as shown in Fig. 16. These figures show that the linear polarization is better than circular polarization during harsh dusty/sandy weather. This result fits the same result of previous research that discussed the microwave attenuation in dust storms in terms of the Rayleigh scattering approximation. It found that the linear polarization at frequencies around 10GHz is the best during dust storms [22]. For circular polarization, the attenuation is more evident when visibility falls below 100 m over about 10 km of path, or below 10m over about 1 km of path. In this study, the critical visibility value is 10m. In other words, the attenuation can be more evident when the visibility is less than 10m at frequencies around 73.5 GHz.

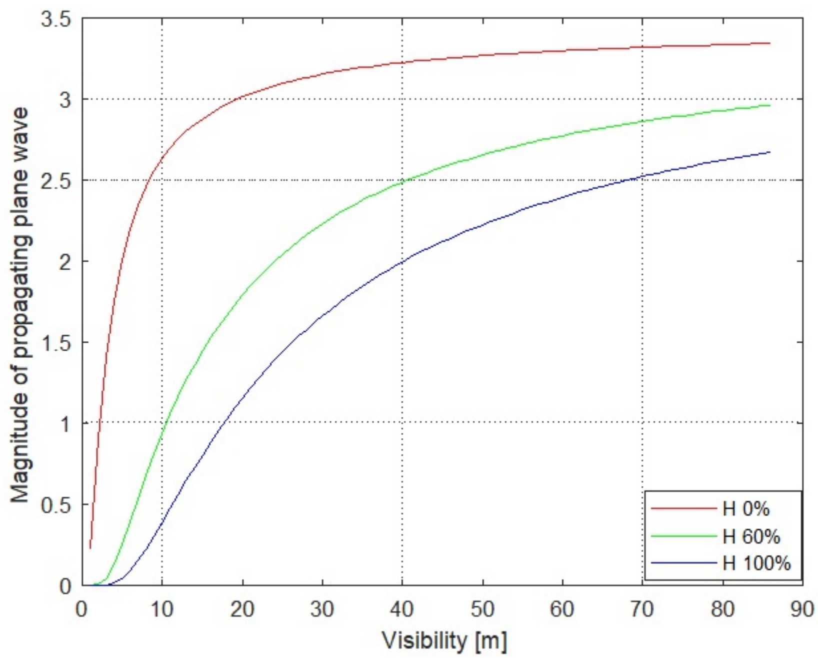

Figure 14. Attenuation factor at f = 28 GHz

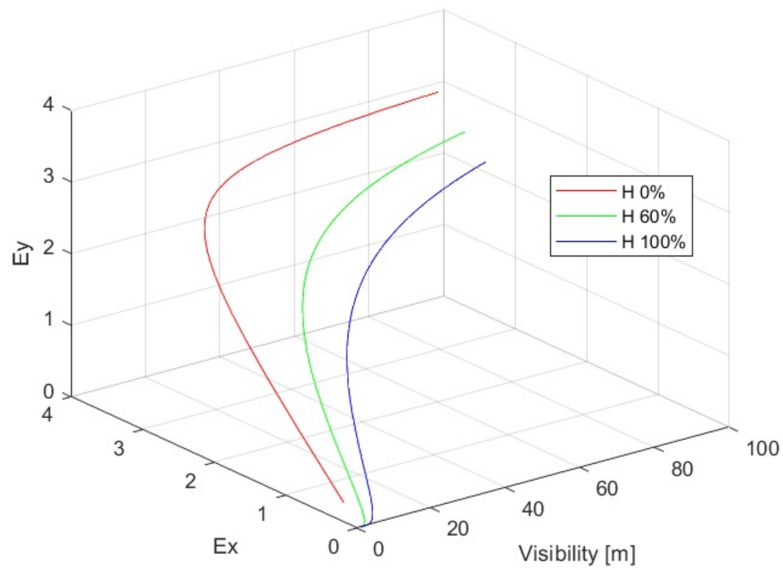

Figure 15. Linearly polarized electric field

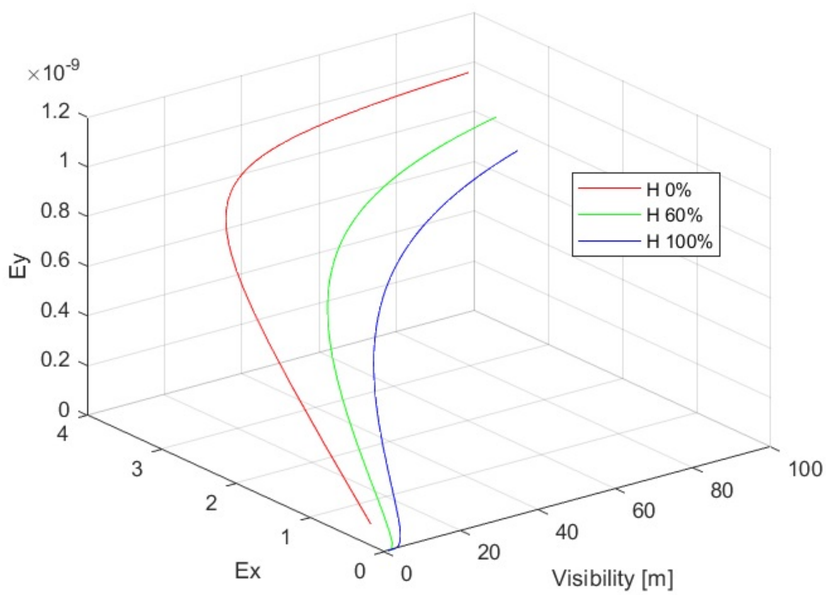

Figure 16. Circular polarized electric field

CHAPTER 6

Conclusions

Our first series of studies weather impacts on 5G mm-Wave and 4G LTE wireless communication for V2V scenarios. The Mie model calculates the propagation path loss in terms of humidity, visibility, and particle size. We also extend our previous work on the 4G LTE channel, and our simulation result shows different threshold values for the 5G mm-Wave and 4G LTE channel under severe weather conditions. Our investigation indicates that LSTM can be used for forecasting future RSSI values.

On the second part, the effect of dust and sand on the propagating millimeter wave is investigated by estimating the attenuation constant of the propagation wave. The Mie model is used to calculate the attenuation constant that is used to estimate the amplitude of propagating wave during dusty/sandy region. The simulation result shows that the amplitude of the propagating electric field in the form of linear polarization is affected less by dust and sand in comparison with circular polarization. The effect of dust and sand is more evident when the visibility is less than 10m. The result shows that the minimum distance of traveling millimeter wave during dusty lossy medium, with visibility V_0 = 10m, is 742.223m, 153.3m and 91.54m when the humidity is 0, 60 and 100 percent respectively. This result helps to design a wireless system in the similar dusty/sandy regions to avoid disconnected channel.

Our future plan is to use the estimated future RSSI values to forecast future channel degradation because of harsh weather. We plan to design an automatic channel switching strategy that can seamlessly choose the better channel in harsh weather. For second simulation part, this work will extend to consider the parallel and perpendicular polarization in the case of oblique incident millimeter wave. Also, the effect of dust and sand on the phase of propagating millimeter wave will be investigated in terms of Mie scattering model.

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