TEMPORAL LARGE SCALE PATH LOSS VARIATION PREDICTION DUE TO SPATIAL CONSISTENCY IN 5G MM WAVE WIRELESS COMMUNICATION

A PROJECT REPORT

Submitted by

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ST. JOSEPH'S COLLEGE OF ENGINEERING

(An Autonomous Institution)

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BONAFIDE CERTIFICATE

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Submitted for End Semester VIVA VOICE Examination held on ________________

INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT

The objective of the project is to use machine learning models to predict and analyze patterns from a generated dataset, this generated dataset is from a simulator called NIYUSIM which gives as many as data points we need,

We can use this predictive model to find accurate pathlosses before transmission and budget our transmission power, the current model is to trial and error the values of transmission power and antenna gain, comparatively this model can help reduce pathloss in a more efficient way.

The machine learning algorithm used for this linear regression which helps scale the value based on the levelof influence through another algorithm called mutual info regression which helps us to classify the variables based on their degree of influence .

Thus we will be able to overcome pathloss and create a more reliable 5G wireless network.

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LIST OF ABBREVATIONS

ML	MACHINE LEARNING
CIR	CHANNEL IMPULSE RESPONSES
TDD	TIME DIVISION DUPLEX
RNN	RECURRENT NEURAL NETWORK
CNN	CONVOLUTIONAL NEURAL NETWORK

CHAPTER 1

INTRODUCTION

1.1 Introduction

The millimeter-wave (mmWave) spectrum is regarded as a promising band to support the unprecedented capacity demand due to the massive available bandwidth. The directional mmWave channel has vastly different channel statistics as compared to the semi-omnidirectional and sectored microwave channels. Accurate channel modeling for mmWaves is essential for the fifth-generation (5G) and beyond wireless communication system design and evaluation. Many promising applications will be enabled using mmWave and sub-Terahertz technologies such as wireless cognition, imaging, and precising positioning

The scattering environment is similar when a user terminal (UT) moves in a local area or when multiple UTs are closely spaced in a local area (e.g. within 10-15 m). Further, the CIRs of these locations in close proximity to each other should be highly correlated. A channel model with spatial consistency can generate correlated and time-variant channel coefficients along the UT trajectory.

Human blockage becomes an important factor in radio signal strength for mmWave communication systems, but did not attract much attention in the microwave (sub-6 GHz) communications era. Owing to very short wavelengths (a few millimeters) and the use of directional antennas, mmWaves are easily blocked by humans and do not effectively diffract around human bodies or vehicles. It is important to take shadowing loss caused by humans and vehicles in account for accurate link budget analysis.

Outdoor-to-indoor (O2I) penetration loss becomes more prominent at mmWave frequencies as shown in measurements and models. Many modern buildings are constructed by concrete and have infrared reflecting (IRR) glass, which induce a large penetration loss when an mmWave signal is transmitted from outdoor to indoor or vice versa. Thus, accurate O2I penetration loss prediction is also critical for the design and deployment of future outdoor and indoor mmWave communication systems.

1.2 Objective

The main objectives are:

- To predict temporal large scale path loss variation in 5G mm wave wireless communication networks.
- To use ML unsupervised algorithms to predict patterns behind these temporal losses for finding patterns and insights of path loss.
- To use these patterns and perform adaptive and preliminary steps to avoid path loss and congestion.

1.3 Introduction to 5G Wireless Network

5G is the fifth-generation technology standard for broadband cellular networks, which cellular phone companies began deploying worldwide in 2019. Like its predecessors, 5G networks are cellular networks, in which the service area is divided into small geographical areas called cells. 5G has higher bandwidth and can thus connect more different devices, improving the quality of Internet services in crowded areas.

5G wireless technology is meant to deliver higher multi-Gbps peak data speeds, ultra-low latency, more reliability, massive network capacity, increased availability, and a more uniform user experience to more users. 5G is based on OFDM (Orthogonal frequency-division multiplexing), a method of modulating a digital signal across several different channels to reduce interference. 5G uses 5G NR air interface alongside OFDM principles. 5G also uses wider bandwidth technologies such as sub-6 GHz and mm Wave.

5G will bring wider bandwidths by expanding the usage of spectrum resources, from sub-3 GHz used in 4G to 100 GHz and beyond. 5G can operate in both lower bands (e.g., sub-6 GHz) as well as mmWave (e.g., 24 GHz and up), which will bring extreme capacity, multi-Gbps throughput, and low latency.

5G is designed to not only deliver faster, better mobile broadband services compared to 4G LTE, but can also expand into new service areas such as mission-critical communications and connecting the massive IoT. This is enabled by many new 5G NR air interface design techniques, such as a new self-contained TDD subframe design.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter introduces various existing researches and technologies that act as pre cursor for our project.

2.2 Related Works

A detailed study was carried out to gain maximum insight into the working, efficiency and the usage of the various modules and components used in our work. The papers which were studied are explained below.

[1] A MILLIMETER-WAVE CHANNEL SIMULATOR NYUSIM WITH SPATIAL CONSISTENCY AND HUMAN BLOCKAGE:

Authors: Shihao Ju, Ojas Kanhere, Yunchou Xing, Theodore S. Rappaport

Accurate channel modeling and simulation are indispensable for millimeter-wave wideband communication systems that employ electrically-steerable and narrow beam antenna arrays. Three important channel modeling components, spatial consistency, human blockage, and outdoor-to-indoor penetration loss, were proposed in the 3rd Generation Partnership Project Release 14 for mmWave communication system design. This paper presents NYUSIM 2.0, an improved channel simulator which can simulate spatially consistent channel realizations based on the existing drop-based channel simulator NYUSIM 1.6.1. A geometry-based approach using multiple reflection surfaces is proposed to generate spatially correlated and time-variant channel coefficients. Using results from 73 GHz pedestrian measurements for human blockage, a four-state Markov model has been implemented in NYUSIM to simulate dynamic human blockage shadowing loss. To model the excess path loss due to penetration into buildings, a parabolic model for outdoor to-indoor penetration loss has been adopted from the 5G Channel Modeling special interest group and implemented in NYUSIM 2.0. This paper demonstrates how these new modeling capabilities reproduce realistic data when implemented in Monte Carlo fashion using NYUSIM 2.0, making it a valuable measurement-based channel simulator for fifth-generation and beyond mmWave communication system design and evaluation.

[2] MILLIMETER-WAVE EXTENDED NYUSIM CHANNEL MODEL FOR SPATIAL CONSISTENCY:

Authors: Shihano Ju, Theodore S. Rappaport

Commonly used drop-based channel models cannot satisfy the requirements of spatial consistency for millimeter wave (mmWave) channel modeling where transient motion or closely-spaced users need to be considered. A channel model having spatial consistency can capture the smooth variations of channels, when a user moves, or when multiple users are close to each other in a local area within, say, 10 m in an outdoor scenario. Spatial consistency is needed to support the testing of beam forming and beam tracking for massive multiple-input and multiple-output (MIMO) and multi-user MIMO in fifth generation (5G) mmWave mobile networks. This paper presents a channel model extension and an associated implementation of spatial consistency in the NYUSIM channel simulation platform [1], [2]. Along with a mathematical model, we use measurements where the user moved along a street and turned at a corner over a path length of 75 m in order to derive realistic values of several key parameters such as correlation distance and the rate of cluster birth and death, that are shown to provide spatial consistency for NYUSIM in an urban microcell street canyon scenario

[3] NYUSIM USER MANUAL:

Authors: Shihao Ju, Shu Sun , Theodore S. Rappaport

NYUSIM provides an accurate rendering of actual channel impulse responses in both time and space, as well as realistic signal levels that were measured, and may be utilized to support realistic physical layer and link layer simulations. The models and simulation approach in NYUSIM involves the research of more than a dozen graduate and undergraduate students, and as of 2021, over 80,000 downloads of NYUSIM have been recorded.

The current NYUSIM software package, version 3.0, extends the simulation scenario from outdoor to indoor environments developed based on the conventional drop-based statistical channel model. Previously, NYUSIM version 1.x implemented the initial drop-based channel model for outdoor scenarios for carrier frequencies from 0.5GHz to 100GHz. Then, NYUSIM version 2.x implemented a spatial consistency enabled channel model with human blockage, and outdoor-to-indoor penetration loss modeling components for outdoor scenarios. The new NYUSIM version 3.0 introduces the indoor scenario in the drop-based channel model and allows the carrier frequency range for the indoor scenario from 0.5GHz to 150GHz.

[4] WIRELESS COMMUNICATIONS, PRINCIPLES AND PRACTICE

Authors: Theodore S. Rappaport

A brief history of the evolution of mobile communications throughout the world is useful in order to appreciate the enormous impact that cellular radio and personal communication services (PCS) will have on all of us over the next several decades. It is also useful for a newcomer to the cellular radio field to understand the tremendous impact that government regulatory agencies and service competitors wield in the evolution of new wireless systems, services, and technologies. While it is not the intent of this text to deal with the techno-political aspects of cellular radio and personal communications, technopolitics are a fundamental driver in the evolution of new technology and services, since radio spectrum usage is controlled by governments, not by service providers, equipment manufacturers, entrepreneurs, or researchers. Progressive involvement technology development is vital for a government if it hopes to keep its own country competitive in the rapidly changing field of wireless personal communications. Wireless communications is enjoying its fastest growth period in history, due to enabling technologies which permit wide spread deployment. Historically. growth in the mobile communications field has come slowly, and has been coupled closely to technological improvements. The ability to provide wireless communications to an entire population was not even conceived until Bell Laboratories developed the cellular concept in the 1960s and 1970s [NobG2], [Mac79], [You791. With the development of highly reliable, miniature, solid-state radio frequency hardware in the 1970s, the wireless communications era was born. The recent exponential growth in cellular radio and personal communication systems throughout the world is directly attributable to new technologies of the 1970s, which are mature today. The future growth of consumer-based mobile and portable communication systems will be tied more closely to radio spectrum allocations and regulatory decisions which affect or support new or extended services, as well as to consumer needs and technology advances in the signal processing, access, and network areas.

[5] PREDICTING THE PATH LOSS OF WIRELESS CHANNEL MODELS USING MACHINE LEARNING TECHNIQUES IN MMWAVE URBAN COMMUNICATIONS

Authors: Saud Aldossari, Kwang-Cheng Chen

The classic wireless communication channel modeling is performed using Deterministic and Stochastic channel methodologies. Machine learning (ML) emerges to revolutionize system design for 5G and beyond. ML techniques such as super-vise leaning methods will be used to predict the wireless channel path loss of a variate of environments base on a certain dataset. The propagation signal of communication systems fundamentals is focusing on channel modeling particularly for new frequency bands such as MmWave. Machine learning can facilitate rapid channel modeling for 5G and beyond wireless communication systems due to the availability of partially relevant channel measurement data and model. When irregularity of the wireless channels leads to a complex methodology to achieve accurate models, appropriate machine learning methodology explores to reduce the complexity and increase the accuracy. In this paper, we demonstrate alternative procedures beyond traditional channel modeling to enhance the path loss models using machine learning techniques, to alleviate the dilemma of channel complexity and time consuming process that the measurements take. This demonstrated regression uses the measurement data of a certain scenario to successfully assist the prediction of path loss model of a different operating environment.

[6] PATH LOSS PREDICTION BASED ON MACHINE LEARNING: PRINCIPLE, METHOD, AND DATA EXPANSION.

Authors: **Gaunshu yang, Yan Zhang and Jing wang.**

Path loss prediction is of great significance for the performance optimization of wireless networks. With the development and deployment of the fifth-generation (5G) mobile communication systems, new path loss prediction methods with high accuracy and low complexity should be proposed. In this paper, the principle and procedure of machine-learning-based path loss prediction are presented. Measured data are used to evaluate the performance of different models such as artificial neural network, support vector regression, and random forest. It is shown that these machine-learning-based models outperform the log-distance model. In view of the fact that the volume of measured data sometimes cannot meet the requirements of machine learning algorithms, we propose two mechanisms to expand the training dataset. On one hand, old measured data can be reused in new scenarios or at different frequencies. On the other hand, the classical model can also be utilized to generate a number of training samples based on the prior information obtained from measured results. Measured data are employed to verify the feasibility of these data expansion mechanisms. Finally, some issues for future research are discussed.

[7] MODEL-AIDED DEEP LEARNING METHOD FOR PATH LOSS PREDICTION IN MOBILE COMMUNICATION SYSTEMS AT 2.6 GHZ.

Authors: Thrane, Jakob; Zibar, Darko; Christiansen, Henrik Lehrmann.

Accurate channel models are essential to evaluate mobile communication system performance and optimize coverage for existing deployments. The introduction of various transmission frequencies for 5G imposes new challenges for accurate radio performance prediction. This paper compares traditional channel models to a channel model obtained using Deep Learning (DL)-techniques utilizing satellite images aided by a simple path loss model. Experimental measurements are gathered and compose the training and test set. This paper considers path loss modelling techniques offered by state-of-the-art stochastic models and a ray-tracing model for comparison and evaluation. The results show that 1) the satellite images offer an increase in predictive performance by ≈ 0.8 dB, 2) The model-aided technique offers an improvement of ≈ 1 dB, and 3) that the proposed DL model is capable of improving path loss prediction at unseen locations for 811 MHz with ≈ 1 dB and ≈ 4.7 dB for 2630 MHz.

[8] LARGE INTELLIGENT SURFACE-ASSISTED WIRELESS COMMUNICATION AND PATH LOSS PREDICTION MODEL BASED ON ELECTROMAGNETICS AND MACHINE LEARNING ALGORITHMS

Authors: Wael Elshennawy.

This paper presents the application of machine learning-based approach toward prediction of path loss for the large intelligent surface-assisted wireless communication in smart radio environment. Two bagging ensemble methods, namely K-nearest neighbor and random forest, are exploited to build the path loss prediction models by using the training dataset. To generate the data samples without having to run measurement campaign, a path loss model is developed owning to the similarity between the large intelligent surface-assisted wireless communication and the reflector antenna system. Simple path loss expression is deduced from the system gain of the reflector antenna system, and it is used to generate the data samples. Simulation results are presented to verify the prediction accuracy of the path loss predictions models. The prediction performances of the trained path loss models are assessed based on the complexity and accuracy metrics, including R2 score, mean absolute error, and root mean square error. It is demonstrated that the machine learning-based models can provide high prediction accuracy and acceptable complexity. The K-nearest neighbor algorithm outperforms random forest algorithm, and it has smaller prediction errors.

[9] MACHINE LEARNING CLASSIFIER APPROACH WITH GAUSSIAN PROCESS, ENSEMBLE BOOSTED TREES, SVM, AND LINEAR REGRESSION FOR 5G SIGNAL COVERAGE MAPPING

Authors: Kamal Ghanshala, R. C. Joshi

This article offers a thorough analysis of the machine learning classifiers approaches for the collected Received Signal Strength Indicator (RSSI) samples which can be applied in predicting propagation loss, used for network planning to achieve maximum coverage. We estimated the RMSE of a machine learning classifier on multivariate RSSI data collected from the cluster of 6 Base Transceiver Stations (BTS) across a hilly terrain of Uttarakhand-India. Variable attributes comprise topology, environment, and forest canopy.

Four machine learning classifiers have been investigated to identify the classifier with the least RMSE: Gaussian Process, Ensemble Boosted Tree, SVM, and Linear Regression. Gaussian Process showed the lowest RMSE, R- Squared, MSE, and MAE of 1.96, 0.98, 3.8774, and 1.3202 respectively as compared to other classifiers

2.3 Inference

All the related works have been referenced above and their ideas and scope have been discussed. The influence of spatial consistency and human blockage in pathloss is explained in [1], [2]. A brief insight about the usage of NYUSIM simulator is given in [3]. The concepts of wireless communication used to understand pathloss is given in [4]. In [5], [6], [7], [8] and [9], the Machine Learning concepts used to predict path-loss has been explained.

2.4 Summary

The papers and publications that have been studied to carry out our project has been summarised in this chapter. In this chapter, we have given a brief about the previous works done in this project right from its initial stages to the current scenario. In the forthcoming chapter, we will be dealing in depth with the modelling of this system and the components used in designing the project.

CHAPTER 3

TEMPORAL LARGE SCALE PATH LOSS VARIATION PREDICTION DUE TO SPATIAL CONSISTENCY IN 5G MM WAVE WIRELESS COMMUNICATION

3.1 Introduction

The millimeter-wave (mmWave) spectrum is regarded as a promising band to support the unprecedented capacity demand due to the massive available bandwidth. The directional mmWave channel has vastly different channel statistics as compared to the semi-omnidirectional and sectored microwave channels. Accurate channel modeling for mmWaves is essential for the fifth-generation (5G) and beyond wireless communication system design and evaluation. Many promising applications will be enabled using mmWave and sub-Terahertz technologies such as wireless cognition, imaging, and precising positioning

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Outdoor-to-indoor (O2I) penetration loss becomes more prominent at mmWave frequencies as shown in measurements and models. Many modern buildings are constructed by concrete and have infrared reflecting (IRR) glass, which induce a large penetration loss when an mmWave signal is transmitted from outdoor to indoor or vice versa. Thus, accurate O2I penetration loss prediction is also critical for the design and deployment of future outdoor and indoor mmWave communication systems.

This chapter is organized as follows:

Section 3.2 provides an overview of the proposed system.

Section 3.3 provides the software model and its detailed analysis

3.2 Proposed System

First, we will be setting the input parameters in NYUSIM Simulator and will be generating a data-set. NYUSIM is an open-source mmWave channel simulator, which can produce accurate omnidirectional and directional CIRs, PDPs, and 3-dimensional (3-D) angular power spectrum.

Then, we will be using ML algorithms like Linear Regression and Mutual Information Regression

I. Linear Regression is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between the variables and forecasting. Different regression models differ based on – the kind of relationship between dependent and independent variables they are considering, and the number of independent variables getting used.

Linear Regression performs the task to predict a dependent variable value(y-output) based on a given independent variable(x-input). So, this regression technique finds out a linear relationship between input and output.

HYPOTHESIS FUNCTION FOR LINEAR REGRESSION

$$y = \theta_1 + \theta_2 . x$$

II. Mutual Information estimates mutual information for fixed categories like in a classification problem or a continuous target variable in regression problems. Mutual Information works on the entropy of the variables. In short, it is the amount of information one variable gives about the other.

The Mutual Information between two random variables X and Y can be stated as

$$\mathbf{I(X;Y) = H(X) – H(X \mid Y)}$$

III. SelectKBest features (feature selection) after performing mutual info regression we have the quantities of variance correlation etc. with these values we need to find the best k value features where k is given by user, thus improving the accuracy of the model as the ml law states that the lower, the feature and simpler the model better the accuracy

Using these two techniques we will be able to predict pathloss more reliably for different datasets.

3.3 Software Model

3.3.1 NYUSIM SIMULATOR

The NYUSIM channel simulator provides a complete statistical channel model and simulation code with an easy-to-use interface for generating realistic spatial and temporal wideband channel impulse response. It is an open-source mmWave channel simulator, which can produce accurate omnidirectional and directional CIRs, PDPs, and 3-dimensional (3-D) angular power spectrum. NYUSIM is developed based on extensive field measurements from 28 GHz to 140 GHz. A 3-D spatial statistical channel model forms the basis for, and is implemented in NYUSIM, which characterizes temporal and angular properties of multipath components (MPCs). NYUSIM can operate over a wide range of carrier frequencies from 500 MHz to 100 GHz and support wide RF bandwidth up to 800 MHz. Different types of antenna arrays are also supported such as uniform linear array (ULA) and uniform rectangular array (URA).

In NYUSIM, when the spatial consistency button is “on”, NYUSIM runs spatial consistency procedure and generates successive and correlated CIRs along the UT trajectory. When the spatial consistency button is “off”, NYUSIM runs the drop-based model which is the same as older versions of NYUSIM and generates independent CIRs for different distances. The human blockage module works for both drop-based mode and spatial consistency mode.

The NYUSIM Simulator consists of 16 input “Channel Parameters” that define the propagation channel and 12 input “Antenna Properties” that specify the TX and RX antenna arrays, 10 input “Spatial Consistency” parameters, five input “Human Blockage” parameters, and two input “O2I penetration” parameters.

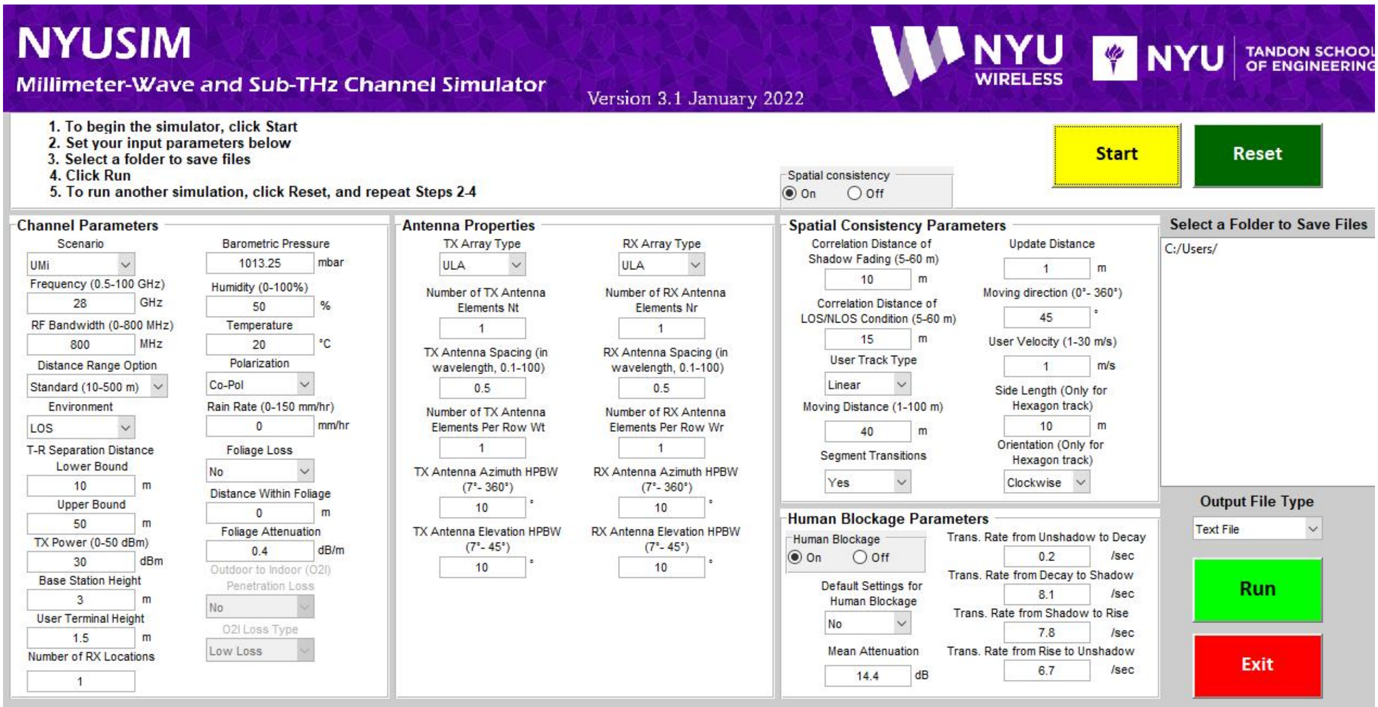

Figure 3.1 GUI of NYUSIM Simulator

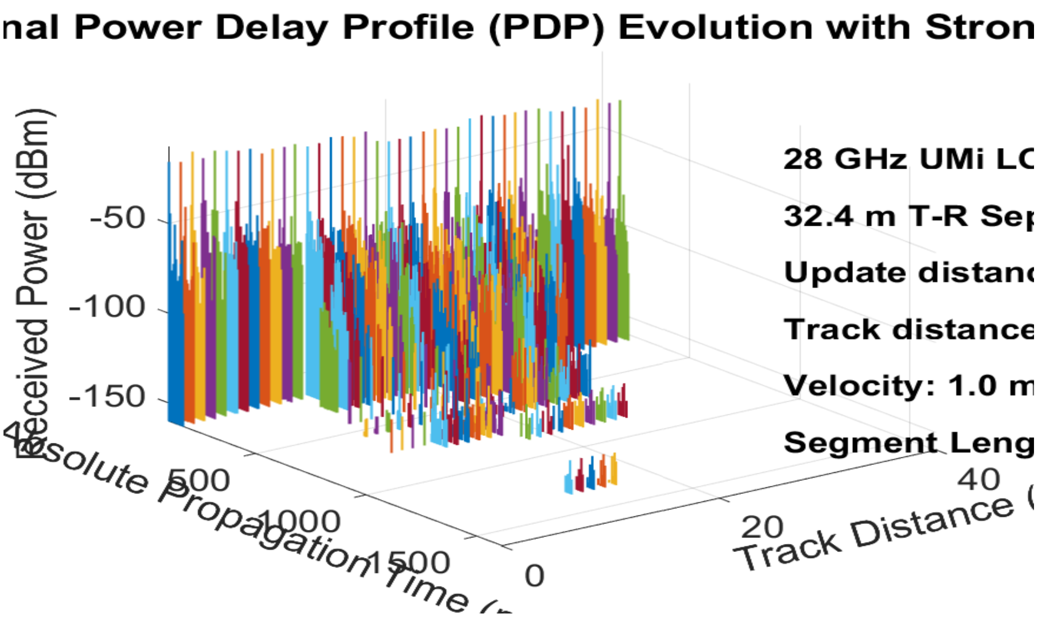

Figure 3.2 Power Delay Profile

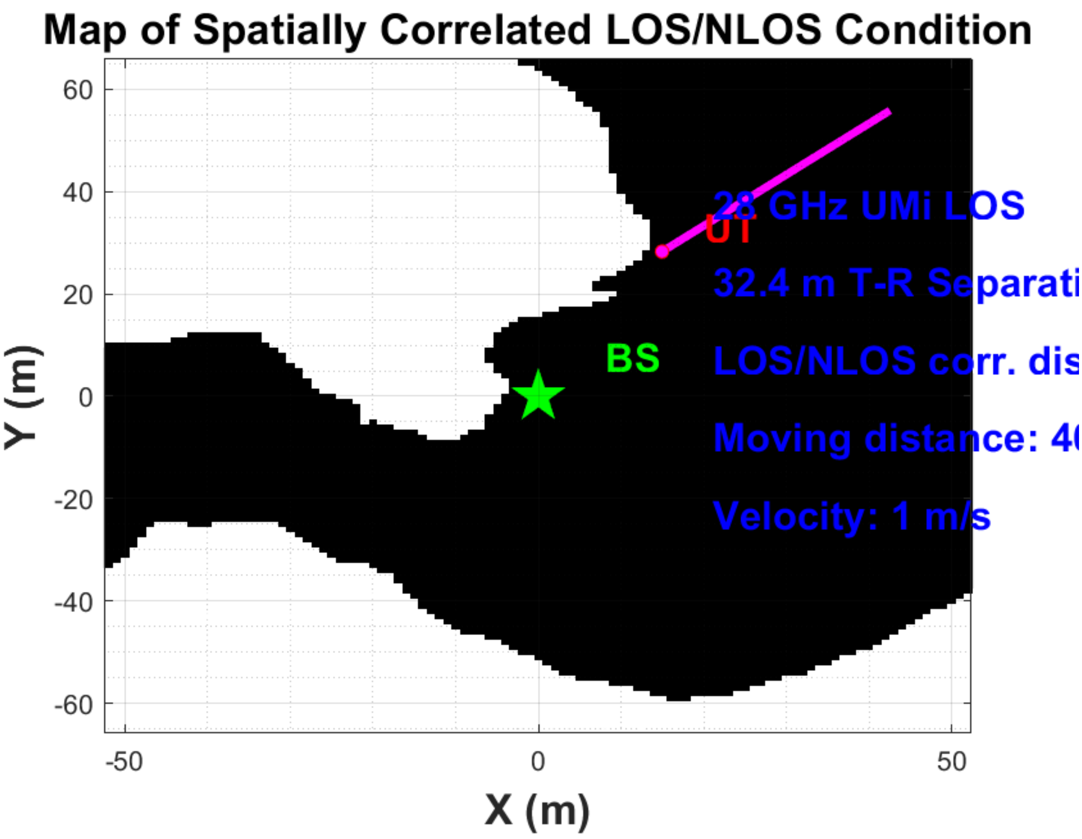

Figure 3.3 Spatially correlated LOS/NLOS

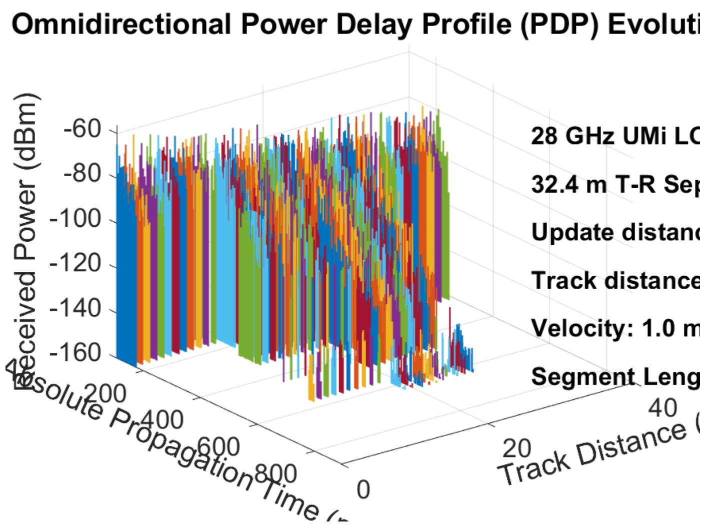

Figure 3.4 Omni-directional PDP

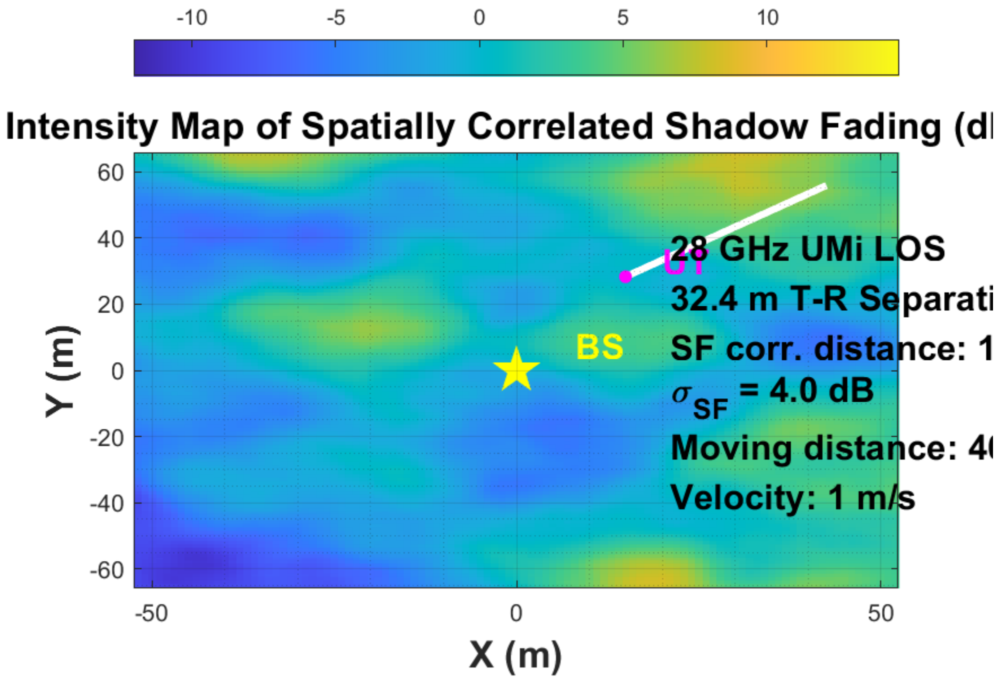

Figure 3.5 Spatially correlated Shadow Fading

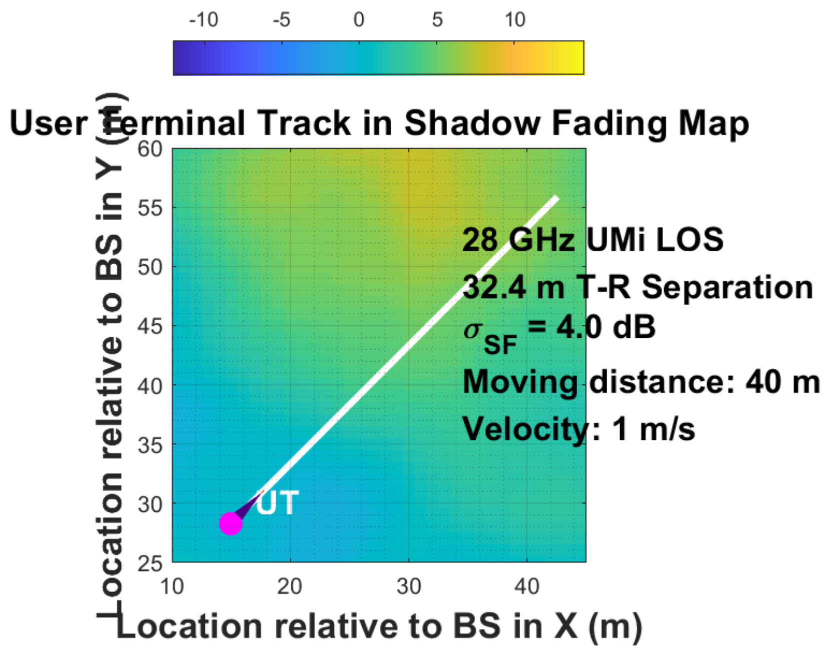

Figure 3.6 User terminal track in Shadow Fading map

CHAPTER 4

RESULTS AND DISCUSSION

4.1 RESULTS

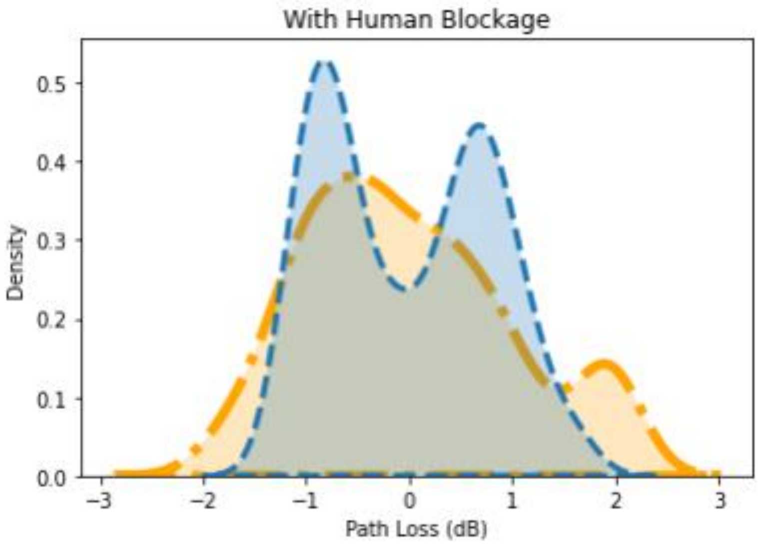

Figure 4.1 Predicted vs Actual (With Human Blockage)

The above graph gives us the comparison between predicted pathloss and expected pathloss with human blockage.

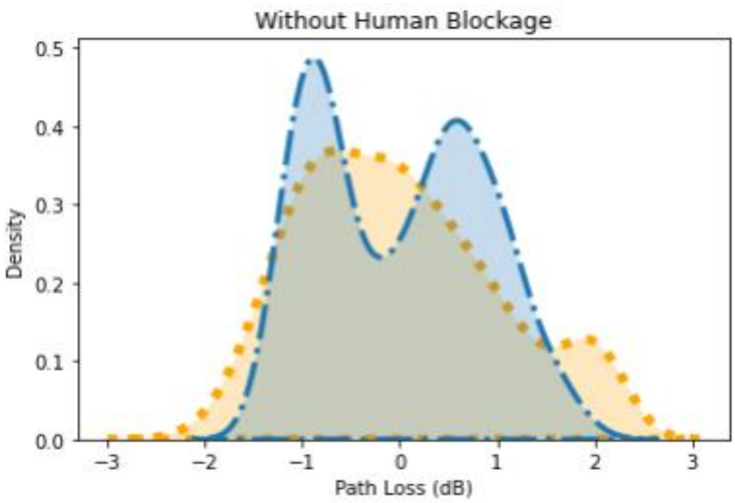

Figure 4.2 Predicted vs Actual (Without Human Blockage)

The above graph gives us the comparison between predicted pathloss and expected pathloss without human blockage.

The below graph depicts the relation ship between T-R Separation Distance(m)and pathloss where we can clearly see they are almost linear to each other which means they are directly proportional to each other.

T-R Separation Distance(m) ∝ Pathloss in (dB)

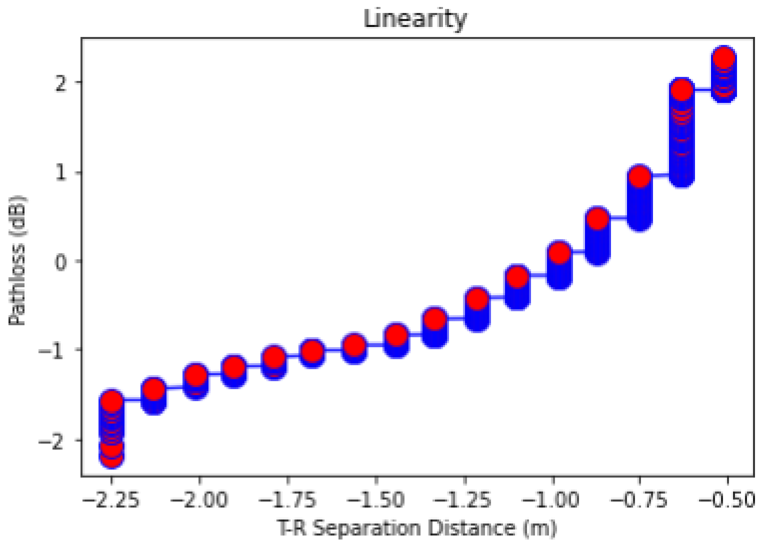

Figure 4.3 T-R Separation vs Pathloss

Likewise time delay and pathloss show inverse proportionality and linear to each other distinctively

Pathloss in (dB) ∝ 1/ Time delay (ns)

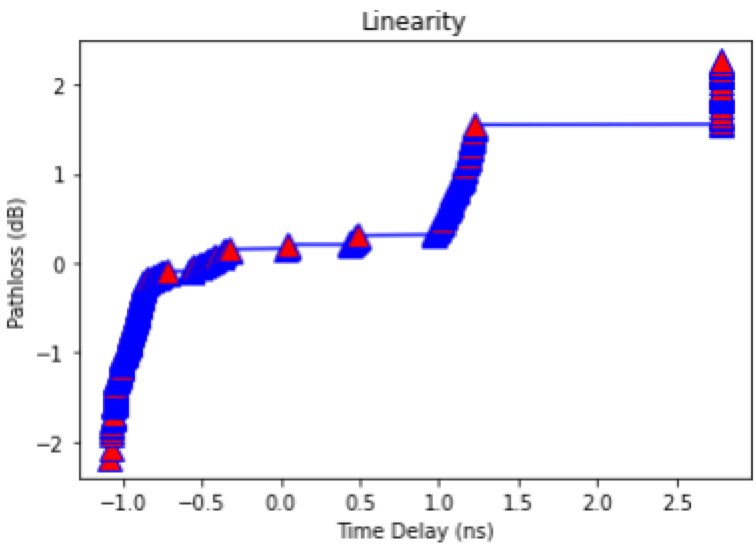

Figure 4.4 Time Delay vs Pathloss

The relationship between pathloss and received power is also the same we can see an inversely proportional graph,

Pathloss in (dB) $\propto 1/\text{Received power in (dBm)}$

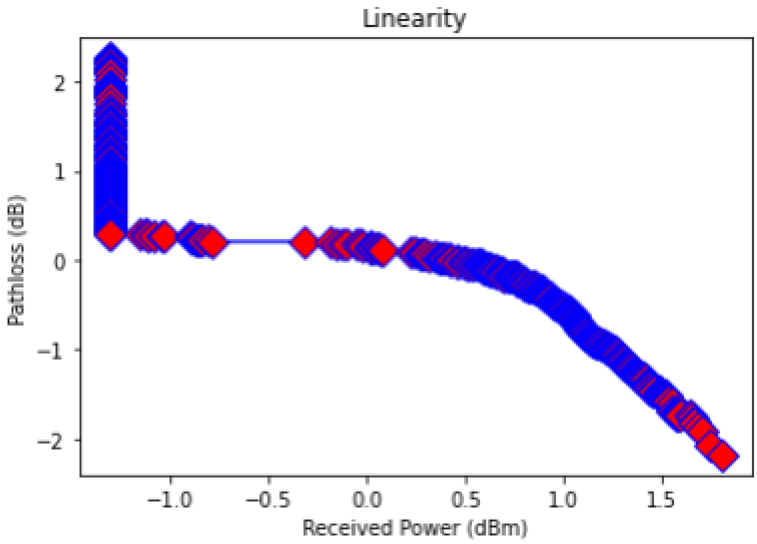

Figure 4.5 Pathloss vs Received Power

Feature selection can be visualized in a heatmap where we can observe the correlation between each and every feature whether they are correlated positively or negatively.

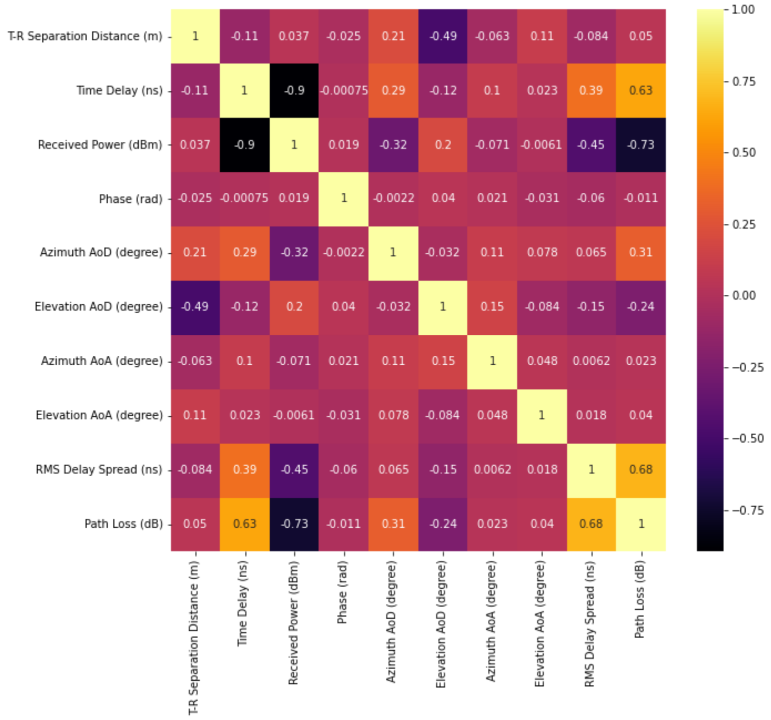

Figure 4.7 Correlation Heatmap of all variables

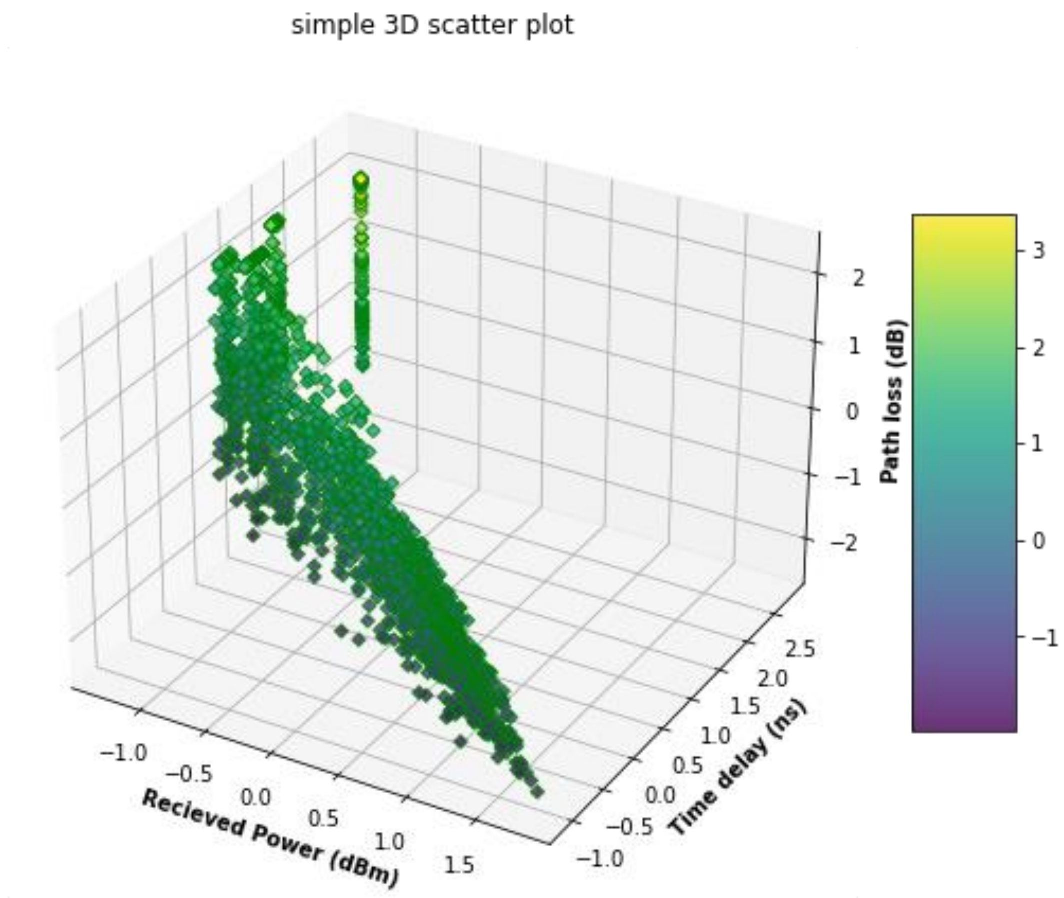

Figure 4.7 Simple 3D Scatter plot

From the above graph we have a relationship between all the three variables pathloss time delay and received power although the graph seems obsolete, this is because of the random state of the dataset generator, it is very non linear and random although in certain places we can see the relationships mentioned are observable.

Thus, from above graphs we can understand and observe the relationships between the target variable and the independent variables used in our machine learning algorithm.

CHAPTER 5

CONCLUSION

5.1 CONCLUSION

From the above results we can leverage the factors affecting pathloss and reduce the path loss thus reducing overall power budget. And also reducing the need to attenuation in any 5G wireless network making the network more reliable as well as efficient. We can clearly see human presence has a very negligible impact on this pathloss model as in using machine learning algorithm we are able to scale the level of impact.

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