Deep Neural Network-Based Channel Estimation Model for Vehicular Communication System

Ekram Ahmed Tuha

A Thesis Submitted to the Department of Electronics and

Communication Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Electronics and Communication Engineering

Office of Graduate Studies

Adama Science and Technology University

June, 2024

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APPROVAL PAGE OF M.SC. THESIS

We, the advisors of the thesis entitled "**Deep Neural Network-Based Channel Estimation Model for Vehicular Communication System**" developed by **Ekram Ahmed Tuha,** hereby certify that the recommendations and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Dr. Rajeev Kumar Shakya		
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We, the undersigned, members of the Board of Examiners of the thesis by **Ekram Ahmed Tuha,** have read and evaluated the thesis entitled "**Deep Neural Network-Based Channel Estimation Model for Vehicular Communication System"** and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Communication Engineering.

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Final approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

Department Head	Signature	Date
School Dean	Signature	Date
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DECLARATION

I hereby declare that this Master's Thesis entitled "**Deep Neural Network-Based Channel Estimation Model for Vehicular Communication System**" is my original work, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citations.

Ekram Ahmed Tuha

Name of student	Signature	Date

RECOMMENDATION

We, the advisors of this thesis, certify that we have read the revised version of the thesis entitled "**Deep Neural Network Based Channel Estimation Model for Vehicular Communication System**" prepared under our guidance by **Ekram Ahmed Tuha**. Submitted in partial fulfillment of the requirements for the degree of Masters of Science in Communication Engineering. Therefore, we recommend the submission of a revised version of the thesis to the department following the applicable procedures.

Dr. Rajeev Kumar Shakya		
Major Advisor	Signature	Date
Dr. Demissie Jobir Gelmecha		
Co-advisor	Signature	Date

ACKNOWLEDGMENT

For me, life is like reinforcement learning. Within this environment of higher-level education journey, different actions are completed with many ups and downs with corresponding rewards and penalties. now I am here at the upper stage and end time of my first thesis. Many agents participated and supported me to succeed in my goal. They deserve acknowledgment from me. My deeper gratitude goes to my God. All praise is due to Allah; so, He truly deserves it. Then, I am immensely grateful to my advisors Dr. Rajeev Kumar Shakya and Demissie Jobir Gelmecha for their patience, motivation, and insightful feedback that greatly improved my work. Their guidance has been instrumental in shaping this thesis.

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I have no word to express how thankful I am to my family. Their unwavering belief in me and constant encouragement have been my pillars of strength throughout this journey. Without their support, reaching this milestone would not have been possible.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
BER	Bit Error Rate
C-ITS	Cooperative Intelligence Transportation System
CP	Cyclic Prefix
CPU	Central Processing Unit
CSI	Channel State Information
CNN	Convolutional Neural Network
CDP	Constricted Date Pilot
DNN	Deep Neural Network
DPA	Data Pilot-Aided
DSRC	Dedicated Short-Range Communication
EL	Ensemble Learning
FFT	Fast Fourier Transform
FNN	Feedforward Neural Network
FPGA	Field Programmable Gate Array
GI	Guard Interval
GPRS	General Packet Radio Service
GPS	Global Positioning System
GSM	Global Systems for Mobile
GDP	Growth Domestic Product
IEEE	International Electrical and Electronics Engineering
ITS	Intelligent Transportation System
IFFT	Inverse Fast Fourier Transform
ISI	Inter Symbol Interference
LS	Least Square
LSTM	Long Short-Term Memory
MMSE	Minimum Mean Square Error
ML	Machine Learning
MIMO	Multiple Input Multiple Output
MMSE	Minimum Mean Square Error-Virtual Pilot
NMSE	Normalized Minimum Mean Square Error

OFDM	Orthogonal Frequency Division Multiplexing
OTFS	Orthogonal Time Frequency Space
PER	Per Bit Error
PHY	Physical Layer
QAM	Quadrature Amplitude Modulation
RX	Receiver
RNN	Recurrent Neural Network
RMSE	Root Mean Square Error
RTV-EX	Roadside to Vehicle - Expressway
ReLU	Rectifier Linear Unit
STA	Spectral Temporal Averaging
SNR	Signal-to-Noise Ratio
SPA	Sum-Product Algorithm
SRCNN	Supper-Resolution Convolutional Neural Network
SDG	Stochastic Gradient decent Method
TDL	Tapped Delay line
TX	Transmitter
US	United State
UN	United Nation
VANET	Vehicular Ad-hoc Network
VTI	Vehicle to Infrastructure
VTV	Vehicle to Vehicle
VTP	Vehicle to Pedestrian
VTX	Vehicle to Everything
VTV-EX	Vehicle to Vehicle-Expressway
VTV-UC	Vehicle to Vehicle-Urban Canyon
VTV-SDWW	Vehicle to Vehicle –Same Direction with Wall

ABSTRACT

Wireless communication plays a pivotal role in intelligent transportation systems, with vehicular communication being a crucial application, particularly with the IEEE 802.11p standard. However, the time-varying nature of vehicular communication channels, characterized by signal propagation in multiple directions and Doppler frequency shifts, poses challenges, resulting in signal strength decline. Reliable and accurate channel estimation is crucial for achieving high system performance. To address these issues, we propose the STA-LRDNN channel estimation model, which offers enhanced reliability, improved accuracy, and remarkable adaptability to diverse channel conditions. The model that integrates the Leakey ReLU-based deep neural network (DNN) architecture with the spectral time averaging (STA) channel estimation technique is proposed for significant improvement including proper hyper-parameter tuning held to get actual Leakey points. The STA-LRDNN model improve channel estimation than conventional methods in vehicle to vehicle (VTV) in express way and urban canyon environment channel models. In high mobility scenarios, it achieves a 20dB SNR gain for 10^{-2} *a bit error rate (BER). In same manner, the minimum value of* 10^{-5} *at 16QAM and* 10^{-3} *at 64QAM are recorded at SNR 30dB. Notably, the STA-LRDNN model exhibits remarkable results in low mobility scenarios as well. This integration plays a crucial role in robust and efficient channel estimation for vehicular communication systems.*

Keywords*: - Bit Error Rate, Channel estimation, Deep Neural Network, IEEE802.11p standard, Vehicular communication, Normalized Mean Squared Error.*

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

Nowadays, wireless communication is in rapid development in this technological era with different innovations, standards, technologies, systems, and other ways to meet the demands of users in different fixed and portable applications(Yan, 2024). From those applications, wireless networks, mobile telecommunications, broadcasting, satellite communication, industrial automation, medical devices, aviation, defense, and transportation are the main areas. In this study, we are going to focus on the transportation application of wireless communication. Starting from past years, wireless technologies are ready to meet the increasing demand for communications services of Transportation Systems (TS) such as high-speed railways, metropolitan railways, buses, and public transportation systems to improve the word TS (Briso-Rodríguez et al., 2017). Different countries adopt standards to govern wireless communication in TS. The IEEE802.11p can be mentioned from the IEEE802.11 family specifically for vehicles handling high mobility and rapidly changing environments. To create agreement between the standards and the rapid growth of technology, Intelligent Transportation Systems (ITS) have been adopted in recent times.

ITS are sophisticated software applications designed to provide state-of-the-art services associated with different transportation modes and traffic management. They also help users become more knowledgeable and utilize transportation networks in a safer, more efficient, and more intelligent manner. With the help of cutting-edge inventions like GPRS, GPS, Wi-Fi, GSM, and cellular data (Shahraz, 2022). By incorporating communications technologies into cars and the transportation infrastructure, ITS increases productivity, safety, and development of Information and communications technologies.

In highly dispersed environments like transportation systems, the wired communication between cars leads to measurable life and makes it hard for management to maintain safety and free movement. The cost of distribution and maintenance also became a critical issue. Otherwise, the presence of wired communication is crucial in some areas. The communication between the objects that are present in movement prefers to have wireless networks for effective communication and wired networks in the stationery support and management systems. Because of the accessibility of enormous amounts of data produced by multiple systems, the six-decade-old idea of Artificial intelligence (AI) has recently acquired appeal thanks to devices, efficient hardware, software, and network infrastructure (Rashad & Ali, 2023; Shahraz, 2022). Which has grown in strength recently, enabling researchers to probe previously undiscovered regions and accelerating interdisciplinary scientific discoveries. The one part of AI that has been widely used until now is machine learning (ML), where its application in the development of the ITS can be mentioned as evidence. It can be applied to vehicular communication, traffic signal control, short-term traffic flow prediction, and traffic mobility management in smart cities to reduce congestion, increase safety, and enhance traffic flow (Rashad & Ali, 2023). Wireless communication contains a lot of processes, including modulation, demodulation, mapping, de-mapping, Fast Fourier Transform (FFT), Inverse Fast Fourier Transform (IFFT), and others based on the type of system, to create communication and exchange information between the receiver (Rx) and transmitter (Tx).

1.1.1 Motivation for the Research

According to a WHO statistic, 1.19 million people die in automobile accidents each year (World Health Organization, 2023). It is the leading cause of death for young adults and children between the ages of 5 and 29. Approximately 60% of all vehicles worldwide are found in low and middle-income nations, which also account for 92% of all road fatalities. Pedestrians, cyclists, and motorcyclists are among the vulnerable road users who sustain more than half of all traffic deaths. Most nations suffer a 3% GDP loss as a result of these traffic accidents. The ambitious goal of halving the number of road traffic crash-related deaths and injuries worldwide by 2030 was established by the UN General Assembly. It's time for the transportation sector to adopt smart technology. As a communication engineer, being one part of the movement and sitting one stone in the prevention of the worldwide issue with recent AI-based technology is very interesting and fuel to do this research.

1.2 Statement of the Problem

Channel estimation in vehicular communication faces challenges due to dynamic and diverse vehicle conditions, including multi-path propagation, fading, and Doppler effects. In addition, traditional estimation techniques struggle with low accuracy and reliability. To mitigate these issues, accurate channel estimation is required. To overcome those challenges, different techniques of channel estimation were proposed at different times. However, Nowadays, AI-based methods are preferred because of superior adaptability, scalability, robustness, and integration capabilities with 5G and beyond, IoT, and ITS over others. Deep Neural Network (DNN) integrated with channel estimation techniques tries to solve issues. The right choice of estimators for the right models also plays a crucial role in proper estimation.

1.3 Objectives

1.3.1 General Objective

The general objective of this proposal is to design a DNN-based channel estimation model for vehicular communication systems.

1.3.2 Specific Objectives

- To apply DNN over conventional channel estimators and compare DNN base channel estimation performance over traditional estimators.
- To demonstrate the effectiveness of the proposed DNN-based channel estimation model in diverse vehicular models.
- To investigate the performance of channel estimation techniques with DNN for high-order modulation schemes, like 16QAM and 64QAM.
- To analyze the DNN-based channel estimation in different mobility scenarios.

1.4 Significant of the Study

This thesis focuses on channel estimation performance enhancement that suits the current intelligence-based world. Specifically, designing a DNN-based model for enhancing the performance of channel estimation in the IEEE802.11p standard-based vehicular communication system. At this point, this thesis has significant implications for removing worries about the safety of people from traffic accidents in transportation, in addition to providing a way to understand the channel characteristics of vehicular communication for further investigation and decision-making processes for the development of accurate and reliable technologies. This leads to enhanced channel estimation in VTV communication.

1.5 Scope of the Study

This thesis aims to address the development of advanced channel estimation for improved vehicular communication, a crucial component of ITS. Specially for reducing traffic accidents and improving road safety problem. The research focuses on analyzing the performance of a deep neural network-based channel estimation technique model in different scenarios. In particular, it evaluates four vehicular channel models while also introducing estimation DNN model. Additionally, the research analyzes the performance of this model according to accuracy and reliability, compares it with other existing ones across diverse vehicular models, and provides a comprehensive overview of the entire process.

1.6 Thesis Contribution

Addressing the current gaps in vehicular communication channel estimation through accurate and reliable techniques and appropriate models is crucial. Based on that, this thesis covers the design of a DNN model for enhancing communication between TX and RX through better channel estimation. The suggested approach, integrating the model with the conventional channel estimation technique, performs better than traditional estimation techniques. The improved DNN architecture with proper hyper-parameters was also introduced considering high and low mobility environment to improve the accuracy and efficiency of the model.

1.7 Limitation of the Thesis

Even though this thesis presents useful techniques, the thesis is limited with simulation-based results only.

1.8 Thesis Organization

To provide clarity and structure to the forthcoming exploration, the following road map describe the trajectory of this thesis, guiding readers through a systematic examination of research findings, theoretical underpinnings, and practical implications. Chapter one contains a brief discussion of the background of the study, the problem statement, thesis objectives, significance of the study, contribution of the thesis, and the scope of the study. The second chapter covers the foundational ideas of ML, OFDM infrastructure, IEEE 802.11p standard specification, and vehicular communication. Different related works and their research gap analysis are covered. The third chapter contains the material and methods of the thesis in sub-fields of materials, system models, mathematical formulas for channel estimators, proposed estimation method, and performance metrics. The detailed system design and training progress of the model are also included. In addition, the result analysis of DNN-based estimation and the comparison of traditional channel estimation with two performance measurements of BER and NMSE in different factors are discussed. Finally, part of the thesis ends with a conclusion and recommendation for future works on DNN-based channel estimation methods.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction

In this chapter, the main concepts and fundamental theories, such as vehicular communication characteristics, OFDM systems, and channel estimation of the system are described in detail. In addition to that, the related works based on their contribution are discussed.

2.2 Vehicular Communication Characteristics

Vehicle-to-everything (VTX), or vehicular communication, is a term used to describe the technology that makes it easier for a vehicle to communicate with other members of the surrounding transportation ecosystem. These members include other vehicles, cyclists, and pedestrians, surrounding buildings, road signs, traffic lights, and other vehicles (Daddanala et al., 2021). Based on the types of communication, different types of vehicular communication exist. Vehicle-to-Vehicle (VTV), vehicle-to-Infrastructure (VTI), and Vehicle-to-Pedestrian (VTP) are some of them (Balkus et al., 2022).

- VTV is communication between vehicles in different situations.
- VTI is the same as VTV but it is a connection between vehicles to surrounding infrastructure.
- VTP is communication between vehicles with pedestrians.

Vehicular communication is wireless communication developed to operate with a Vehicular Ad-hoc Network (VANET), which is distinguished as a network that can be flexibly changed and set up temporarily. VANET enables vehicles to communicate in a local area wireless network through wireless access points or with a link between vehicles. As with other choices, both ways of communicating will be hybrid. In addition to this, a protocol of VTX follows Dedicated Short Range Communication (DSRC), which is used by the United State(US) and the Cooperative Intelligent Transport System (C-ITS) of Europe in the frequency range of 5.855 GHz to 5.925 GHz with a bandwidth of 75 MHz (Ezenwa, 2022; Katrin Sjöberg, Peter Andres, Teodor Buburuzan, 2017). Because of its doubly dispersive nature, vehicular communication may have unique characteristics and some challenges. From the main characteristics, the predictable movement nature is one. The position and location of vehicles that travel on a road network can be predicted. Roadway information is frequently available from positioning systems and map-based technologies like Global Positioning System (GPS). A vehicle's eventual location can be forecasted using its average speed, present speed, and road direction. On the other hand, the network nodes (vehicles) are characterized by their high power and storage capacity. Increased computational capacity is the other issue. Vehicles that are operated have greater processing, communication, and sensing capacities.

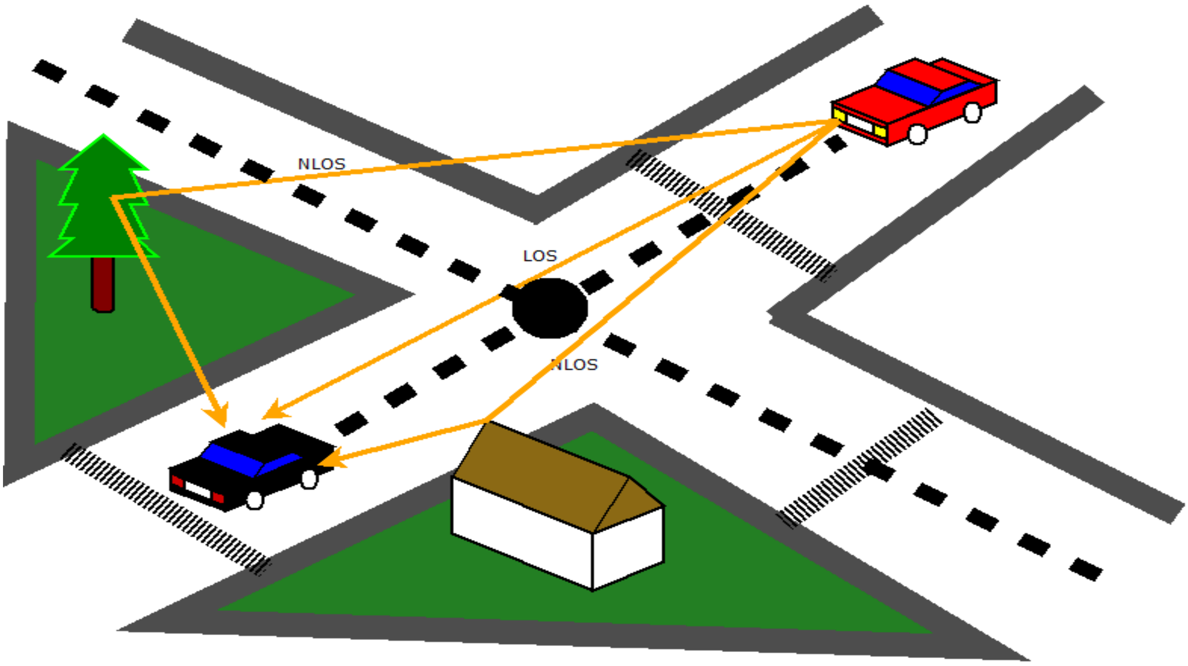


Figure 2.1 Vehicle to vehicle communication

VTV communication offers cooperative collision warning among neighboring vehicles on the road, ensuring people's security and safety. However, VTV communicates vehicle with vehicle assists humans in various ways, but it is most effective when the wireless communication network is fast and capable of transforming data to other vehicles. If there are any impediments in communication pathways and the message is sent at the wrong time, accidents may grow rather than decrease (Daddanala et al., 2021).

2.3 Orthogonal Frequency Division Multiplexing (OFDM) System in Vehicular Communication

In vehicular communication, OFDM systems play a crucial role due to their ability to combat multipath fading and mitigate inter-symbol interference, which are common challenges in high-mobility environments. OFDM is designed to divide the available spectrum into multiple narrowband sub-carriers, which carry a portion of the total data. The system is based on frequency division multiplexing.

2.4 IEEE 802.11p Standard

ITS is being programmed globally for the control of traffic systems in an intelligent way with the aim of safe vehicular and smart traffic management. US used the physical (PHY) layer protocol based on IEEE 802.11p standard (Rohde & Schwarz GmbH Co, 2019).The arrangement of standards in the protocol layers is present in Figure 2.3. This is the bottom layer, responsible for transmitting and receiving raw data bits over the wireless channel. The IEEE 802 standard required modification for V2X communication, considering the unique characteristics of the vehicular environment like signal fading due to obstacles and high mobility. Channel estimation serves as the backbone to overcome the reliability of channels and the invention of new technologies of vehicles and systems, which enable control of them and sustainable communication vehicles for everything, by estimating the channel characteristics. The characteristics are basic for decisions on systems. The updated form of the standard has changed some features of VTX communication in frequency and bandwidth to sustain the reliability and performance of channel estimation. The IEEE 802.11p standard employs optical OFDM.

OFDM is permeable where channel estimation is done on these first signals. Due to the time-variant nature of the system, the estimated channel has to be updated quickly and regularly; otherwise, the channel becomes in worse condition. This situation leads to poor performance of the system in a realistic vehicular environment.

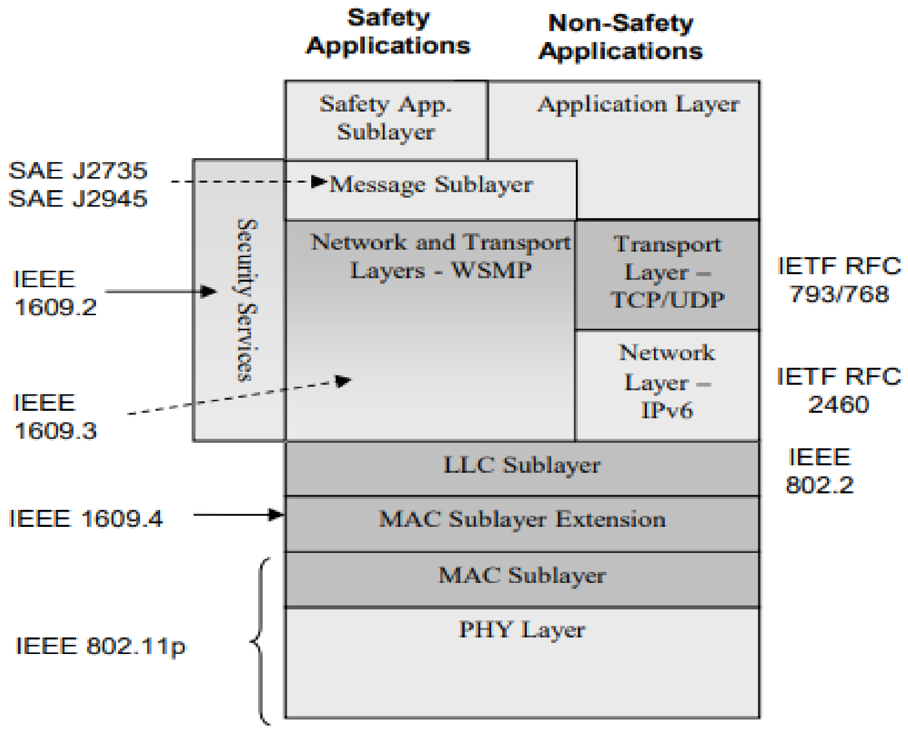


Figure 2.3 IEEE standard protocol layer (Rohde & Schwarz GmbH Co, 2019)

2.5 Channel Estimation

Chanel estimation is the process of estimating the channel characteristics of the medium used to exchange a message between the transmitter and receiver based on channel state information (CSI). CSI in a wireless network gives the known channel attributes of the link. It describes in detail how signals travel from the transmitter to the receiver and discusses the effects of fading and propagation. The CSI can integrate transmission data with current channel conditions to achieve reliable communication. The receiver should estimate this CSI and provide feedback to the transmitter. There are two ways to drive the channel estimation in V2V. The first one is by modifying the basic structures of the IEE802.11p standard. The other one is by maintaining the present structure. Most of the time, the second one became more preferred according to the cost of spectrum bandwidth. Therefore, channel estimation techniques are modified in different scenarios. Several channel estimating techniques can be used to gather the CSI. A known sequence of distinct bits specific to a given transmitter can be used for this estimation, and it can be done again for each burst of broadcast (Rakshit Govil, 2018). Channel estimation can be divided into three types, as discussed in Figure 2.1. Training-based channel estimation demands that training sequences or recognized pilot symbols be inserted into the delivered signal. These recognized pilot symbols are used by the receiver to assess the amplitude-phase distortion of the channel. Techniques for estimating how much it successfully delivers may be listed. Minimum Mean Square Error (MMSE) and Least Squares (LS) are two examples. Although training-based approaches are less difficult, they are less spectacularly efficient because of the pilot overhead. For the blind channel estimation, no pilot or training symbols are needed. To estimate the channel, it depends on the received signal's statistical characteristics, such as second or higher-order statistics. Blind approaches, particularly in fast-fading channels, exhibit increased spectral efficiency but are constrained by more computational complexity and lower estimation accuracy. Semi-blind channel estimation is a combination of the two techniques.

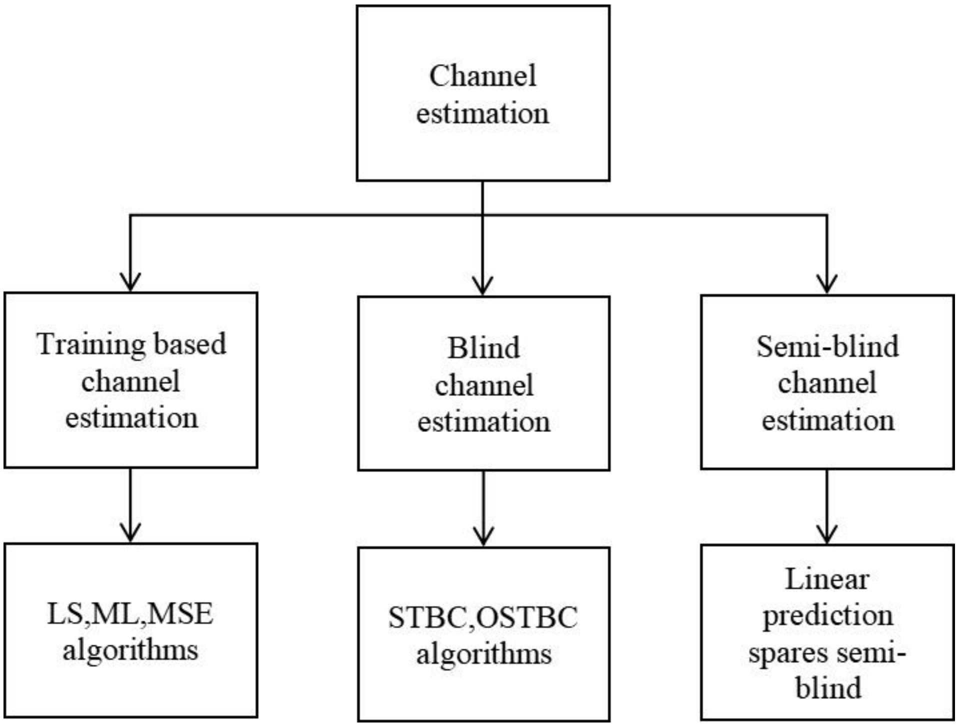


Figure 2.2 Types of channel estimation

Channel estimation in the IEEE 802.11p standard starts early and has many techniques, which we can call traditional channel estimation techniques. From those, Spectral Time Average (STA), Constructed Data Pilot (CDP), Data Pilot-Aided (DPA), and MMSE can be mentioned. STA uses both time and frequency correlation between the successive OFDM symbols to update the channel estimation for the current symbol. A pilot signal is used to estimate the characteristics of the channel in DPA, and the advantage of constricted data as a pilot signal makes CDP different from it. To overcome the absence of both time and frequency considerations, the TRFI method was proposed. Two processes are held. Those are the reliability tests in the time domain, and then the interpolation after the symbols change to the frequency domain. MMSE assumes two virtual data pilots at input and output and estimates the channel by taking the mean squared average of the two pilots, assuming the static channel. The performance is a system between the TX and RX. All those techniques have their drawbacks, commonly, they are noise-sensitive and less reliable. To overcome the problems, different research has been conducted several times. Nowadays, to overcome the challenges of communication in rapidly moving environments, the role of ML has become increasingly prominent.

2.6 Machine Learning (ML)

AI models inspired by the human brain's structure and function contain ML, a sub-field of AI that focuses on building algorithms that allow computers to learn from data and past experiences without explicit programming. In addition, ML contains both Artificial Neural Networks (ANNs) and DNNs, as shown in Figure 2.2. These are intricate algorithms that process information in layers using neurons, which are networked nodes (Laakso, 2022). DNNs decrease the discrepancy between their predictions and real data by fine-tuning their connections based on massive datasets. DNNs can be computationally costly, challenging to comprehend, and biased because of the bias in their training data, even when they are accurate.

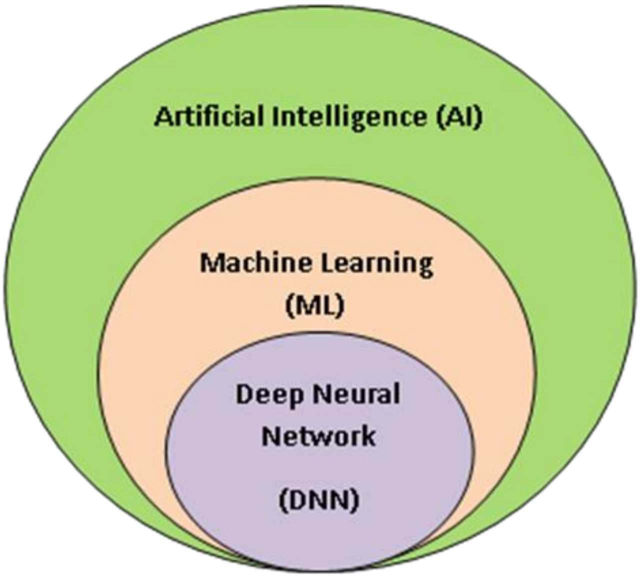


Figure 2. 3 Graphical representation of artificial intelligence (Taye, 2023)

DNN differs from ANN by having an input layer, many hidden layers, and an output layer. Rather than trying to understand the communication characteristics in a time-varying channel, training the machine with some features and the input data becomes a very effective way with vehicular communication applications, including cooperative communication, resource allocation, channel estimation, and network security (Ferrag et al., 2020; Udeogu et al., 2022).

There are several types of DNN networks. Feedforward Neural Networks (FNN) are the most basic neural networks, processing data from input to output layers, often employed for tasks like classification and regression. Convolutional Neural Networks (CNN) specialize in grid-like data, such as images, utilizing convolutional layers for feature learning, typically applied in tasks like image classification and object detection. Recurrent Neural Networks (RNN) are tailored for sequential data, incorporating loops to retain information order, and are commonly used in tasks like natural language processing and time series prediction. Long Short-Term Memory Networks (LSTM) are a type of RNN that addresses the vanishing gradient issue, is suited for capturing long-term dependencies, and is often applied in memory-intensive tasks like language modeling and machine translation. ML especially DNN has many applications in different areas of wireless communication, such as application in the prediction of channels in vehicular communication (Joo et al., 2019), channel estimation of Multiple Input Multiple Output (MIMO) communication systems (Tran et al., 2023), for the system of mining (Wang et al., 2023). The ML model training goes through different learning methods, as discussed below.

2.7 Machine Learning (ML) Mechanisms

Machine learning mechanisms are computational algorithms that permit computers to automatically learn from data and improve performance on a task without being explicitly programmed. these mechanisms form the backbone of modern artificial intelligence systems. They are working by identifying patterns and relationships within data to make predictions or decisions. There are different types of learning mechanisms, including supervised learning, unsupervised learning, and reinforcement learning (Taye, 2023).

2.7.1 Supervised Learning

In this learning mechanism, the model is trained with a dataset containing input feature values and the appropriate labels or outputs that correspond to them. The main aim is to produce accurate predictions. The algorithm learns by creating a mapping function that minimizes the error between expected outputs and the labels. The model can generalize during this learning process, which makes it capable of making precise predictions for brand-new, untested data. To verify the supervised learning model's efficacy on real-world data when the results are initially unknown, its performance is evaluated by comparing its predictions on a different test set to the true labels. Under this mechanism, there are two main types classification and regression. Registration finds the best-fit line by utilizing continuous data to predict continuous values. The discrete values are substituted for the continuous values in classification to determine the decision boundary that divides the data into distinct classes (Laakso, 2022)(Taye, 2023).

2.7.2 Unsupervised Learning

The learning mechanism which did not want any supervision is unsupervised learning mechanism. It does not use any labeled data as supervised. Algorithms are like explorers in this scenario, which go through the data, analyzing its characteristics and relationships without any predefined categories. The learning is held by detecting the patterns rather than adapting them. The main aim is to discover hidden patterns or structures within unlabeled data. This is achieved through self-organization, where the algorithm analyzes the data and identifies relationships or groupings without any predefined categories or classifications. Their ability to group the data and simplify the complex one, allow to learn fast. Clustering and anomaly detection are included under these categories (Taye, 2023).

2.7.3 Reinforcement Learning

Reinforcement learning mechanism unique from the two types by the inspiration to learn from trial and error. There are key components which are define the whole process of learning by integrating each other. The agent is assigned as entity which learn and make decisions within the environment, where the environment is the world which gives feedback to the agent as reward for or penalty for beneficial and detrimental actions. Agents are interacting with it and done action, that is the other component. Q-Learning is known type of reinforcement learning(Taye, 2023).

2.7 Related Works

The performance of the IEEE 802.11p physical layer in vehicular communication was discussed in (Fernandez et al., 2012). In this paper, the two main reasons for the degradation of performance of IEEE 802.11p were explained and compared with IEEE 802.11a. The STA is proposed as channel estimation and then implemented on FPGA in all data rate values of the standard. Also try to show the integration of packet payload size, data rate, and communication performance in terms of physical layer throughput and PER. This method has better results in low SNR values. Prior knowledge about the channel is needed to estimate accurately, in addition to having some challenges in high SNR.

The CDP channel estimator was discussed in (He et al., 2014) to overcome the complexity and impractical need for prior knowledge of the channel in STA. The method leverages a high correlation between two adjacent data symbols and integrates a preamble-based estimated CDP. The proposed method shows good performance as compared to the STA and Least Squares (LS) methods. However, complexity and proper utilization of parameters related to channels were the issues for the utilization of the four-phase tracking pilots.

The other technique, DPA, is used as channel estimation in orthogonal time frequency space (OTFS) modulation, which is a pioneer OFDM in doubly selective environments recently (Yuan et al., 2021). According to this, pilot symbols were placed at the top of the data symbols. Because of this, no need for a guarded band. The initial channel estimation was done using a modified threshold to account for data interference. Symbol detection was done by the sum-product algorithm (SPA) to leverage the estimated channel. However, the technique is vulnerable to interference, and it has a threshold value that is affected by noise.

The overview and comparison analysis of LS and MMSE channel estimation methods for vehicular communication are presented in (Dutta et al., 2021) . The two methods are contrasted for several practical channels in bit BER across different SNR ratios. The pilot-aided arrangement serves as the substructure for the estimate process. The outcome shows that, due to a lower error, the MMSE performs better with a higher complexity than the LS. Compared to the LS approach, the MMSE approximates a gain of 15 dB signal-to-noise ratio relative to LS.

This system is less sophisticated than traditional MMSE since it uses virtual pilot sub-carriers to generate a covariance matrix, whereas conventional MMSE requires previous knowledge of a channel. Even so, while the MMSE technique performs better in some scenarios, in low-signal regions it still performs worse than STA. The data pilot-aided estimation was also proposed by (Khan et al., 2023) to mitigate the estimation of channels in the MIMO-OFDM system. The system outperforms LS and LMMSE and gets better results in BER.

In recent times, conventional channel NMSE than before, even though the performance is very low as compared to ML-based estimations. estimation methods have been updated with ML models. The best result of the integration of ML with those techniques inspired many works, and it became a hot research area in different ways for vehicular communication to undergo a lot of issues until now. For instance, in (Rakshit Govil, 2018), estimation was done by 2D image to fine-tune unknown values of the channel response using some known pilot locations in the OFDM system. Several pilots consider the used channel grid to be a low-resolution image, and the estimated channel is a high-resolution channel. This paper proposes the Super Resolution CNN (SRCNN) and the DN-CNN. The performance of the model is compared to the ideal MMSE, estimated MMSE, and ideal approximated linear version of MMSE by using 48 pilots. The trained model, especially the ALMSSE, shows good performance for SNR values less than 20 dB. However, the models fall for high SNR values that exceed 20 dB.

In (Gizzini et al., 2020) channel estimation schemes for the IEEE 802.11p standard based on deep learning, which uses STA-DNN in advance, are proposed. In this paper, the description of the OFDM system in the IEEE 802.11p Standard is widely discussed in addition to the standard detail descriptions. The introduction of DNN to overcome the challenge of packet length is the main work. The compared estimation types were based on BER and NMSE in terms of modulation orders in two vehicular models. The performance of the proposed model was better than the others in terms of low SNR and mobility. However, the model training does not consider the input data types. In addition, the method is poor for high SNR values and high mobility.

(Asrar et al., 2023) can be seen. They try to modify the LS estimation. A simple DNN with more than 2 layers is used. The study explores the design and implementation of DNN-augmented LS-based channel estimation (LSDNN) for the preamble-based OFDM physical layer (PHY) on the SoC to show improved performance compared to traditional LS and LMMSE techniques. The performance evaluated was resource utilization, power consumption, and execution time of LSDNN on Zynq Multiprocessor System-on-Chip (ZMPSoC) and ASIC systems.

The other ML model is Long Short-Term Memory (LSTM). LSTM is known for suffering from high computational complexity, as reviewed in A study on deep learning-based channel estimation in doubly dispersed environments (Gizzini & Chafii, 2022a), which leads to difficult real-time applicability, different works are done by using it. As evidence, the performance of deep learning in terms of Doppler shift effect and complexity compared to MMSE and LS with the proposed LSTM-based channel estimator scheme (Abderrahim Mountaciri, My Abdelkader Youssefi, 2019) shows 2.5 and 5.5 dB BER performance. Roadside unit-to-vehicle Suburban Street (RTV-SS) and VTV-EX channel models are examined. The proposed method has better performance than the LS estimator. However, the complexity of the proposed model became high, and the performance in the Doppler frequency shift became less than MMSE. For high-frequency performance, degradation became a problem.

A survey of deep learning-based channel estimators in (Gizzini & Chafii, 2022b) review eight estimator types which are proposed at different times. As it says, the traditional techniques STA, TRFI, DPA, and others are combined to FNN in (Gizzini et al., 2020), CNN and LSTM in addition to the combination techniques of two DNN types. The complexity, BER performance, and robustness are used as comparison factors. The survey analyzed the FNN-based estimators that have less complexity, especially STA and TRFI while LSTM, CNN, and a combination of the two became more complex. The STA integrating with FNN has better BER performance than DPA-FNN and two dimensions radial basic function interpolation (2D RBF), which is an initial estimation for Channel net (Soltani et al., 2019) (Pan et al., 2021).

In contrast to more conventional techniques like LS and minimum mean square error (MMSE), the study (Mohammed et al., 2023) investigated the effectiveness of deep learning with LSTM networks for channel estimation and symbol detection in OFDM systems. It found that deep learning-based channel estimation outperforms traditional methods like LS and MMSE in terms of BER at low signal-to-noise ratios, with small pilot numbers and a reduced cyclic prefix. However, this channel estimation becomes complex with more antennas and relies heavily on the quality and quantity of training data.

The characteristics of IEEE 802.11p and power amplifier non-linear distortion were discussed in (Reis et al., 2023), which is about Ensemble Learning (EL) for LSTM-based vehicle channel estimation generalization. The combination method was proposed as a data-pilot-aided long-short-term memory neural network (DPA-LSTM-NN) by combining the algorithm of ensemble language (EL). Performance measurement held by NMSE and BER after the training models V2V-EX and roadside unit to vehicle in urban canon (RTV-UC) in 50 and 200 km/hr velocity in different data sets only and get good performance by adding their advantages with bagging system of EL. However, it is when the models train at the same power profile delay, otherwise, different values of power profile at different datasets lead to performance degradation, that is the main issue.

Table 2. 1 Summary of related work

Reference	Title	Contribution	Gap
(Rakshit Govil, 2018)	Different Types of Channel Estimation Techniques Used in MIMO-OFDM for Effective Communication Systems	SRCNN and DN-CNN for channel estimation in OFDM systems	The performance of the models degraded at high SNR values exceeding 20dB.
(Abdulrahim Mountaciri, My Abdelkader Youssefi, 2019)	Vehicular channel estimation by deep learning in high mobility scenario	LSTM-based channel estimator scheme	Higher complexity and less performance in high Doppler frequency shifts.
(Asrar et al., 2023)	Deep Neural Network Augmented Wireless Channel Estimation for Preamble-based OFDM PHY on Zynq System on Chip.	Integrating LS with DNN (LSDNN) for preamble-based and implement on SoC.	Not robust for rapidly changing environment, high mobility
(Mohammed et al., 2023)	Deep Learning Channel Estimation for OFDM 5G Systems with Different Channel Models	LSTM networks for channel estimation and symbol detection in OFDM systems	The channel estimation becomes complex with more antennas and relies heavily on the quality and quantity of training data.

2.8 Research Gap Analysis

As ML becomes a pioneer for improving wireless communication in different aspects, some works are tried to be discussed above. Even if channel estimations are conducted in different DNN models, there is also a gap in those works. The main issue with performance degradation is technique complexity. It does not enable the designs to be implemented in real-time scenarios, even if the performance is good. The other issue is the up-and-down achievement of SNR values in mobility. All the above issues indicate that the area needs very vast investigation and improvement until the IEEE 802.11p standard efficiency becomes better and more compatible with current situations.

CHAPTER THREE

3. MATERIAL AND METHODOLOGY

3.1 Materials

Design and simulation are two of the main parts of this research. For the utilization of channel estimation with deep learning in vehicular channel models, MATLAB 2023A software is going to be used to design the system of feature extraction and integration with DNN. It is a well-known software with an understandable environment and a facilitated library, especially for communication fields. The design of diagrams and flow charts is done using DIA diagram software. For better performance, the combination of those programs will give a good result.

3.2 Methodology

For computing this work effectively, the methods that follow are concerned with the identification of the problem by considering the significance of the area. Then different related works are reviewed to understand and examine the original works and to decide on better ways. After that, the system is designed and modeled as required for the selected area. Next, examine the proposed system and the existing one as required in different ways. The performance evaluation became an analysis of the result. In this chapter, the fundamental design process is discussed.

3.3 IEEE 802.11p Standard Transceiver, Specifications and Parameters

The IEEE 802.11p transceiver takes data, converts it to a binary stream, and adds randomness to improve efficiency. Then, error correction is applied, which rearranges the bits to spread the error. Next, it assigns specific symbols to each group of bits, adds pilots for better estimation, and converts the data to a time-domain signal. To prevent interference, it adds a cyclic prefix and amplifies the signal for transmission. The receiver reverses these steps, amplifies the signal, converts it back to the frequency domain, estimates the channel characteristics, compensates for distortions, maps the symbols back to bits, and corrects any errors. This process ensures reliable data transmission in VTX communication. Figure 3.1 shows the general transceiver.

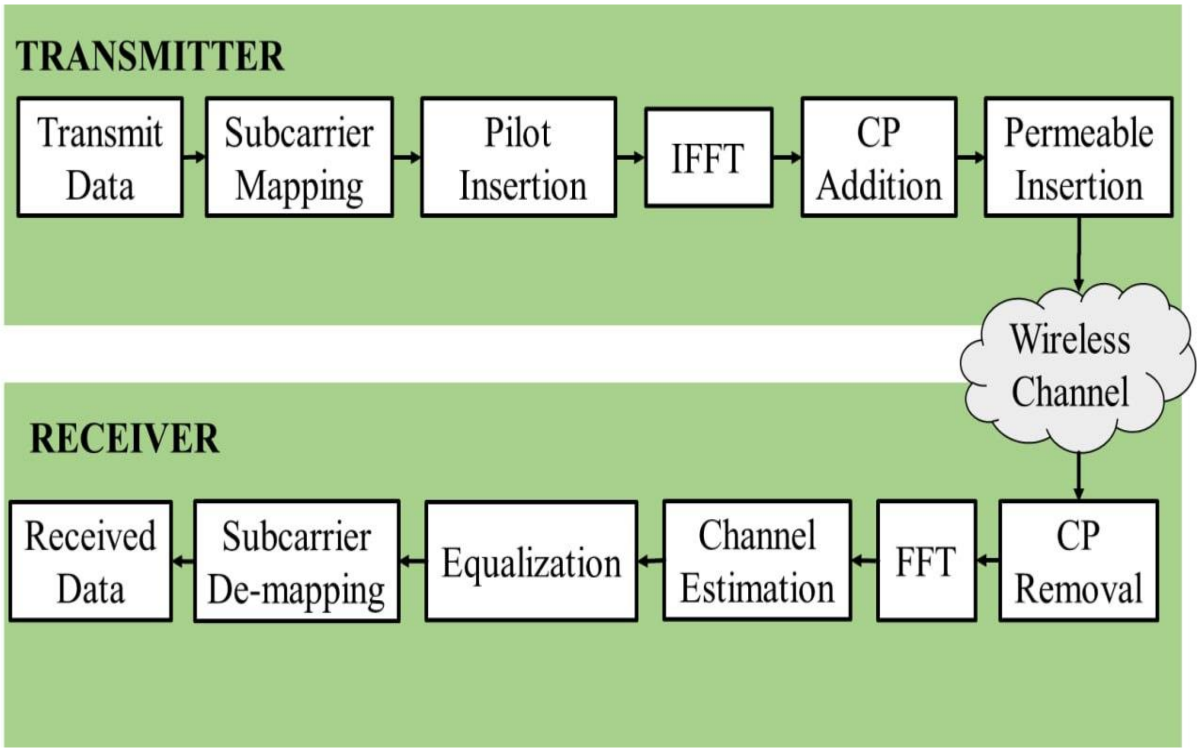


Figure 3.1 IEEE802.11p transceiver block diagram

The change of frequency band from 10 MHz in the IEEE 802.11p helps to decrease inter-symbol interference (ISI). Also, the band is 5.9 GHz, which enables it to offer less susceptibility to fading compared to IEEE 802.11a. The method of arrangement of pilot and symbols has large effect on estimation performance. In Training based channel estimation, two block arrangement types are there. There are two types of data arrangements such as Block type and combination type. The combination type pilot arrangement contains pilot tones which are included in each OFDM symbols with unique period of frequency. This arrangement is chosen for its adaptability with fast time varying environment. It contains ten training symbols (S1 up to S10) for packet detection and synchronization, with 1.6 µs for each. The two training symbols (L1 and L2) have 6.4 µs each. They are used for channel estimation. While the VTV system uses the OFDM system, the symbols have two 3.2 µs guard band intervals, which are used to prevent ISI. The packet payload is followed by information about the packet's length and data rate in the signal field. With a guard band of 1.6 µs, all data symbols have a length of 8 µs.(Rohde & Schwarz GmbH Co, 2019) The symbol structure is shown in Figure 3.2.

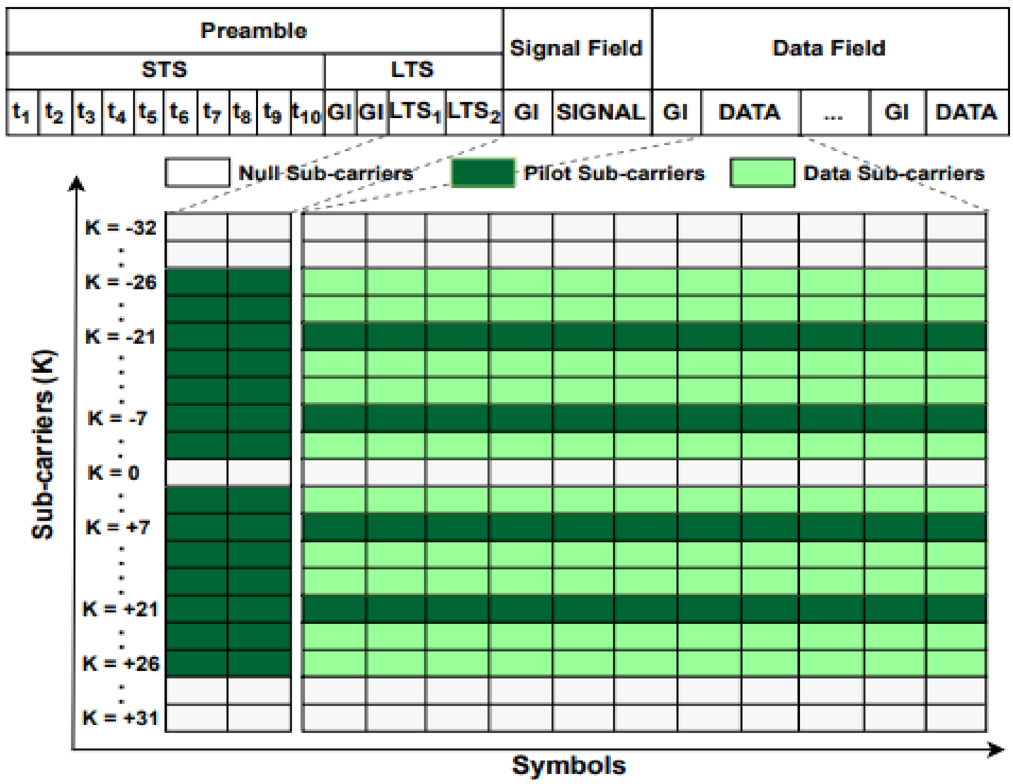


Figure 3. 2 Symbol arrangement of IEEE802.11p standard (Asrar et al., 2023)

In OFDM system of vehicular communication standards, there are three types of sub-carriers. Data sub-carriers, pilot sub-carriers, and zero sub-carriers. The real data payload is transmitted between vehicles and infrastructure using data sub-carriers. 52 of the 64 sub-carriers in the 10 MHz OFDM channel bandwidth specified by IEEE 802.11p are data sub-carriers. To ensure dependable data transmission, the data sub-carriers must be built to withstand issues like Doppler shifts and multi-path fading, which are common in V2X settings. Pilot sub-carriers are essential for channel estimation, frequency and phase tracking, and overall synchronization, ensuring reliable and efficient communication in vehicular environments. As the standard specifies the parameters, in this work they are used to model the system of ieee802.11p by following the standard as shown in Table 3.1 below.

Table 3. 1 List of IEEE802.11p standard specifications (ETSI, 2019)

No	Parameters	Values
1	Bandwidth	10MHz
2	Total sub-carriers	64
3	Pilot sub-carriers	4
4	Data sub-carriers	48
5	Null sub-carriers	12
6	FFT size	64
7	FFT Period	6.4 µs
8	Guard Interval	1.6 µs
9	Symbol duration	8 µs
10	Modulation Scheme	QPSK,16QAM, 64QAM

3.4 Vehicular Communication Channel Models

Generally, the environment of vehicular communication has a time-varying nature, which is conducive to multipath propagation and a larger Doppler shift. For this reason, they can be modeled as a common model for multipath propagation called the tapped delay line model (TDL). TDL gives insights into signal propagation and reception in dynamic vehicular systems by enabling researchers to examine and comprehend the impacts of Doppler shift in V2V communication channels. Environments. Each tap is summed up to get the Rayleigh fading channel (Choi et al., 2019). The expression for the impulse response of fading, in correlation to Doppler and delay spread, can be expressed as shown in Eq. (3.1).

$$(t,\tau) = \sum_{l=1}^{L} \alpha_l(t)\delta(t-\tau_l)e^{j2\pi f d \tau_l} \tag{3.1}$$

where, $\alpha_{l(t)}$, f_d , $\delta(t-\tau_\mathrm{l})$ and τ_l are Complex amplitude, Doppler frequency and The Dirac Delta function represents delay and relative delay at the multipath component, respectively. Depending on the position, status, and types of objects that communicate with each other, there are different categories or models. In this work, the channel model has been adopted from (Gizzini et al., 2020). The models are defined in detail below.

- **VTV-Express (VTV-EX): This** model expresses the two vehicles that start traveling on the highway at the same time but in different directions. Both are accelerated to achieve

104 km/hr. in the absence of wall separation on the road. The channel between them may not be very venerable for multipath propagation, but it is venerable for high-doppler shifts because of the high-speed movement.

- **VTV-Urban Canyon (VTV-UC):** The urban canyon environment is known for its dense buildings and tall structures, which can affect the propagation of radio signals highly. Vehicles are going in this dense environment at 32–48 km/hr. and, on average, 100 m.
- **VTV-Expressway Same Direction with Wall (VTV-SDWW):** Two vehicles with a separation distance of 300–400 m is traveling on the highway that has a center wall between lanes to mitigate 104 km/hr. This model has a relatively high path loss.
- **RTV-Expressway (RTV-EX)**: The RSU is placed on the highway, and then, vehicle going towards the RSU with speed of 104 km/hr. The distance of the vehicle is 300–400, which is more than VTV-EX and VTX-SDWW unless the Doppler shift is different because of path delays.

Table 3. 2 Summary of channel models parameter (Gizzini et al., 2020)

Models	Distance(m)	Velocity (Km/hr)	Maximum Doppler Shift (Hz)
VTV-EX	300-400	104	1200
VTV-UC	100	32-48	500
VTV-SDWW	300-400	104	1150
RTV-EX	300-400	104	700

3.5 Conventional Channel Estimation

Mathematically the input-output relation of signals in the OFDM system of IEEE802.11p vehicular communication system is shown in Eq.3.2, where the number of sub-carriers is Ks, $Y_i[k]$ is received symbol, $X_i[k]$ is transmitted symbol and $n_i[k]$ is the noise of the Kth sub-carrier in the i^{th} order. hi[k] is the frequency response of the channel in the system.

$$Y_i[k] = H_i[k]X_i[k] + n_i[k] \tag{3.2}$$

3.5.1 Least Square (LS) Channel Estimator

It is a training-based channel estimation technique designed to reduce the square error between the signal that was originally transmitted and the signal that was received. It is also called permeable because it uses permeable symbols that are transmitted at the start of each frame to allow the receiver to synchronize its clock, acquire the signal, and establish the estimation. based estimator. Because it uses permeable symbols that are transmitted at the start of each frame to allow the receiver to synchronize its clock, acquire the signal, and establish the estimation. In vehicular communication both the time and frequency are varied. The estimation is done by taking the two received permeable sums and taking the average by the pre-defined frequency domain of the transmitted symbol. as shown in Eq. 3.3 the sum of two permeable symbols Yp_1[k] and Yp_2[k] is divide to both values of F_d[k] (Choi et al., 2019).

$$h_0[k] = \frac{Y_{p1}[k] + Y_{p2}[k]}{2F_d[k]} \tag{3.3}$$

3.5.2 Spectral Time Averaging (STA) Channel Estimator

STA is updated after the data pilot-aided estimator (DPA), where both were proposed by Fernandez et al. (2012) to track the rapidly changing channel variation. It is working by continuously updating the channel estimates. This estimation is dependent on the LS estimation. As shown in Eq. (3.3), the first step is dividing the received symbol by its frequency domain by the previous channel estimate. We can call the process equalization, as discussed in (Gizzini et al., 2020).

$$Ti[k] = \frac{Yi[k]}{h_{i-1}[k]}\ , i = 1, \dots, \mathrm{I} \tag{3.4}$$

When i =1, the $h_{i-1}[k]$ value becomes as $h_0[k]$ which is the LS estimate in Eq. (3.2). Then the next step is de-mapping $Ti[k]$ to Zi[k] and this de-mapped estimate is used to get the initial estimation hi[k], as follows.

$$h_{FDi}[k] = \frac{Y_i[k]}{Z_i[k]} \tag{3.5}$$

The next step is performing the moving average of data subcarrier frequency domain received symbol is implemented in both frequency and time domain as below,

$$\hat{\hat{h}}_i[k] = \sum_{\lambda=\beta}^{\lambda=\beta} w_c hi[k+c]\ , \qquad wc = \frac{1}{2\beta+1} \tag{3.6}$$

$$\hat{\hat{h}}_{STA}[k] = \left(1 - \frac{1}{\alpha}\right)\hat{\hat{h}}_{i-1}[k] + \frac{1}{\alpha}\hat{\hat{h}}_{FDi}[k] \quad (3.7)$$

where w_c is a set of weighting coefficients with unit sum and 2β + 1 is the number of averaged sub-carriers position numbers between 1 and 52, excluding the first and last two, are the sub-carriers included in the frequency domain.

3.5.3 Constructed Data Pilot (CDP) Channel Estimator

To mitigate the consequences of de-mapping errors when updating the estimation, the CDP channel estimation technique is used. The high-time correlation of the channel response between two nearby OFDM symbols is the foundation of the CDP system. The first three steps needed for the initial channel estimate process are shared by this approach. As a result, CDP channel estimation happens after steps (3.2), (3.3), and (3.4) and only uses the data sub-carriers present in the OFDM symbol that was received as adopted by Choi et al. (2019). Given the strong time correlation between consecutive received OFDM signals, CDP suggests two distinct stages in place of the time and frequency averaging carried out in STA. The expression for this channel estimation is as follows:

$$T_{eq1}[k] = \frac{T_{i-1}[k]}{h_{initial}[k]} \quad (3.8)$$

$$T_{eq2}[k] = \frac{T_{i-1}[k]}{h_{cdp\ i-1}[k]} \quad (3.9)$$

The next step will be de-mapping and the Eq (3.5) and (3.6) are assigned as $t_{eq1}[k]$ and $t_{eq1}[k]$. If the two de-mapped values are equal, then h_{cdp} [k] equal to $h_{initial}$. But as discussed above time correlation leads h_{cdp} [k] equal to $h_{cdp\ i-1}[k]$.

3.5.4 Minimum Mean Square Error Using Virtual Pilot (MMSE)

To improve the accuracy of the channel estimate, the MMSE technique assigns random virtual pilot sub-carriers in frequency-domain received symbols. To maintain the correlation with the sub-carriers, namely the data and comb pilot sub-carriers, the virtual pilots are uniformly allocated and originally designated as data sub-carriers. The MMSE scheme performs frequency-domain channel analysis using virtual pilots to generate channel covariance matrices.

In this scheme the initial estimation in (3.10) is arranged in matrix form as by two pilot as the beginning (k = -21, -7) and two pilots at the end (7,21). The expression is as follows:

$$h_{vpi}[k] = \left[h_{FDi}[k]\ [-21], h_{FDi}[k]\ [k], \dots, h_{FDi}[k]\ [21]\right]; \tag{3.10}$$

Following this, the MMSE scheme calculates the final for each received OFDM symbol, as shown below:

$$h_{MMSEi} = R_{h_{FDi}h_{vpi}}(R_{h_{vpi}h_{vpi}} + \delta^2 I)^{-1} h_{vpi} \tag{3.11}$$

Where $R_{h_{FDi}h_{vpi}}$, δ^2, I are cross-correlation matrix of the two vectors, means initial and virtual pilot estimation vectors, the ith received OFDM symbol average noise power and identity matrix respectively (Choi et al., 2019).

3.6 Proposed Leakey ReLU DNN Model Based Channel Estimation

The proposed DNN model structure is characterized by one input layer, three hidden layers, and one output layer, with several nodes in each layer to create non-linear relationships between channel parameters, noise, and received signals, as shown in Figure 3.3. Each node connects to learn the data and to have related transitions to other nodes by evaluating with weight ‘w’ and bias ‘b’. The supervised learning process is used to learn the known output and test it with other unknown data to evaluate the model. The weight and bias have a large impact on the learning process of the model. They are governed by the back-propagation method. The nodes are learned both in a forward and backward direction to adapt to diverse circumstances. This adaptability makes DNNs the leading choice for channel estimation. Moreover, they offer significantly higher estimation accuracy and lower complexity compared to traditional methods and some recent techniques.

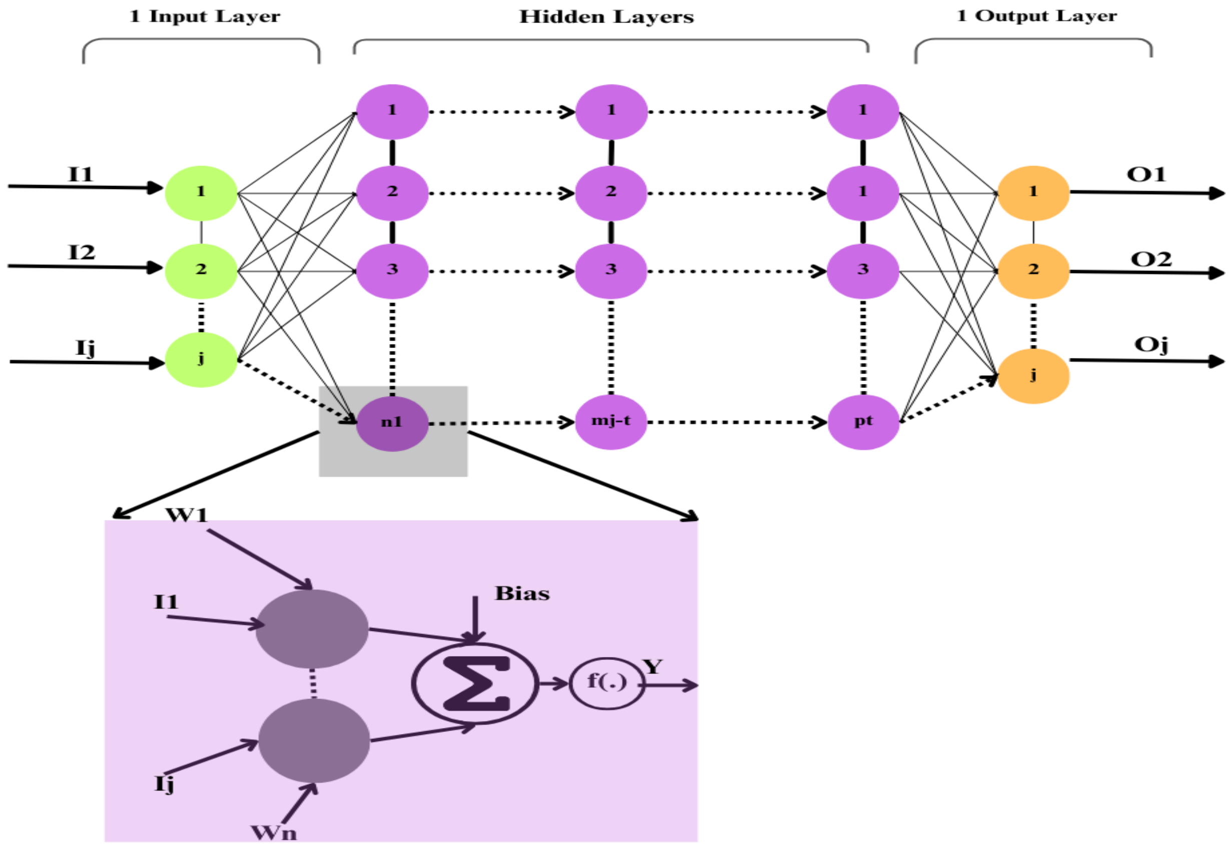


Figure 3.3 Detailed structure of the DNN model

The model has an input layer with j number of input and output Neurons that received the input data $I = [I_1, I_2, \ldots, I_j]$ and $o = [o_1, o_2, \ldots, o_J] \in \mathrm{R}^{j \times 1}$. The hidden layer of the network consists of N neurons where $2 \leq t \leq t-1$, where t is the number of layers in hidden layers. For the proposed model same number of neurons is considered for all hidden layers. There N number of nodes are present in each hidden layer. the output layer also has the same number of nodes. Internally, in one node there is a weigh $w^{Nl-1 \times Nl}$ and biase b_{Nl} adjustment. An artificial neuron's activation range is determined by its activation function $f_{(t,J)}$ which has non-linearity. This is applied to the total of the neuron's weighted input data. The DNN output of one node is expressed as below:

$$O_{(t,j)} = f_{(t,j)}\left(b_{(t,j)} + w_{(t,j)}^T I_t\right) \tag{3.12}$$

The overall equation of DNN which govern input and output by adjusting weight and bias is as below:

$$O_{(t)} = f_{(t)}\left(b_{(t)} + w_{(t)}^T I_t\right) \tag{3.13}$$

The value for $\beta(w, b)$ estimated through learning progress. It is gained by minimizing a loss function Loss(β) as shown equation (3.14) between the predicted ($O_{(t)}^{(P)}$) and true values ($O_{(t)}^{(T)}$) of DNN.

$$Loss(\beta) = arg_{\beta}^{min}\left(O_{(t)}^{(P)} - O_{(t)}^{(T)}\right) \tag{3.14}$$

The governing methods to have optimal convergence values of 'w' and 'b' are optimizer. Choosing the write optimizer is one of the main factors for the model performance.

3.6.1 Adam Optimizer

Optimizer is an algorithm that looks for the best combination of models or parameters to reduce the inaccuracy in calculating the wireless channel characteristics, thereby enhancing the communication system's overall performance.in deep learning-based model design, different optimizers like Stochastic Gradient Descent method (SDG), SDG with momentum, Adaptive gradient algorithm (Adagrad), and Adaptive moment estimation (Adam) can be used. When it comes to combining the momentum notion from SDG with the adaptive learning rate concept from AdaDelta optimizer, Adam is the optimizer of choice. Its benefits include an easy-to-implement design, computational efficiency, low memory requirements, and suitability for applications with highly noisy gradients.

$$\beta_{new} = \beta - \rho\frac{\partial Loss(\beta)}{\partial \beta} \tag{3.15}$$

Where, ρ is the learning rate. There are different activation functions used for DNN model training. However, the most known are the ones discussed below.

3.6.2 Activation Function

The Rectifier Linear Unit (ReLU) activation function follows the principle that when x > 0, no gradient saturation is shown in Figure 3.4(a). It is used to avoid the presence of a vanishing gradient. It also has a very small computational footprint, and its convergence speed is faster than that of the sigmoid and tanh (Agarap, 2019). The occurrence of over-fitting as the number of layers increases will be tolerated by dropping out of hidden layers accordingly. Eq. (3.12) shows that φ(x) is a ReLU function of x.

$$\varphi(x) = \begin{Bmatrix} x, & x > 0 \\ 0, & x < 0 \end{Bmatrix} \tag{3.16}$$

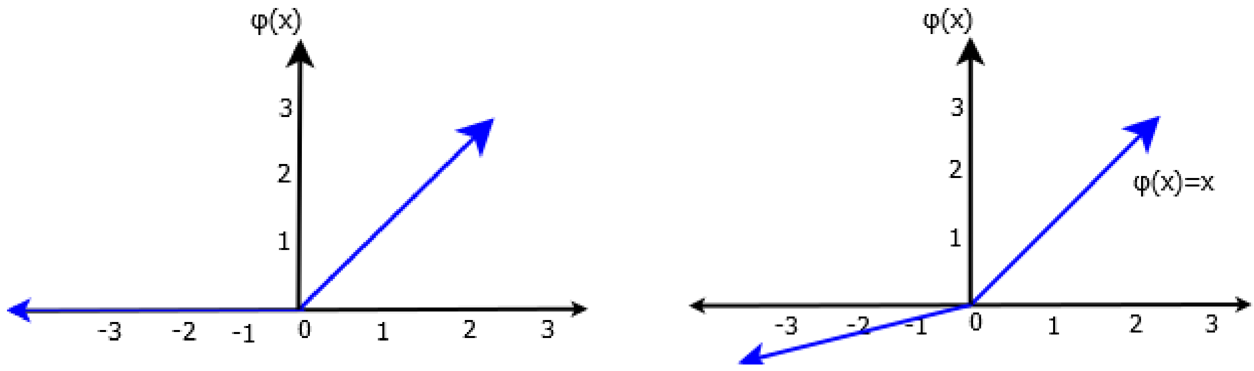


Figure 3.4 Activation function (a, ReLU   b, Leaky ReLU)

As shown in Figure 3.4 (b), the Leakey ReLU activation function is an updated form of the ReLU function to overcome dead nodes. When the ReLU was set to zero value for x<0, the negative input numbers were not going to be considered and the effect of those values was ignored. The performance of the model degrades because of this action. In the Leakey ReLU function, some constants are added to multiply the values below x<0. Even the constants are very low numbers.

$$\varphi(x) = \begin{Bmatrix} x, & x > 0 \\ \alpha x, & x < 0 \end{Bmatrix} \tag{3.17}$$

3.6.3 Proposed System Block Diagram

The model is used to estimate and understand the characteristics of the channel by using DNN. The deep learning process is held together by using Doppler shift, path delay, and average path gains. This DNN-based channel estimation model estimates the channel based on the DNN train's results and input, as shown in Figure 3.5. The received symbol is used to estimate the past channel by comparing it with the initial estimation. Initial estimation is the output after the LS estimation result equalization and demmaping. Then, time and frequency averaging process of STA estimation is held. The output or estimated data is normalized, which is process of adjusting the input data to ensure that it has a consistent scale, often with a mean of zero and a standard deviation of one, after the complex and real data arrangement in cascaded matrix. The result after the normalization is used to train to DNN in different vehicular models. the trained model is tested by predicting the result with new testing data and the result will be a DNN-based channel estimation.

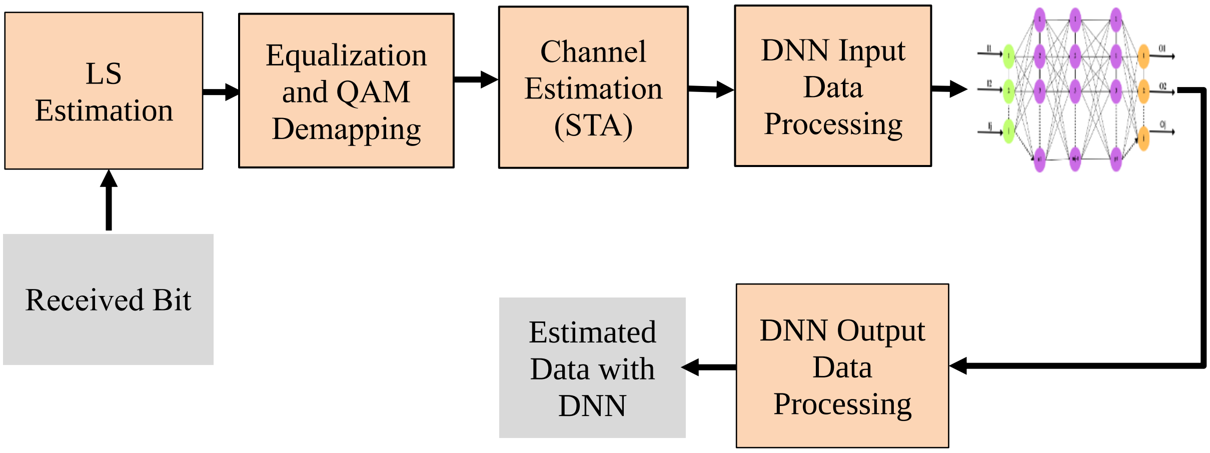


Figure 3.5 DNN-based channel estimation model system block diagram

3.6.4 Model Training and Testing

DNN-based model training needs to be more accurate and take less time to train in the simulation. For this reason, some pre-procedures are conducted before the model trained. The first is data analysis, the data is separated into three parts. Training, testing, and validation. Separating data enables the training to prevent over-fitting issues. The model was trained with 4000 data points that were used for training, testing, and validation, with a ratio of 20:80 (64% for training, 16% for validation, and 20% for testing), as shown in Table 3.3 below. The analyzed data feed to the model in two stages, training testing. The validation data used to evaluate performance and progress of training. In the training stage the training parameters play a great role. There are two types of parameters in the modeling process.

Table 3.3 Training data allocation

Data Allocation	Number of Data
Training data	2560
Validation data	640
Testing data	800

The hyper-parameters are one type of parameter in the top-level role that is chosen and filled manually based on the specific reason for the modeling. The other parameter is modeling parameters. They are estimated from the data automatically depending on the hyper-parameters. For effective design optimization, the hyper-parameters in DNN design must be chosen carefully. The particular datasets, learning tasks, and DNN algorithms utilized for model training tend to influence the best learning rules for a given learning function (Wu &

Liu, 2023). For this reason, hyper-parameters tuning is done for choosing important and variable parameters. hyper-parameters tuning is the crucial process in ML model training. Where hyper-parameters are settings that control optimize the learning process itself, but are not directly learned by the model as parameters. They define the overall behavior and capabilities of the model. The process can be done in different way. In this work learning rate and Leakey point are act as parameters where the architecture of model defined before. In training phase of the model, the training data which is estimated data with STA is feed to the DNN model by separating the real and complex values.

User sub-carriers are capture the data. Both the transmitted and estimated data are recorded for supervised learning. This process is repeated for testing datasets processing. Those data pass normalization to prevent the gradients became too large or too small and formal stability. Shuffling in every epoch guide the learning to adapt different sequences. After the architecture of model is defined, it trained with ‘I’ transmitted and ‘O’ is corresponding output data with given epoch. The full process is as drawn as Figure 3.6 below. The prediction process allows to get the result of model after trained. By taking the difference between the predicted value and the error can be calculated.

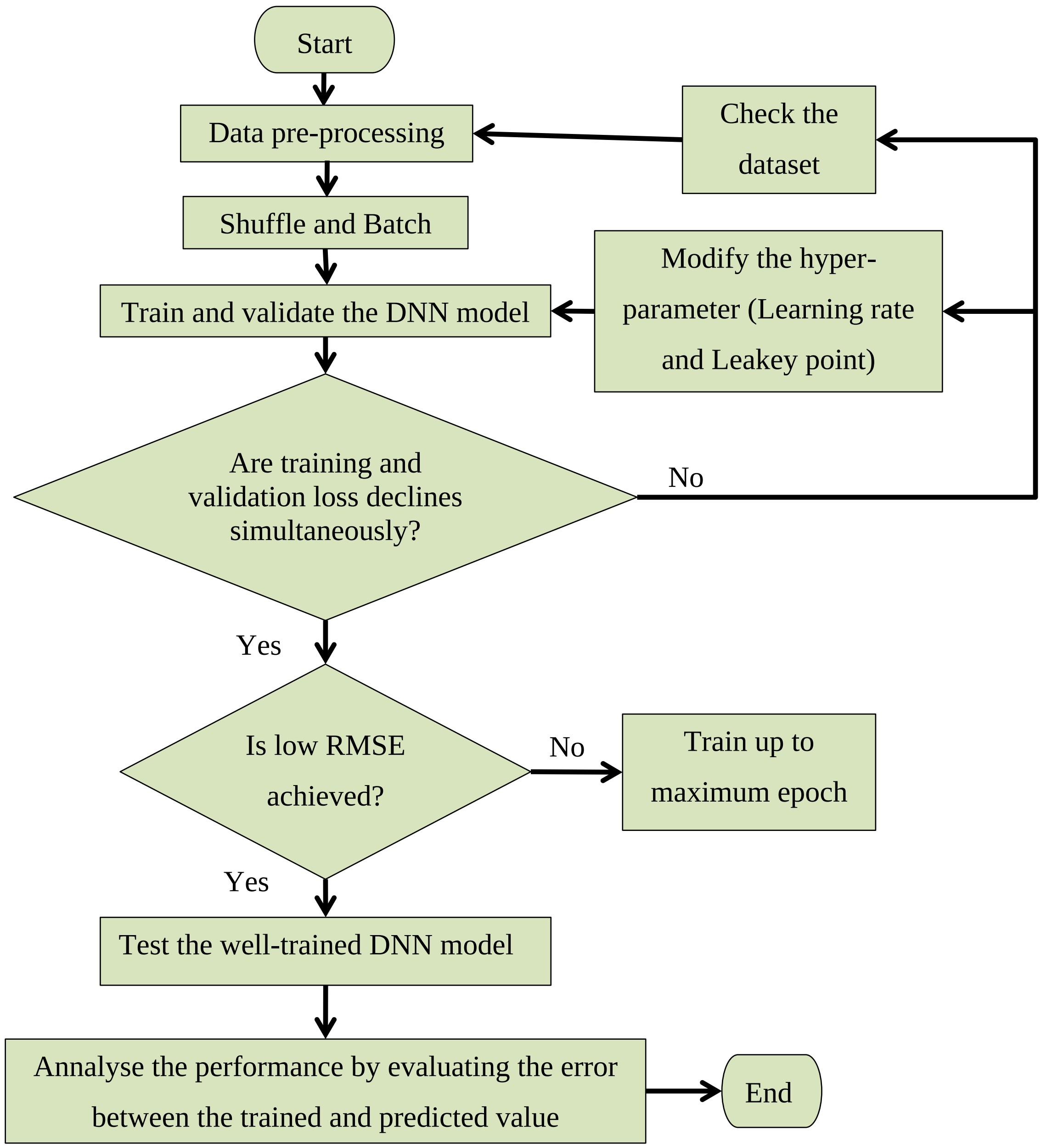


Figure 3. 6 Flow chart of DNN model training

3.7 Performance Metrics

The performance measurement of the proposed channel estimation system is done in various ways by comparing the first transmitted value to the received one. The difference between them is expected to be minimal for a good-performing system or model. In this thesis, metrics like BER, MSE, and validation loss are used. The performance measurement will include testing progress, comparison of the proposed model with the existing method, and performance of the proposed method in different factors.

CHAPTER FOUR

4. RESULTS and DISCUSSIONS

4.1 Chapter Overview

In this chapter, the simulation result of training progress with the description of performance factors, various channel models based on traditional channel estimation results, that are simulated with the proposed parameters on the papers as itself, and proposed STA-LRDNN channel estimation are obtained in graphical and table forms. Furthermore, the effect of channel models in modulation order, mobility, and DNN architectures are simulated and examined. Comparison and performance evaluation examined in BER and NMSE main parts.

4.2 Simulation Parameter

The parameters for the model training are listed in Table 4.1. For better results and simulation, the model training parameters are collected in two ways. The first is by analyzing manually for the best iteration and the second (remark by '#') is by observing the best results of the existing works such as (Gizzini et al., 2020; Gregorians et al., 2022; Ingénierie et al., 2021; Liu Jiayi, 2023; Pan et al., 2021; Reis et al., 2023).

Table 4. 1 DNN model training simulation parameters

No	Name of parameter	Type	Remark
1	Number of layers	3	Assumption
2	Number of nodes	30,50	Assumption
3	Optimizer	Adam	#
4	Learning rate information	0.001	After observations
5	Mini-batch size	128	#
6	Symbols	30	Assumption
7	Epoch	500	#
8	Leakey Point	0.1,0.06	After observation
9	Verbose Frequency	100	After observations
10	Validation Frequency	500	Assumption

4.3 Progress and Performance Analysis of Model Training

The training performance of the regression-type DNN model is measured by loss versus iteration and validation in RMSE versus iteration form. As sample the training progress of model for VTV-EX channel model is discussed below.

The Figures 4.1 shows the training progress proposed model STA-LRDNN, which takes 53 minutes and 15 sec to complete 500 epochs, with 600 iterations per epoch. The training was conducted on a single CPU with a constant learning rate of 0. 001.The iteration goes from 0 to 100 epoch it is down very much at all. The sample for the iteration progress of VTV-EX is shown below in Table 4.1. As the table present channel estimation training progress is significantly performance as the mini-batch and validation RMSE decrease from 10.85 and 10.48 to 0.20 respectively. The decrement in mini-batch RMSE and positive sign of the value indicates how the model is effectively capturing the patterns in the training data in addition to memorizing the training data. The validation RMSE decrement can be taken as evidence for the generalizing well to unseen estimation data and demonstrating that the model is not over-fitting to the training data. The convergence between the two values also is evidence for not over-fitting.

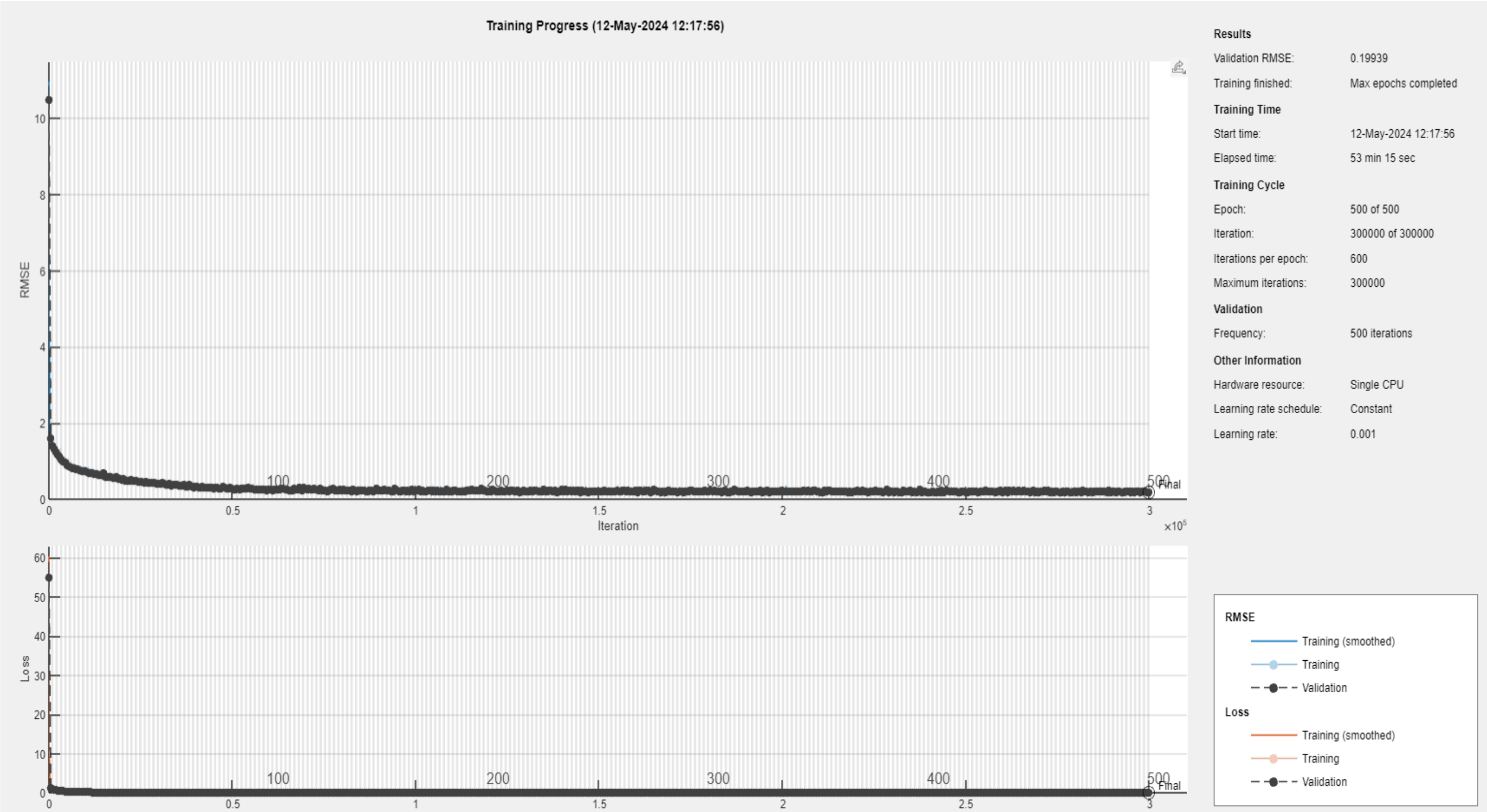


Figure 4. 1 Training progress of DNN model with Leakey ReLU activation function

Table 4. 2 Iteration progress values of DNN model

Epoch	Iteration	Time Elapsed (hh:mm:ss)	RMSE (Mini-Bach)	Validation RMSE	Loss (Mini-Bach)	Validation Loss	Learn Rate
1	1	00:00:04	10.85	10.48	58.8592	54.9291	0.001
100	59500	00:08:26	0.27	0.24	0.0364	0.0298	0.001
200	119500	00:17:16	0.23	0.23	0.0257	0.0256	0.001
300	179500	00:28:14	0.22	0.21	0.0252	0.0214	0.001
400	239500	00:40:16	0.20	0.20	0.0208	0.0200	0.001
500	300000	00:53:14	0.20	0.20	0.0206	0.0199	0.001

4.4 Comparison of Traditional Channel Estimators with Proposed STA-LRDNN in Different Channel Models

In the comparison of the proposed STA-LRDNN method with traditional channel estimators for various channel models, performance analysis was carried out considering the Doppler shift and vehicle velocity in the recorded values from Atlanta campaign environment along with multiple SNR values. For every case, the model performance based on BER and NMSE was examined. The following 16 QAM modulation simulation results are presented in this section.

4.4.1 Bit Error Rate (BER) Analysis in VTV-EX Channel Model

The simulation result of channel estimation by considering the VTV-EX channel model is recorded in Figure 4.2. The figure presents that, at low values of SNR region, LS estimator outperforms than the STA, CDP and MMSE. There shows a minimum convergence due to high noise and interference behavior of the region. In other side the LS estimator enables to handle noise by taking noise average in two predefined frequency domain intervals. Therefore, it can outperform than others. However, the proposed STA-LRDNN method shows significant and consistent improvement with fast adaption of environment; even the CDP and MMSE improve their values after SNR of 15dB. The STA-LRDNN use advantage of time and frequency averaging of STA and generalization ability of the DNN model.

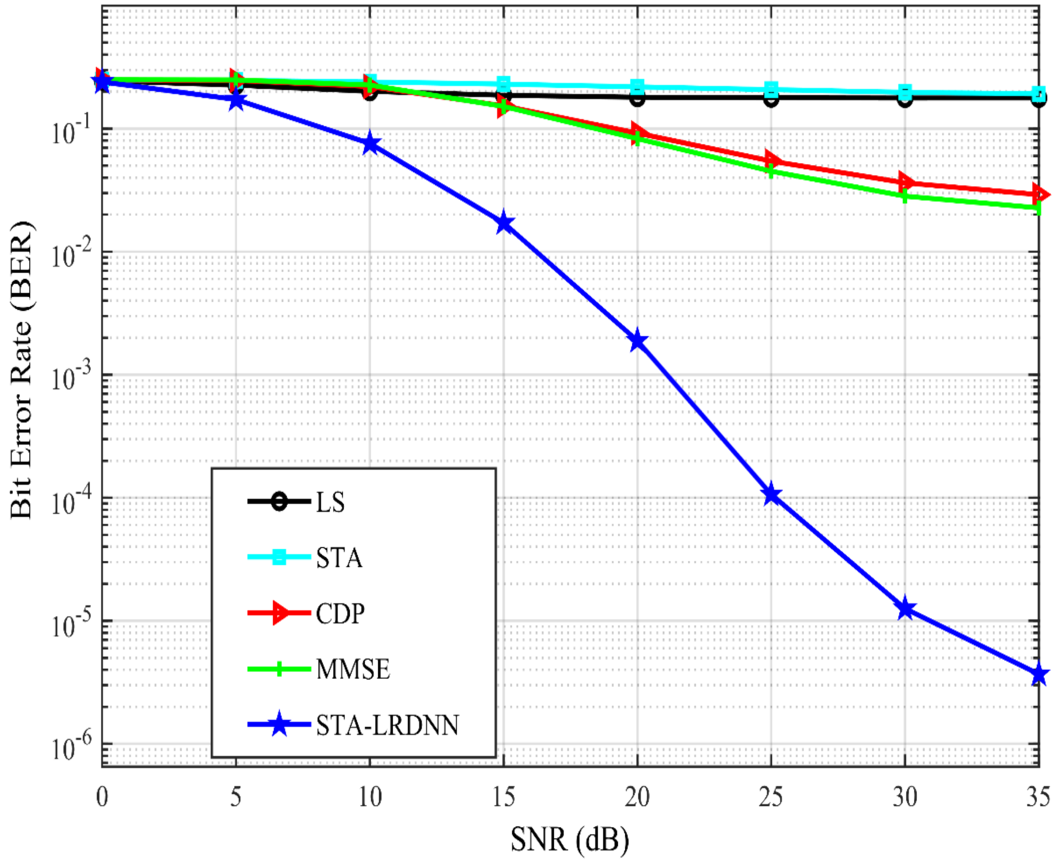


Figure 4.2 BER Result Analysis of VTV-EX channel model

Statically, as summarized in Table 4.3, STA-LRDNN recorded 0.0002, 0.0171, 0.0019, and 0.00015 differences from effective estimators in SNR values 0, 10, 20, and 30, respectively, for 16QAM. That means SNR gain of 20 dB is recorded for 0.01 BER value with final achievement of around 1 error per 1000 signals.

Table 4. 3 Summary of BER analysis of VTV-EX channel model

SNR (dB)	LS	STA	CDP	MMSE	STA-LRDNN
0	0.2455	0.2492	0.2497	0.2501	0.2501
10	0.2010	0.2396	0.2199	0.2261	0.0171
20	0.1783	0.2185	0.0919	0.0829	0.0019
30	0.1775	0.1973	0.0362	0.0282	0.000015

4.4.2 Bit Error Rate (BER) Analysis in VTV-SDWW Channel Model

The other channel VTV-SDWW is known by high doppler shift and dynamic change of channel property. As shown in Figure 4.3 below, more significant gains with less errors are recorded by CDP and MMSE, especially after 10 dB SNR. This is observed because of freedom of equalized OFDM Symbol at the receiver without any position shift.

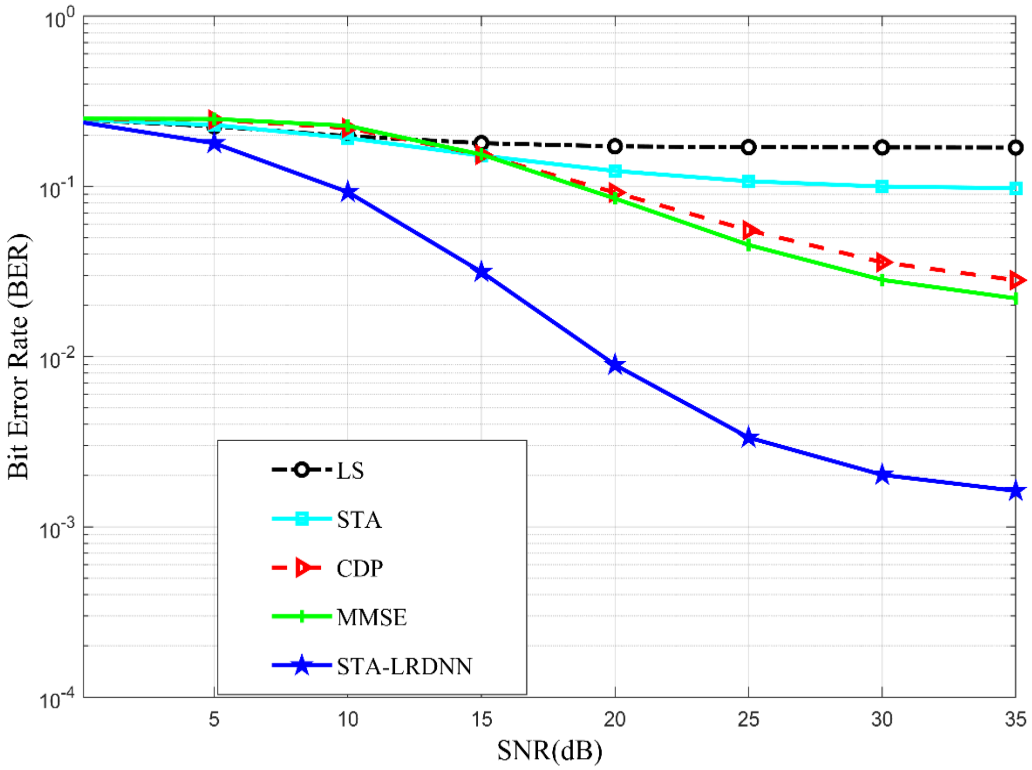


Figure 4. 3 BER Result Analysis of VTV-SDWW channel model

Statically as Table 4.4, at 20 dB CDP and MMSE estimators achieve 0.0928 and 0.0854 BER values respectively while STA-LRDNN has 0.0089. There is significant 10 and more than 15 dB SNR gain for 0.1 and 0.01 BER. The overall achievement of STA-LRDNN outperforms all other techniques, showing an almost complete decrement from 0 to 35 SNR. This remarkable performance is especially noticeable at higher SNR values.

Table 4.4 Summary of BER analysis in VTV-SDWW channel model

SNR (dB)	LS	STA	CDP	MMSE	STA-LRDNN
0	0.2458	0.2466	0.2498	0.2498	0.2384
10	0.1965	0.1926	0.2210	0.2281	0.0926
20	0.1719	0.1230	0.0928	0.0854	0.0089
30	0.1692	0.1010	0.0363	0.0287	0.0020

4.4.3 Bit Error Rate (BER) Analysis of VTV-UC Channel Model

The VTV-UC channel is known for the presence of large buildings. As shown in Figure 4.4 below while STA estimator has constant values defined as 2, they became smooth lines. After 15 dB SNR the MMSE and CDP can Same as before, proposed STA-LRDNN model also shows higher performance than traditional channel estimators. That means the channel estimation becomes more valuable than the traditional estimation methods.

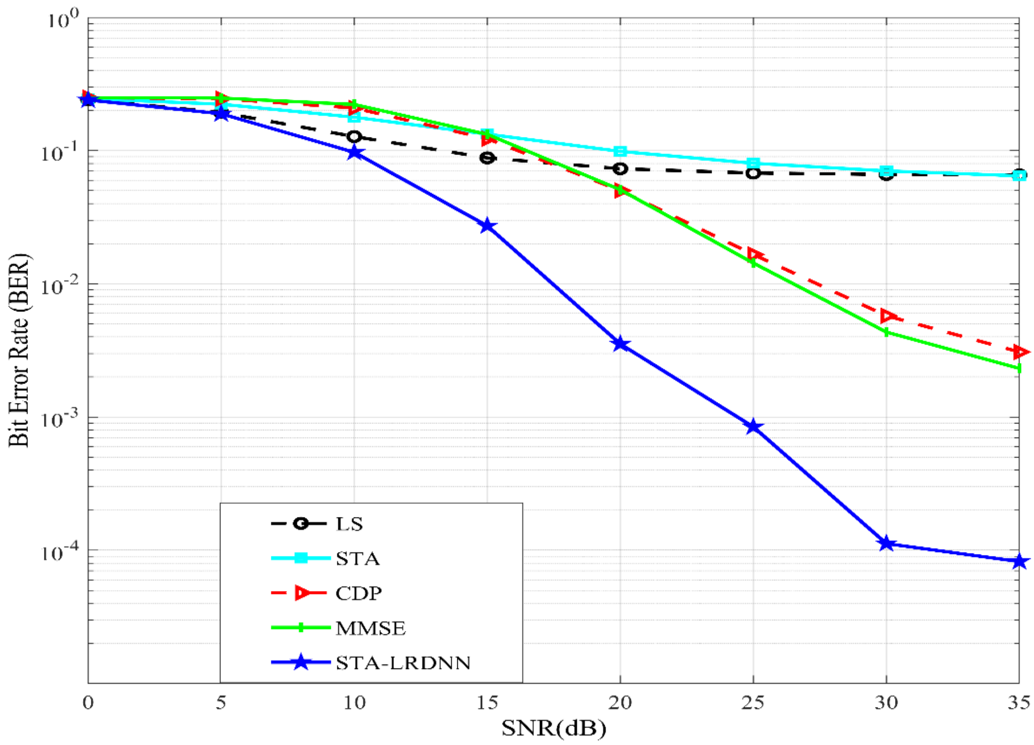


Figure 4. 4 BER analysis of VTV-UC channel model

Numerically the difference in result is discussed in Table 4.5. The LS estimation has high values observed until around 17dB SNR whereas the MMSE and CDP scheme performance Superior above 20 SNR than MMSE. However, STA-LRDNN outperforms by 0.0473 and 0.004188 for 16 QAM at 20 and 30 SNR values respectively than the MMSE. To achieve BER of 0.1, 10 dB gain is achieved with introduced method.

Table 4. 5 Summary of BER analysis VTV-UC channel model

SNR (dB)	LS	STA	CDP	MMSE	STA-LRDNN
0	0.2413	0.2455	0.2496	0.2499	0.2399
10	0.1274	0.1781	0.2089	0.2221	0.0971
20	0.0731	0.0986	0.0501	0.0508	0.0035
30	0.0662	0.0703	0.0058	0.0043	1.12e-04

4.4.4 Bit Error Rate (BER) Analysis of RTV-EX Channel Model

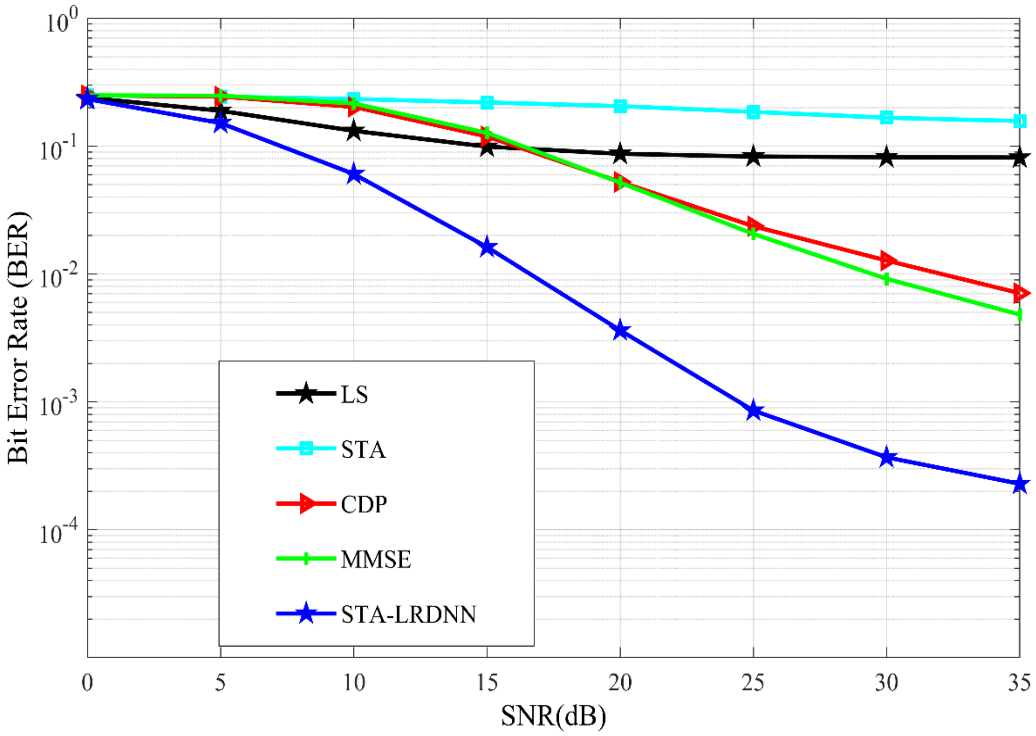


Figure 4.5 BER performance of RTV-EX channel model

As shown in Figure 4.5, at 0 dB SNR, all techniques exhibit comparable performance, albeit with LS slightly lagging. However, as the SNR increases, there's a discernible improvement in performance across all techniques. Notably, MMSE and STA-LRDNN consistently emerge as the top-performing techniques, with the performance gap between them and the other methods widening as SNR levels rise. This trend underscores the superior adaptability and robustness of MMSE and STA-LRDNN, especially in higher SNR environments. Table 4.6 shows going through 0,10,20 and 30 SNR STA-LRDNN recorded low values of 0.2336,0.06058,0.0036 and 0.00036 respectively.

Table 4. 6 Summary of BER analysis in RTV-EX channel model

SNR (dB)	LS	STA	CDP	MMSE	STA-LRDNN
0	0.2393	0.2491	0.2496	0.2498	0.2336
10	0.1318	0.2338	0.2029	0.2155	0.06058
20	0.0871	0.2056	0.0525	0.0518	0.0036
30	0.0802	0.1670	0.0127	0.0092	0.00036

4.4.5 Application Comparison of the Four Channels STA-LRDNN Model Channel Estimation

The analysis of each channel model result in 16QAM modulation was discussed in detail above section. The analysis covers the comparison of the effectiveness of the proposed LRDNN estimation method in those channels related to the nature of the channels. The summary result shown in Figure 4.6 illustrates the performance of different channels in vehicular communication systems. Among them, VTV-EX exhibits the lowest BER, indicating its superior reliability even under high-speed, Doppler-shift-prone conditions. Following closely is VTV-UC, which demonstrates relatively robust performance despite navigating through dense urban environments with signal propagation challenges. Meanwhile, VTV-SDWW consistently shows higher BER, reflecting its vulnerability to signal degradation despite attempts to mitigate path loss with a center wall on the highway. RTV-EX, communicating with roadside units on the expressway, falls between VTV-UC and VTV-SDWW in terms of BER, suggesting moderate performance under varying signal SNR conditions. These insights provide valuable guidance for optimizing communication protocols and technologies in vehicular networks, considering real-world scenarios and challenges.

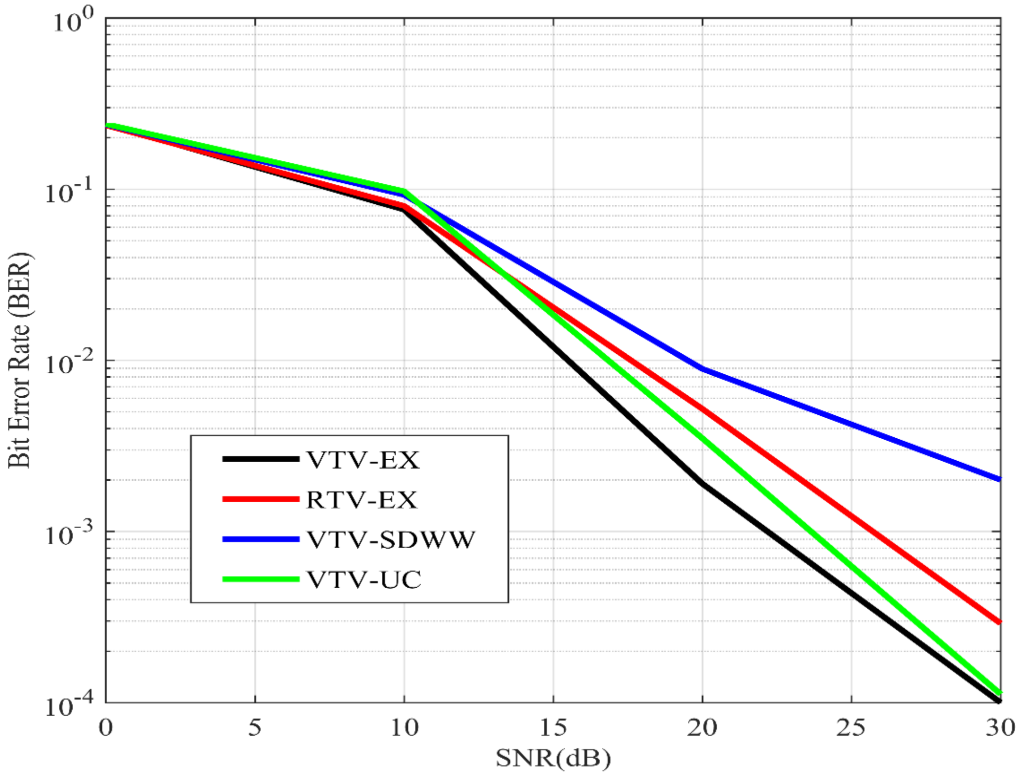


Figure 4. 6 Comparison of performance of STA-LRDNN in different channel models

4.4.6 Normalized Mean Squared Error (NMSE) Analysis in VTV-EX Channel Model

The performance comparison of traditional channel estimator with the proposed STA-LRDNN is analyzed through the examination of NMSE, shedding light on the efficiency of the novel STA-LRDNN approach in comparison to the conventional channel estimation method. The results are discussed below. NMSE analysis, as illustrated in Figure 4.7, reveals intriguing trends in the performance of various channel estimation techniques across different SNR levels, particularly within the realm of 16QAM modulation. At lower SNR values, both LS and STA estimations exhibit superior performance compared to CDP, MMSE, and Initial Estimation methods, but as SNR levels increase, LS and STA effectiveness diminishes while others improve.

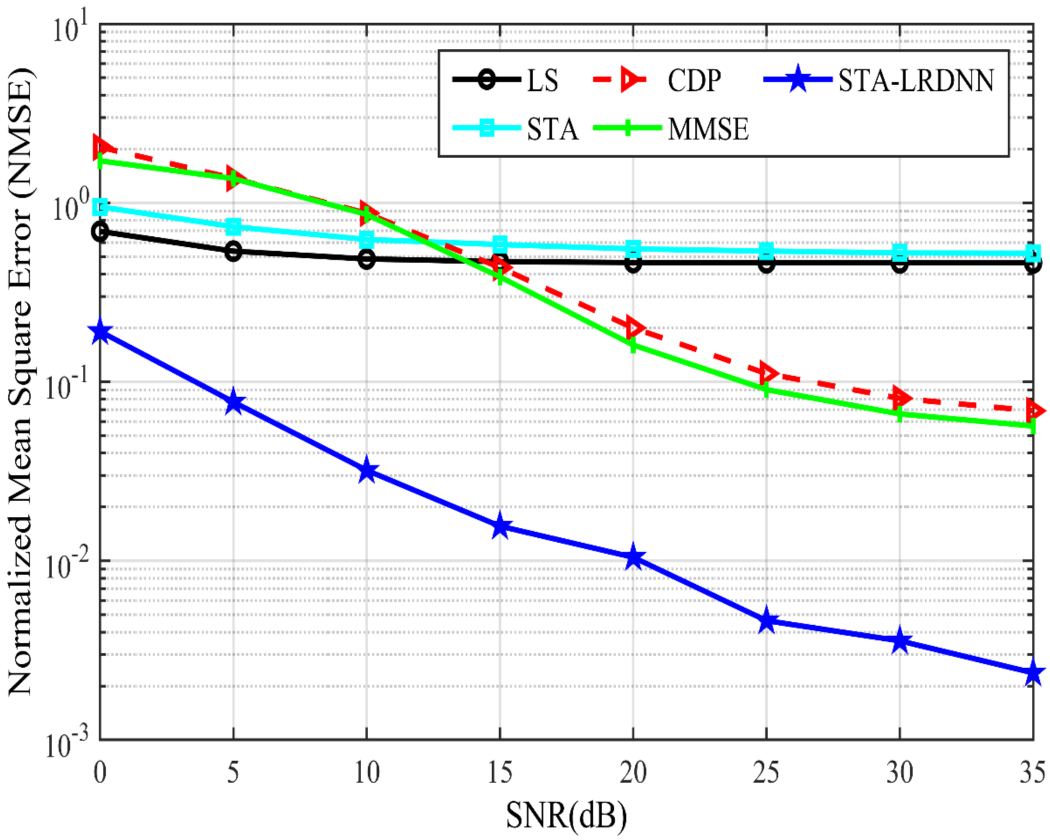


Figure 4. 7 NMSE value of VTV-EX channel model

Notably, STA-LRDNN consistently outperforms all other methods as shown in Table 4.7, demonstrating remarkable efficacy across the SNR spectrum. At higher SNR levels, STA-LRDNN achieves an impressively low NMSE value of 0.0036, significantly surpassing MMSE. This translates to an average improvement percentage of 93.46% and 94.56% over MMSE at 20 dB and 30 dB SNR, respectively. It highlights the exceptional performance of STA-LRDNN in channel estimation tasks, particularly under challenging SNR conditions, and suggests promising implications for communication system enhancement.

Table 4. 7 Summary of NMSE in VTV-EX channel model

SNR (dB)	LS	STA	CDP	MMSE	STA-LRDNN
0	0.6928	0.9501	2.0470	1.7180	0.1914
10	0.4859	0.6242	0.8751	0.8611	0.0321
20	0.4641	0.5530	0.2001	0.1606	0.0105
30	0.4623	0.5248	0.0809	0.0662	0.0036

4.4.7 Normalized Mean Squared Error (NMSE) Analysis VTV-SDWW Channel Model

The simulation results of the VTV-SDWW channel reveal the NMSE trends, as depicted in Figure 4.8 below. STA and LS estimation values closely track each other up to an SNR of 15, after which they converge to higher NMSE values. Conversely, CDP and MMSE show lower NMSE values before 15 SNR, but their effectiveness improves notably after this threshold. These trends persist across the entire SNR range from 0 to 35. Specifically, Table 4.8 indicates, that at 0 dB SNR, LS estimation yields an NMSE of 0.7053, followed by STA with 0.6256, while CDP and MMSE exhibit higher NMSE values of 2.1128 and 1.7382, respectively. STA-LRDNN shows the lowest NMSE at 0.1727. As the SNR increases to 10 dB, there's a noticeable reduction in NMSE across all methods, with LS and STA still exhibiting relatively higher NMSE. At 20 dB SNR, LS, and STA further reduce NMSE, while CDP and MMSE notably improve, with CDP showing the lowest NMSE among all methods. STA-LRDNN consistently demonstrates exceptional performance with the lowest NMSE across all SNR levels boasting the lowest NMSE of 0.0083.

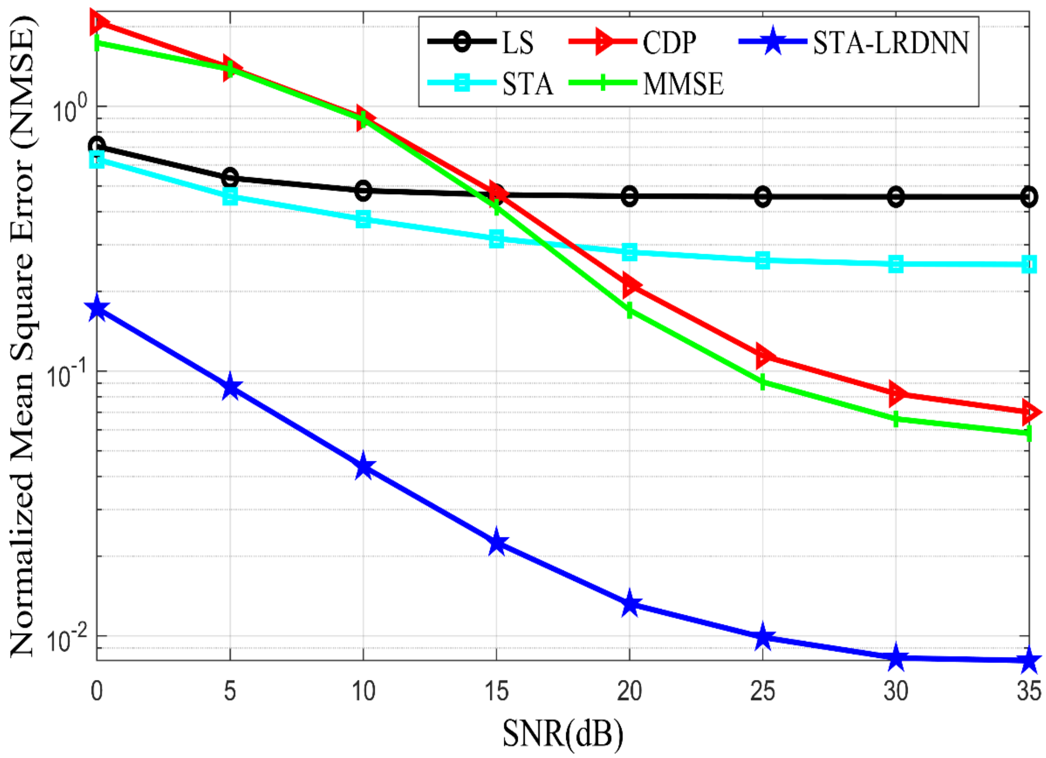


Figure 4. 8 NMSE of VTV-SDWW channel model

Table 4.8 Summary of NMSE analysis in VTV-SDWW channel model

SNR (dB)	LS	STA	CDP	MMSE	STA-LRDNN
0	0.7053	0.6256	2.1128	1.7382	0.1727
10	0.4802	0.3717	0.8965	0.8979	0.0436
20	0.4559	0.2801	0.2134	0.1684	0.0132
30	0.4553	0.2546	0.0819	0.0671	0.0083

4.4.8 Normalized Mean Squared Error (NMSE) Analysis in VTV-UC Channel Model

The analysis of NMSE in the channel model of VTV-UC is expected to be more accurate according to the environmental traffic. The simulation result of channel estimation is shown in Figure 4.9 graphically. The numerical values extracted from the graph are shown in Table 4.8 below. At an SNR of 0 dB, LS estimation yields an NMSE of 0.7053, followed closely by STA with 0.6256, while CDP and MMSE exhibit higher NMSE values of 2.1128 and 1.7382, respectively. STA-LRDNN performs favorably with an NMSE of 0.2189. As the SNR increases to 10 dB, there is a noticeable reduction in NMSE across all methods, with LS and STA still exhibiting relatively higher NMSE compared to CDP, MMSE, and STA-LRDNN. At 20 dB SNR, LS, and STA further decrease their NMSE values, while CDP and MMSE demonstrate substantial improvement, with CDP showing the lowest NMSE among all methods.

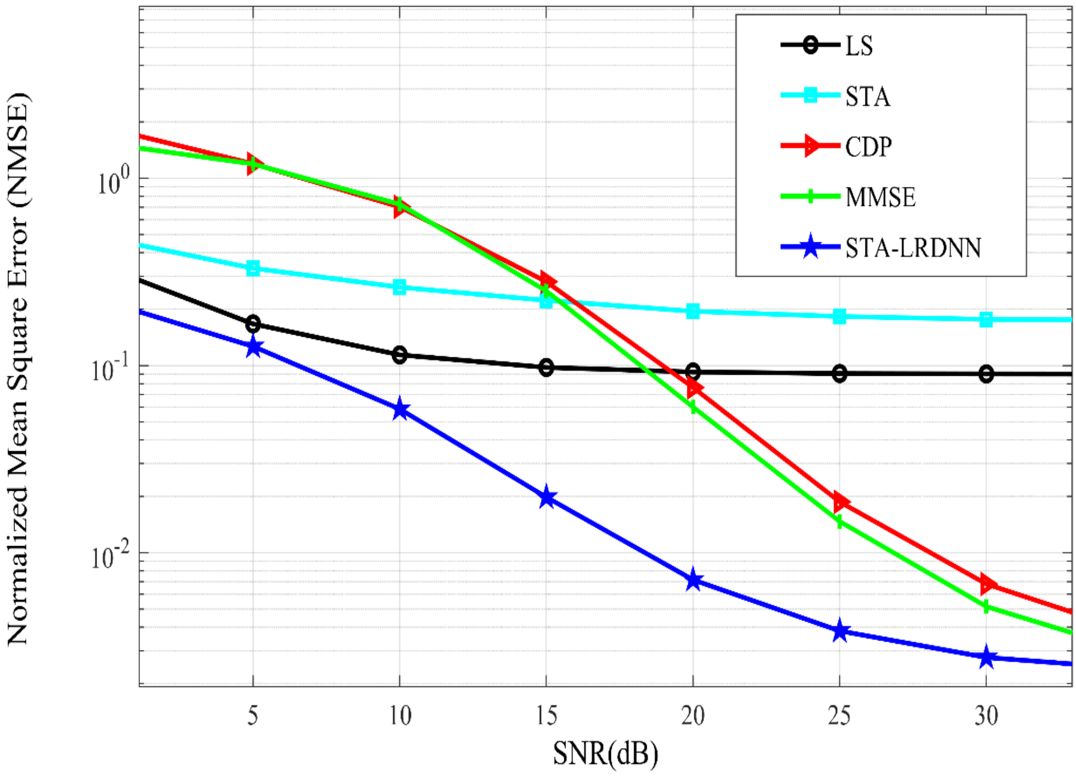


Figure 4. 9 NMSE of VTV-UC channel model

STA-LRDNN maintains exceptional performance with the lowest NMSE across all SNR levels. By 30 dB SNR, all methods achieve significantly low NMSE values, with STA-LRDNN consistently outperforming others, boasting the lowest NMSE of 0.0028.

Table 4.9 Summary of NMSE analysis in VTV-UC channel model

SNR (dB)	LS	STA	CDP	MMSE	STA-LRDNN
0	0.7053	0.6256	2.1128	1.7382	0.2189
10	0.4802	0.3717	0.8965	0.8979	0.0585
20	0.4576	0.2801	0.2134	0.1684	0.0072
30	0.4553	0.2546	0.0819	0.0671	0.0028

4.4.9 Normalized Mean Squared Error (NMSE) Analysis in RTV-EX Channel Model

The simulation result of the channel is illustrated below in Figure 4.10. the figure shows that the proposed method also performed better than the traditional method.

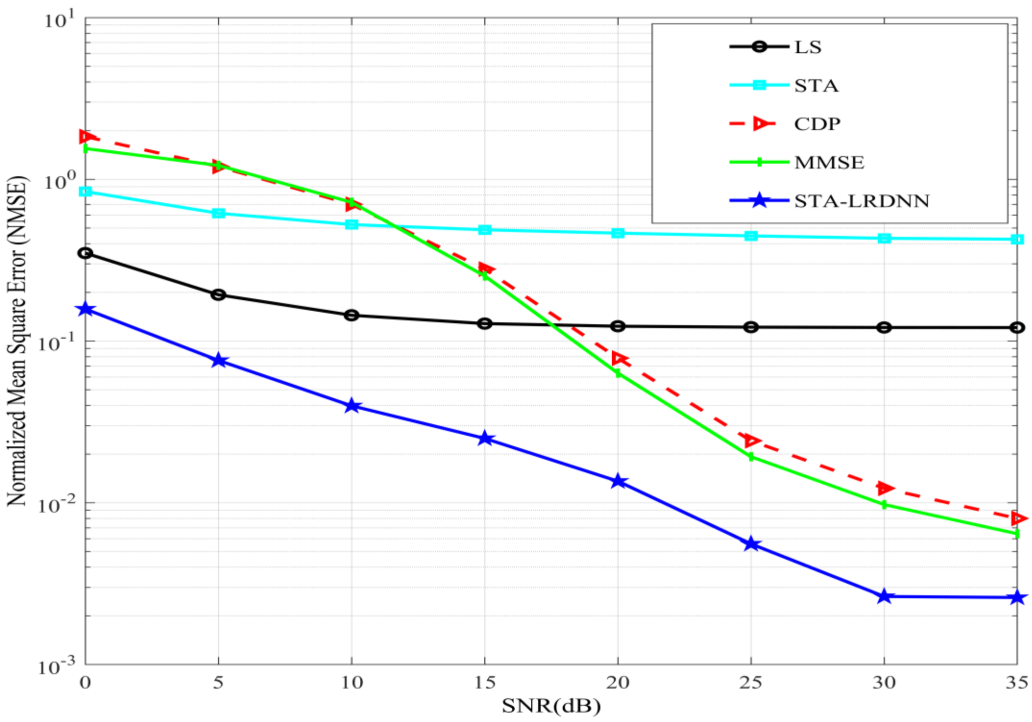


Figure 4. 10 NMSE of RTV-EX channel model

As the data available in Table 4.10, STA-LRDNN performs substantially better than the others at 0 dB, with the lowest error value (0.1579) and the largest error (1.8382) compared to CDP. When SNR rises to 10 dB, LS indicates a significant improvement (0.1444), while STA-LRDNN maintains its superior performance (0.0398). While CDP produces a significant error reduction (0.0784) at 20 dB, STA-LRDNN continues to be the greatest (0.0136). Lastly, error rates for all approaches drop even further at 30 dB, with STA-LRDNN obtaining the lowest error (0.0026), closely followed by MMSE (0.0098). All things considered, STA-LRDNN continuously exhibits the lowest error across all SNR levels, demonstrating its resilience and better performance under all noise circumstances.

Table 4.10 Summary of NMSE in RTV-EX channel model

SNR (dB)	LS	STA	CDP	MMSE	STA-LRDNN
0	0.3599	0.8408	1.8382	1.5498	0.1579
10	0.1444	0.5250	0.7005	0.7210	0.0398
20	0.1235	0.4647	0.0784	0.0634	0.0136
30	0.1213	0.4319	0.0123	0.0098	0.0026

4.4.10 Normalized Mean Squared Error (NMSE) Comparison of the Four Channels with STA-LRDNN Model Channel Estimation

The NMSE evaluation of the four channels is summarized in Figure 4.11 below. the figure illustrates that the variance of SNR has its behavior in those channels beyond the environment's situation. The vehicles in urban canyon environment communication channel estimation becomes less at lower SNR values while expressway and same direction going to the wall experience near values but better than the first. As SNR goes too high, the VTV-UC recorded better performance while the VTV-SDWW has less performance with high error than the others.

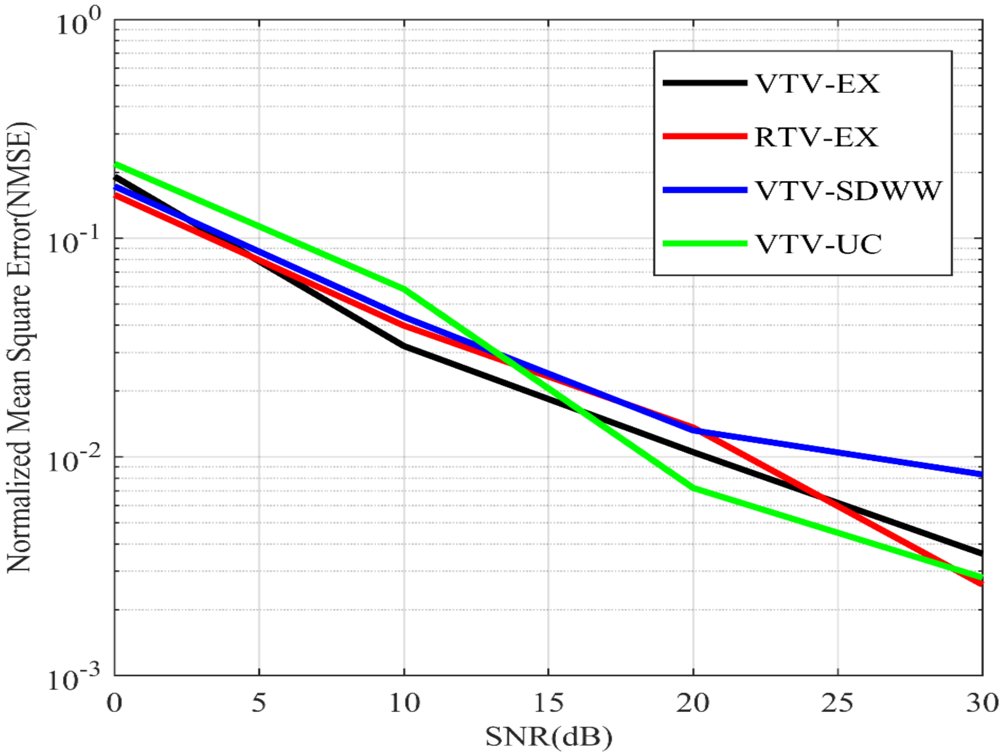


Figure 4.11 Performance comparison of STA-LRDNN on different channel models

4.5 Performance of Proposed Model at Different Modulation Order

Reliable data transmission in the context of vehicle communication depends on good channel estimation. The suggested channel estimation model, which is based on a DNN, exhibits variable levels of performance in different modulations as shown in Figure 4.12. Quadrature Phase Shift Keying (QPSK) is shown to perform better than 16-QAM and 64-QAM. Because noise and interference are common in dynamic vehicular situations, the model's increased tolerance to them and lesser complexity are responsible for its improved performance when using QPSK. The model continues to function effectively as the modulation order rises to 16-

QAM, although its accuracy is somewhat diminished because there are more complicated signal states. The model performs worse when 64-QAM is used because the greater modulation order greatly increases the signal states. The simulation is observed at VTV-EX channel estimation for more clear observation. The other performance evaluated in Figure 4.13 with NMSE. As shown below, the achievement of performance improvement in higher order modulations are observed. This is happened due to the robustness of estimation techniques.

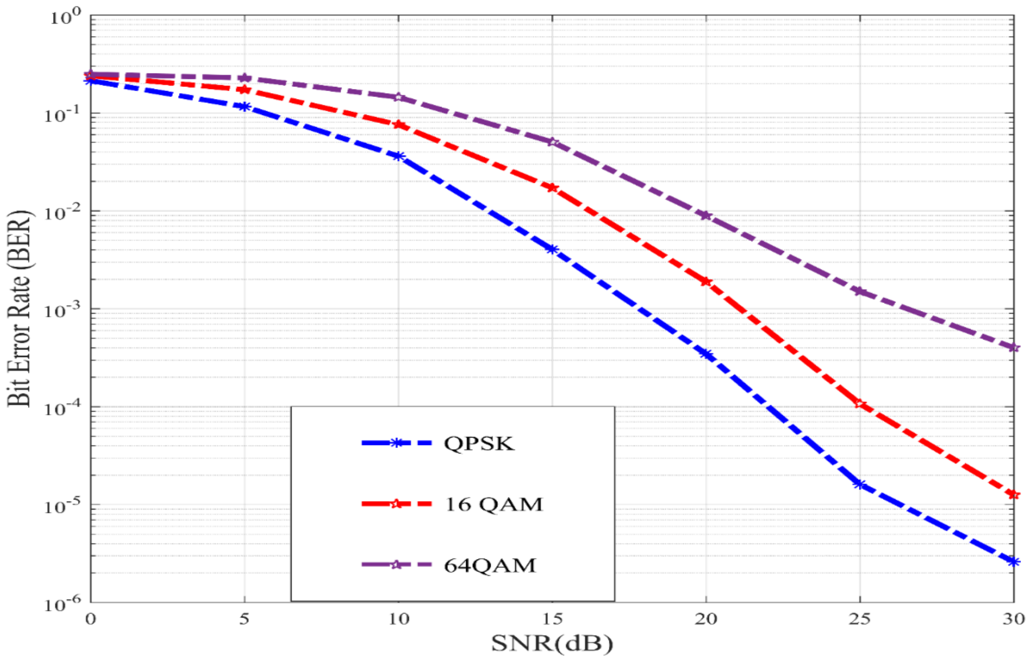


Figure 4. 12 Effect of modulation order on the proposed system in BER

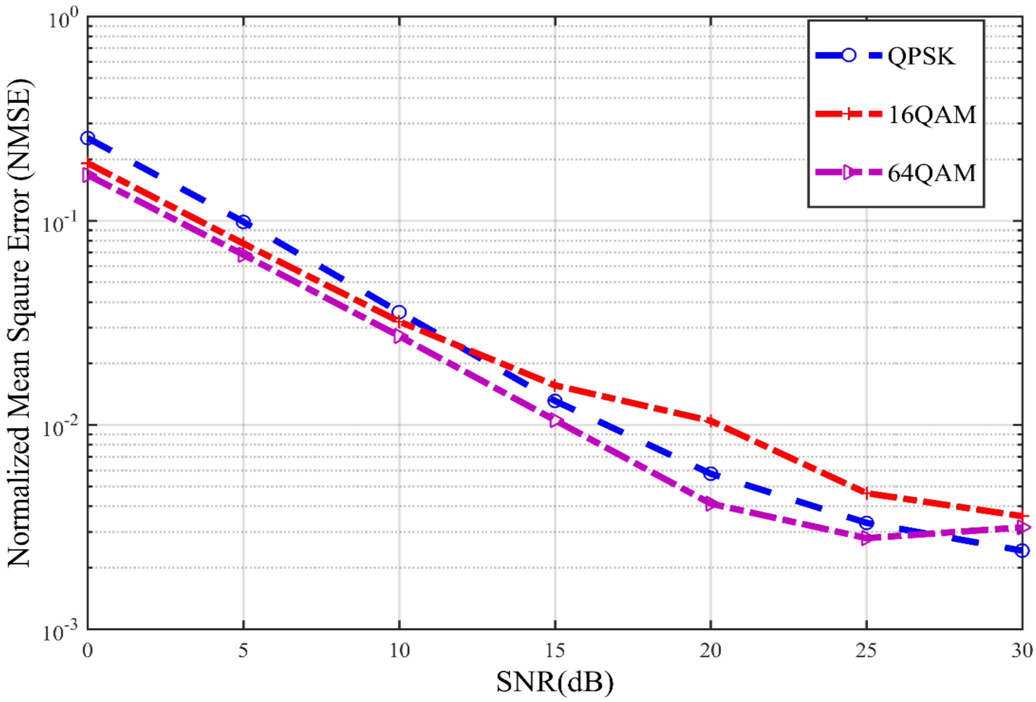


Figure 4.13 Effect of modulation order on the proposed system in NMSE

4.6 Performance of the Proposed Model in Different Mobility Environment

In a doubly dispersion environment, the main issue to the area becomes more sensitive to error is the movement of vehicles.

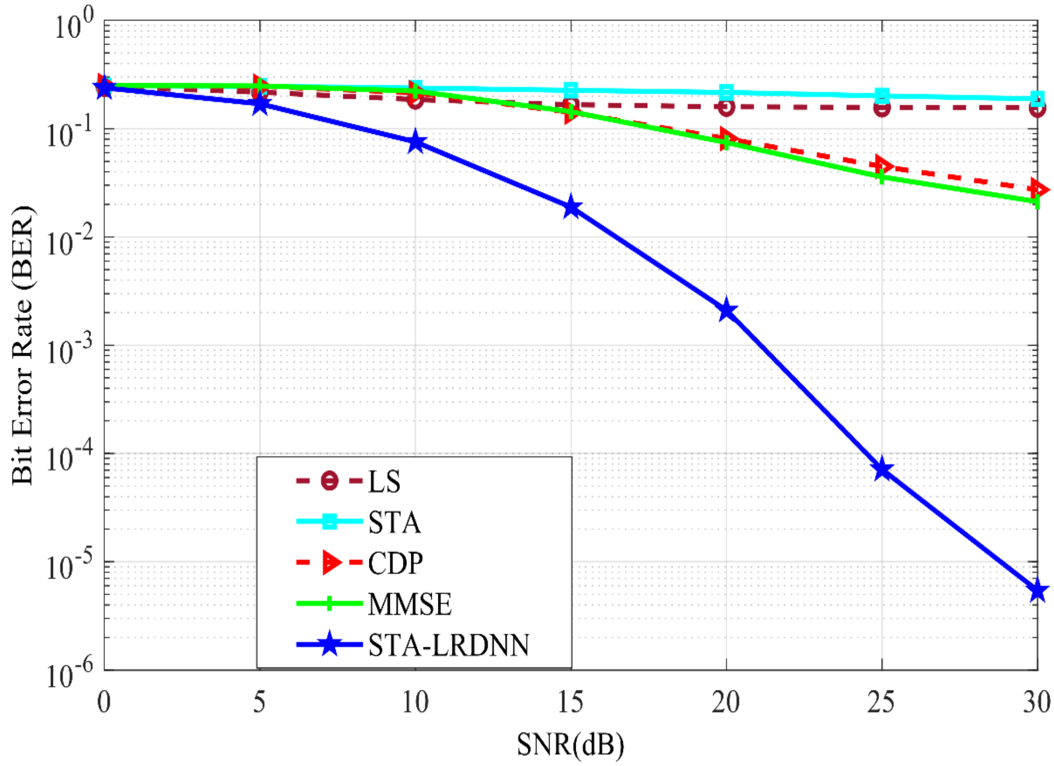


Figure 4. 14 BER analysis for very high mobility environment

Vehicles accelerate at different velocity leads to variations of Doppler shift. The communication performance is affected by this variation. Under this, the proposed model efficiency is measured in low, high, and very high mobility in environments. The first was observed that very high mobility in VTV-EX with 180 Km/hr speed of the car and 1000 Hz Doppler frequency. illustrated in Figure 4.14 with BER analysis and in Figure 4.15 with NMSE, the proposed model can estimate this high mobility scenario also means the model can handle the rapid change of motion and has high adaptability for changes that makes it effective. NMSE value also recorded a minimum of 10^{-2}.

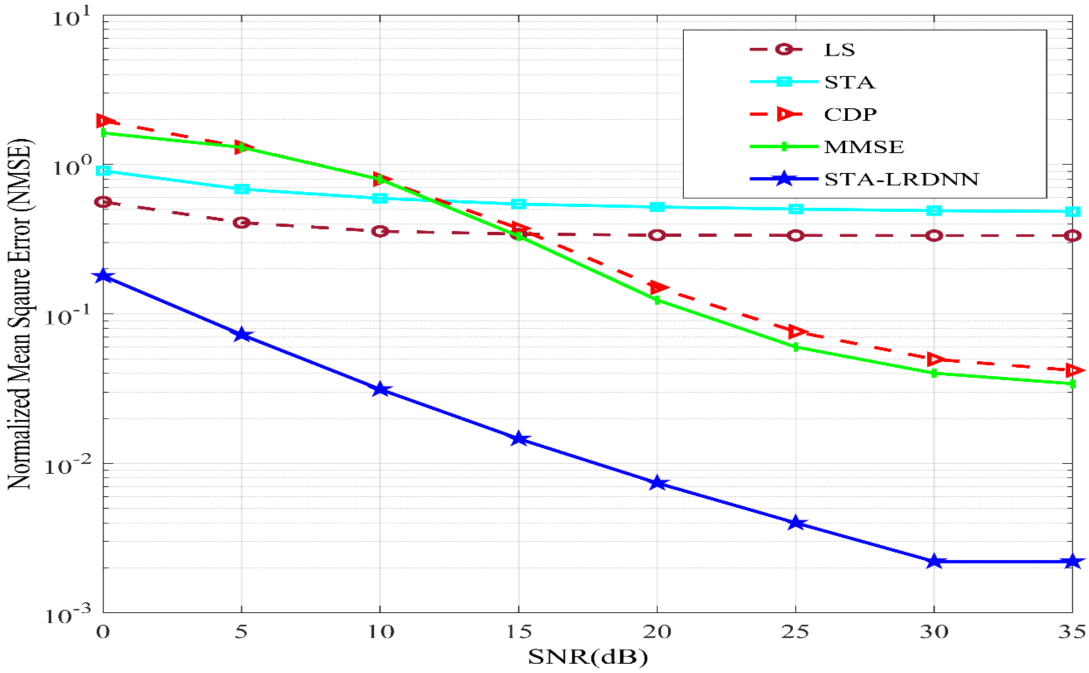
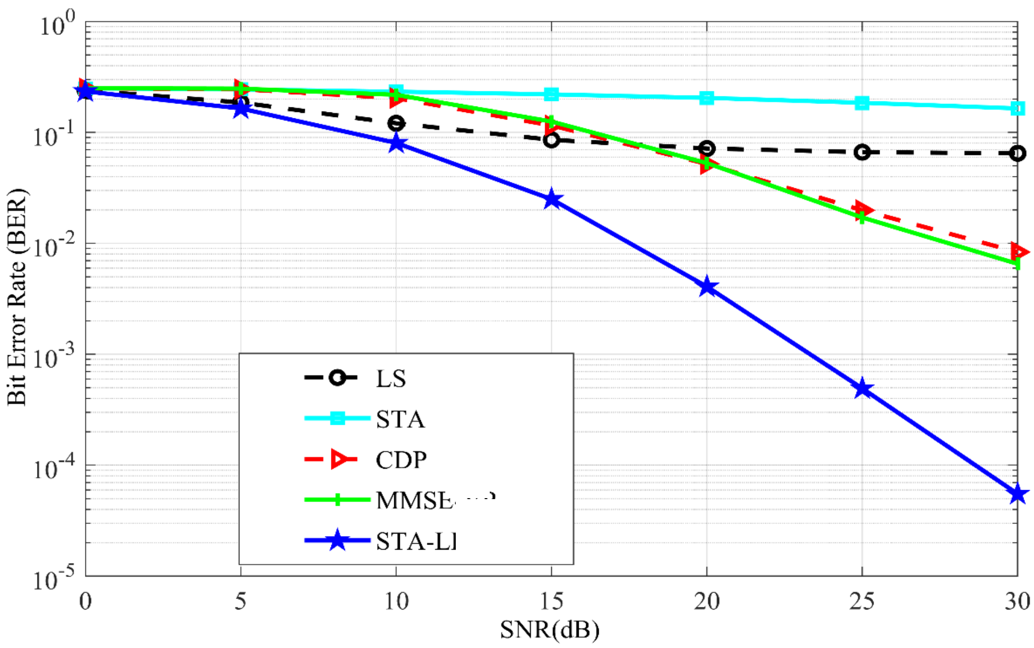


Figure 4. 15 NMSE analysis for very high mobility environment

The second observation was highly mobile in the same environment VTV-EX but different velocities and Doppler frequencies were simulated. The velocity 100Km/hr and the Doppler shift of 500. The analysis was done for BER and NMSE versus SNR. as below in Figures 4.16 and 4.17



. Figure 4. 16 BER analysis in high mobility environment

As the figure illustrates that the proposed STA-LRDNN model shows significant improvement even the transmission affected with high Doppler shift as the movement of vehicles in high speed.

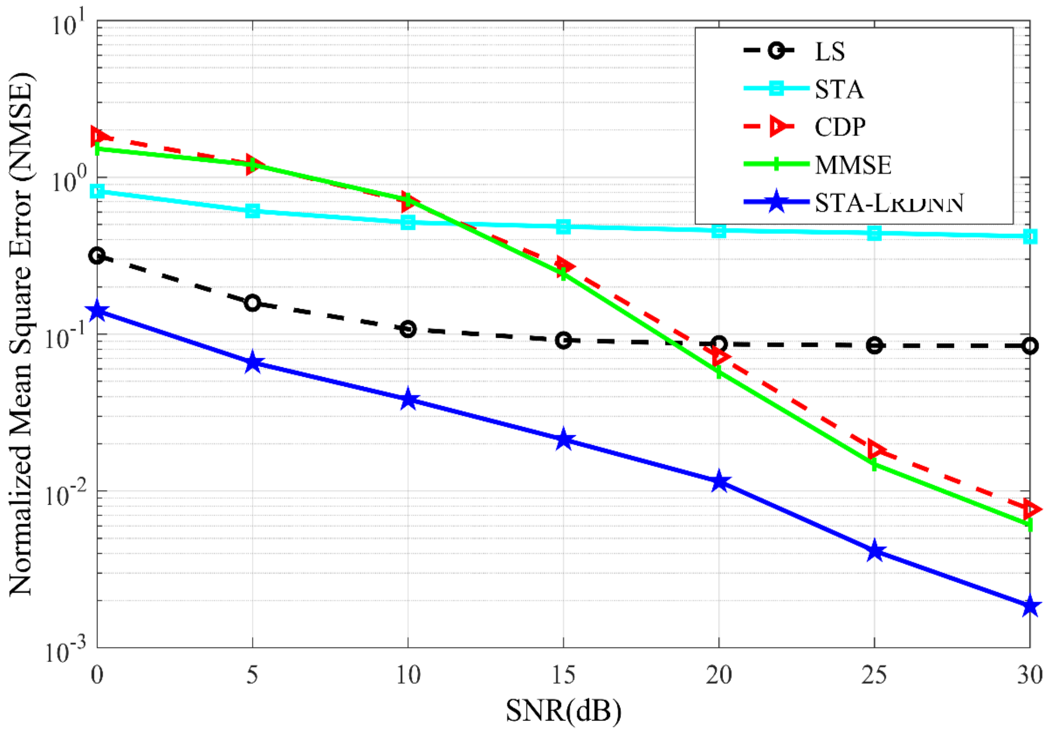


Figure 4. 17 NMSE of high mobility environment

The leaky ReLU activation function has adaptability behavior in that enables the model to train the changes in rapid manner. In addition to that it can converge while the mean value become to zero. This factor is different in ReLU based estimations.

Low mobility is examined by urban canyon channels where there is high multipath propagation because of the environment's nature. The VTV-UC channel with a velocity of 48Km/hr and 250 Doppler shifts is assigned to see the applicability of the proposed model in low mobility scenarios. Only one model is used to investigate the result. The graphical simulation result is illustrated below as Figure 4.18 in BER analysis. As the figure present in low mobility scenarios, channel estimation methods exhibit varying levels of performance. STA-LRDNN stands out as the most effective, achieving the lowest BER consistently across different SNR values, indicating its superior accuracy and robustness. MMSE also performs well, showing a significant reduction in BER as SNR increases, demonstrating good adaptability and effectiveness. CDP provides moderate performance, better than some methods but still with a relatively higher BER compared to STA-LRDNN and MMSE.

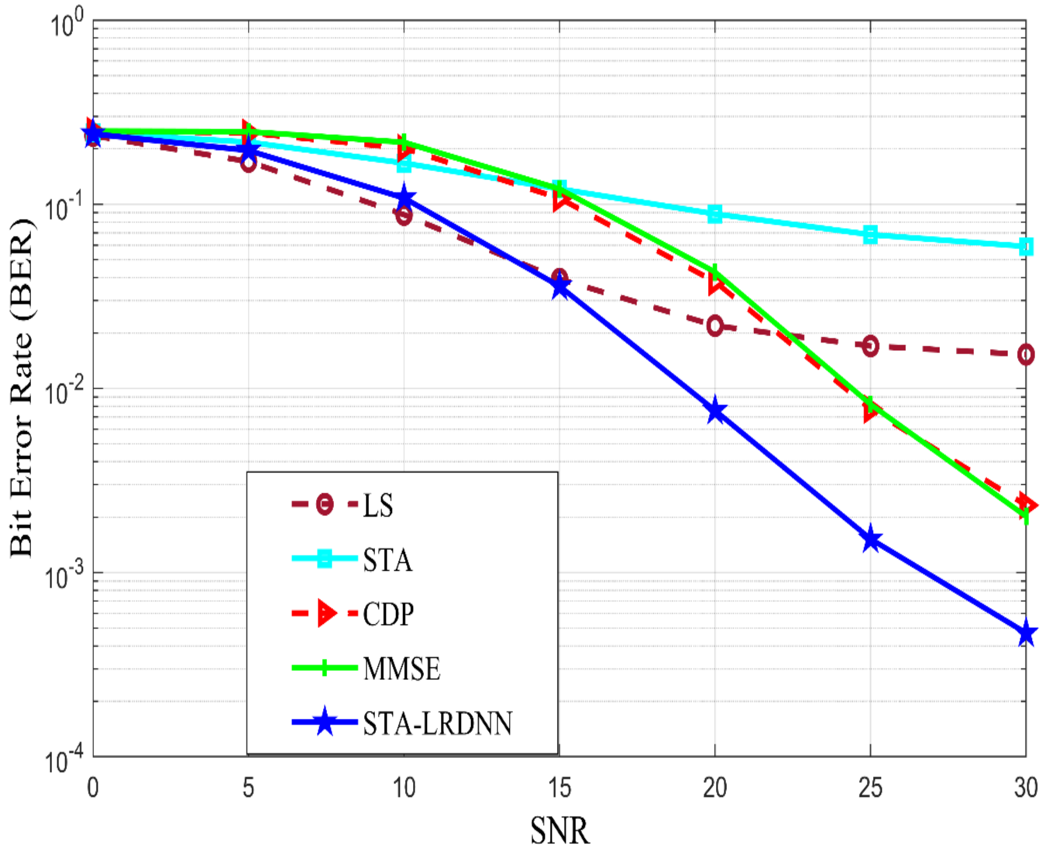


Figure 4. 18 BER of low mobility environment

The STA method has a higher BER and shows limited improvement with increasing SNR, reflecting moderate effectiveness. LS is the least effective, with the highest BER and minimal improvement across the SNR range, indicating its unsuitability for low mobility conditions. Overall, STA-LRDNN and MMSE are the preferred methods for channel estimation in low mobility scenarios due to their lower BER and better performance.

The second performance was examined as in Figure 4.19, STA-LRDNN stands out as the most effective, achieving the lowest NMSE consistently across different SNR values, indicating its superior accuracy and robustness. MMSE also performs well, showing a significant reduction in NMSE as SNR increases, demonstrating good adaptability and effectiveness. CDP provides moderate performance, better than some methods but still with a relatively higher NMSE compared to STA-LRDNN and MMSE. The STA method maintains a higher NMSE across the SNR range and shows limited improvement with increasing SNR, reflecting moderate effectiveness. LS is the least effective, with the highest NMSE and minimal improvement across the SNR range, indicating its unsuitability for low mobility conditions.

Overall, STA-LRDNN and MMSE are the preferred methods for channel estimation in low mobility scenarios due to their lower NMSE and better performance.

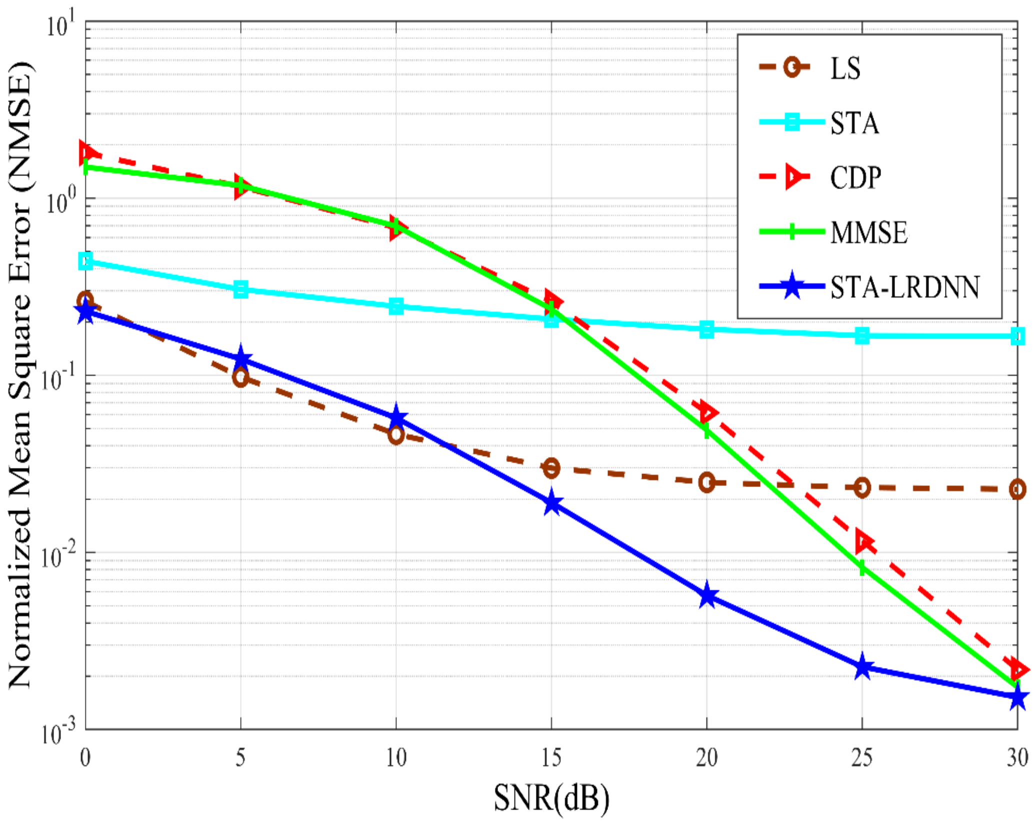


Figure 4. 19 NMSE of low mobility environment

4.7 Performance of the Proposed Model in Different Architectures

The architecture of DNN vary with number of nodes and number of layers. The selection need Complexity and size of the data consideration. The architecture with simple layers can analyze simple and basic patterns while the architecture with large network an extract complex and much features. In this work DNN model chosen as 3 layers and 30 nodes each basically. But different observations are conducted to see effect of number of layers. As shown below in Figure 4.20, two different models with three number of layers but with different nodes are considered in VTV-EX channel model. The large model with 3 layers and 30 nodes with input and output layers and 50 with hidden layers show significant improvement of BER which is near to the proposed model, but has improved at high SNR values. The convergence time is some less than the model. However, the complexity is as well increased.

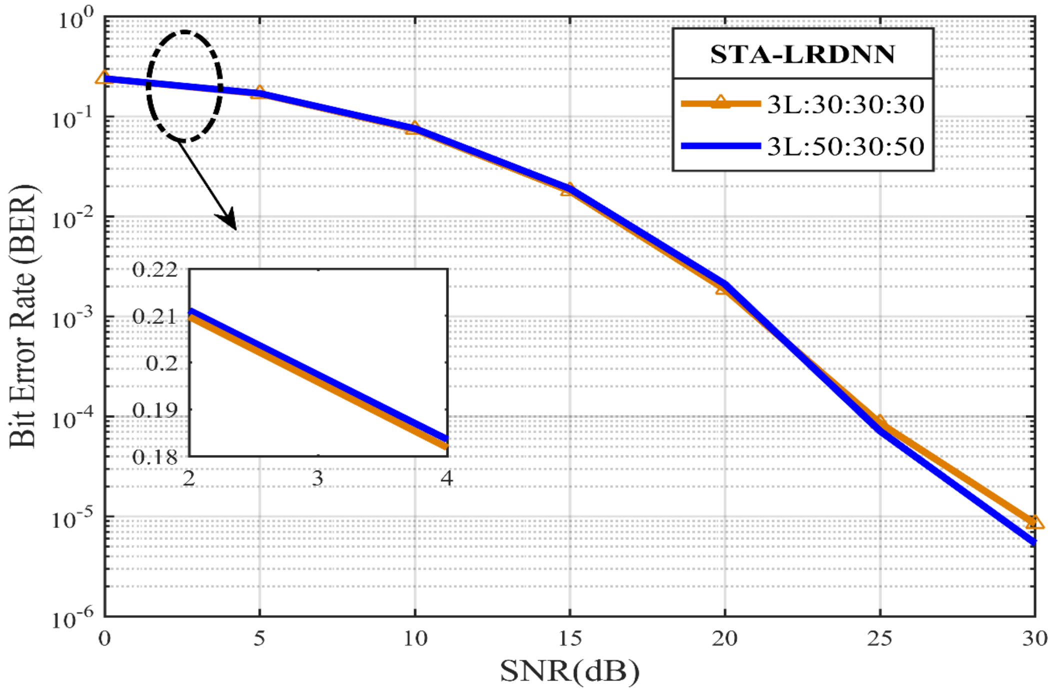


Figure 4. 20 BER analysis of STA-LRDNN with different architectures

Figure 4.21 illustrate the NMSE comparison of the two models. Both models record almost same improvement even the model with high number of nodes outperform in some range.

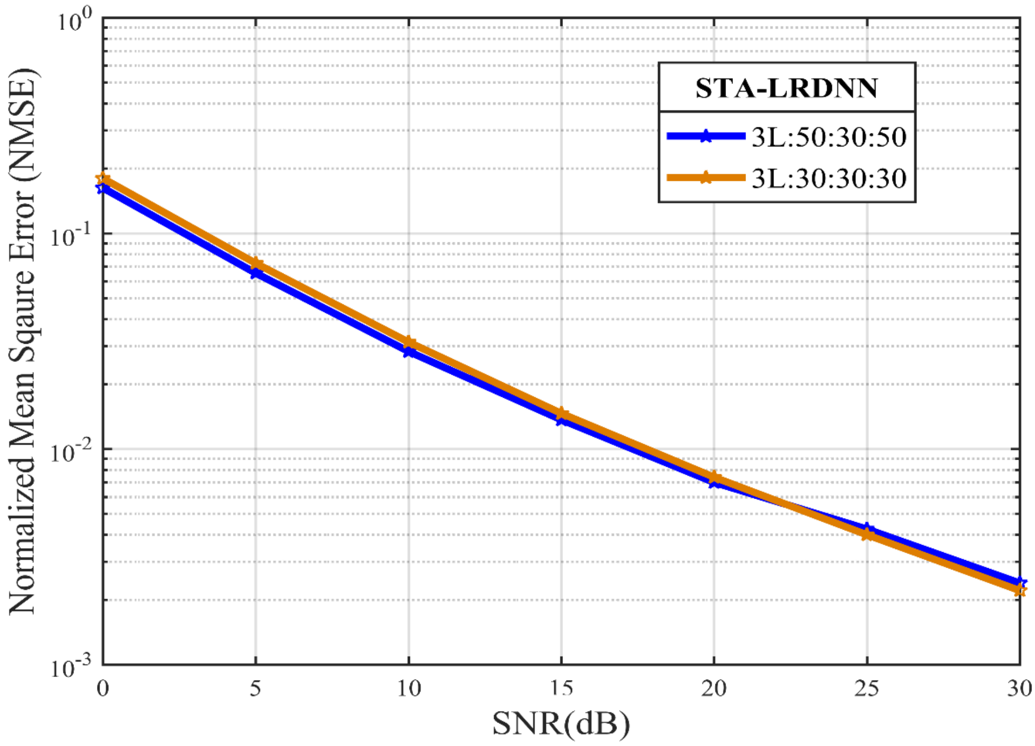


Figure 4. 21 NMSE analysis of STA-LRDNN with different architectures

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this thesis, we have addressed the critical challenge of reliable and accurate channel estimation in vehicular communication systems, which is essential for the effective deployment of intelligent transportation systems under the IEEE 802.11p standard. Given the time-varying and dynamic nature of vehicular communication channels, traditional channel estimation methods often fall short of maintaining high system performance. To overcome these limitations, we proposed a novel deep neural network (DNN) based channel estimation model specifically tailored to the unique conditions of vehicular environments. The proposed model design works by integrating ML with STA channel estimation, to provide enhanced reliability, improved accuracy, and remarkable adaptability across a variety of channel conditions and vehicular scenarios. Through rigorous testing and comprehensive validation, our DNN-based approach was evaluated against traditional channel estimation techniques using crucial performance metrics such as bit error rate (BER) and normalized mean squared error (NMSE). The results demonstrated that the proposed STA-LRDNN model significantly outperforms traditional methods, particularly across QPSK,16QAM, and 64QAM modulation orders, showcasing its robustness and effectiveness. The minimum values of 0.000015, 0.0020, 0.00001, and 0.00036 BER are recorded for VTV-EX, VTV-SDWW, VTV-UC and RTV-EX channel models respectively. The enhanced performance of the DNN-based model is attributed to its ability to learn and adapt to the complex and rapidly changing channel conditions typical of vehicular communication systems.

Furthermore, the extensive validation of the model across various vehicular scenarios underscores its practical applicability and versatility. This comprehensive evaluation ensures that the proposed model is well-suited for real-world deployment, potentially revolutionizing vehicular communication by providing a robust foundation for future intelligent transportation systems. In conclusion, this thesis makes a significant contribution to the field of wireless communication by introducing a cutting-edge solution for channel estimation in vehicular environments. The proposed DNN-based model not only meets the stringent requirements of modern vehicular communication systems but also sets a new benchmark for future research and development in this rapidly evolving domain.

5.2 Recommendation

The field of vehicular communication development with sustainability and compatibility still needs more investigation. To further enhance the performance and applicability of DNN-based channel estimation models in vehicular communication systems, several key recommendations are proposed. The use of advanced processors like GPUs or TPUs is crucial to decreasing training and inference times, making real-time applications more feasible. Expanding the dataset to include a wide range of vehicular scenarios and environmental factors will improve the model's robustness and accuracy. Increasing the number of training iterations can lead to better model convergence and performance, with careful monitoring to prevent overfitting. Real-world deployment and testing across various vehicular environments are essential to validate the model's practical applicability. Implementing continuous learning mechanisms will ensure the model remains adaptable and relevant as technologies and standards evolve. The other activation functions also can be taken as to examine future without using hyper parameter tunning. By following these recommendations, DNN-based channel estimation models can achieve greater reliability, efficiency, and adaptability, contributing significantly to the advancement of intelligent transportation systems.

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