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Présentée par:

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Dedication

From the depths of my heart, I dedicate this work to all those who are dear to me,

To The Memory of My Father

I dedicate this thesis to the memory of my father, ***HAKIM***, an inexhaustible source of inspiration. Thanks to his encouragement and confidence in my abilities, I embarked on the path of a doctorate. His persevering convictions continue to guide me.

To My Dear Mother

I dedicate this work to the most incredible woman in my life, ***Yamina SAOULI***. Your unfailing support, love, and encouragement have been my main strength throughout this academic career.

To My Wonderful Brother and Sister

Rami and ***Ranim***, your love and support mean the world to me. This work is dedicated to both of you with heartfelt gratitude.

To My Little Family

To my dearest family, my husband, ***Foudhil DAKHIA*** and my wonderful son ***Iyad Ali***. Your continued support and love have been my source of strength. I dedicate this achievement to you both with all my heart.

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Rima BENELMIR

Abstract

In today's world, road transport is essential to our daily routines and business activities. However, the exponential growth in the number of vehicles has led to problems such as traffic congestion and road accidents. Vehicular communication presents an innovative solution, envisaging a future where vehicles communicate with each other, the road infrastructure, and even the road itself, sharing real-time data to optimize traffic flow and enhance safety. This thesis focuses on 5G and Beyond 5G (B5G) technologies, which promise to revolutionize Vehicle-to-Everything (V2X) communication. With the emergence of millimeter-wave (mmWave) communication, high-speed, low-latency data transmission is essential for vehicular networks. However, mmWave communication faces problems with signal attenuation and interference. Our research focuses on solving these problems using a deep learning-based approach. Three significant contributions are proposed. First, we introduce a classical optimization technique, the simulated annealing algorithm, to improve beam alignment in 5G vehicular networks. This reduces latency and improves data transmission between millimeter-wave base stations and vehicles. Our second contribution is a new approach involving a hybrid deep-learning model that predicts optimal beam angles. Combining a 1D CNN and a BiLSTM improves the accuracy of the prediction and reduces errors. This approach eliminates time-consuming computations and iterations critical to the success of B5G vehicular networks. The third contribution introduces a BiLSTM-based model to select the optimal beam pair angles at the mmWave base station (mmBS) and the moving vehicle side. This approach improves the reliability of data transmission while minimizing the error probabilities and overheads during beam search. This research contributes to advancing vehicular communications, offering innovative solutions for 5G and B5G networks. We aim to enhance the efficiency, reduce the latency, and improve the reliability of communications for connected vehicles. This thesis explores beam alignment through classical and deep learning techniques and presents solutions for the challenges of millimeter-wave vehicular networks. Our research provides the foundation for the next generation of vehicular communication and its vital role in making road transport safer and more efficient.

Keywords: Autonomous Vehicle, Internet-of-Vehicle (IoV), Vehicular Communication, 5G/B5G networks, Millimeter-Wave, Deep Learning.

Résumé

Aujourd'hui, le transport routier est essentiel à nos routines quotidiennes et à nos activités commerciales. Cependant, la croissance exponentielle du nombre de véhicules a entraîné des problèmes tels que la congestion du trafic et les accidents de la route. La communication entre véhicules présente une solution innovante, envisageant un avenir où les véhicules communiquent entre eux, avec l'infrastructure routière, voire avec la route elle-même, partageant des données en temps réel pour optimiser la circulation et renforcer la sécurité. Cette thèse se concentre sur les technologies 5G et Beyond 5G (B5G), qui promettent de révolutionner la communication vehicle-to-everything (V2X). Avec l'avènement de la communication à ondes millimétriques (mmWave), une transmission de données à grande vitesse et à faible latence est essentielle pour les réseaux de véhicules. Cependant, la communication mmWave est confrontée à des problèmes d'affaiblissement du signal et d'interférences. Notre recherche se concentre sur la résolution de ces problèmes en utilisant une approche basée sur l'apprentissage. Trois contributions significatives sont proposées. Tout d'abord, nous introduisons une technique d'optimisation classique, l'algorithme du recuit simulé, pour améliorer l'alignement des faisceaux dans les réseaux de véhicules 5G. Cela réduit la latence et améliore la transmission de données entre les stations de base à mmWave et les véhicules. Notre deuxième contribution est une nouvelle approche impliquant un modèle hybride d'apprentissage profond qui prédit les angles optimaux des faisceaux. La combinaison d'un réseau de neurone convolutif 1D (1D CNN) et d'une mémoire récurrente bidirectionnelle à long terme (BiLSTM) améliore la précision de la prédiction et réduit les erreurs. Cette approche élimine les calculs et itérations qui prennent du temps et qui sont essentiels au succès des réseaux de véhicules B5G. La troisième contribution propose un modèle basé sur BiLSTM pour prédire les angles adaptés aux paires de faisceaux à la station de base à mmWave et du côté du véhicule en mouvement. Cette approche améliore la fiabilité de la transmission de données tout en minimisant les probabilités d'erreur et les surcharges lors de la recherche de faisceaux. Notre objectif est d'améliorer l'efficacité, de réduire la latence et d'améliorer la fiabilité des communications pour les véhicules connectés. Notre recherche pose les bases de la prochaine génération de communication entre véhicules et de son rôle essentiel dans la sécurité et l'efficacité du transport routier.

Mots Clée : Véhicule Autonome, Internet des véhicules, Communication Véhiculaire, Réseaux 5G/B5G, Ondes Millimétriques, Apprentissage Profond.

Publications

Journal Paper

- [1]: Rima Benelmir, Salim Bitam, Scott Fowler, and Abdelhamid Mellouk, A novel MmWave Beam Alignment Approach for Beyond 5G Autonomous Vehicle Networks. IEEE Transactions on Vehicular Technology, 2023. **(Impact Factor = 6.239).**

Conference Papers

- [2]: Rima Benelmir, Salim Bitam and Abdelhamid Mellouk, An efficient autonomous vehicle navigation scheme based on LiDAR sensor in vehicular network. IEEE 45th Conference on Local Computer Networks (LCN), 2020, p.349-352.

- [3]: Rima Benelmir, Salim Bitam and Abdelhamid Mellouk, Simulated annealing-based beam management for 5G vehicular networks. IEEE 22nd International Conference on High-Performance Switching and Routing (HPSR), 2021, p- 1-4.

- [4]: Rima Benelmir, Salim Bitam and Abdelhamid Mellouk, Deep Learning-Based Beam Pair Angle Prediction for Beyond 5G Millimeter-Wave Vehicular Communication. IEEE Global Communications Conference (GLOBCOM), 2022, p. 401-406.

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Chapter 1

Introduction

1.1 Context

In our modern world, road transport is like the lifeblood that supports everything we do. It plays a massive role in our economies, accounting for around 12% of a country's total economic activity, and is an essential part of our daily lives. Just think: people spend around 8% of their working day, or about two hours, traveling to and from work [14]. Nevertheless, here is the thing: Over the last fifty years, we have seen an explosion in the number of vehicles on the road. Around 60 million cars were sold annually between 2005 and 2020 [15]. This rapid growth has created a significant problem, particularly in our cities. It is called traffic congestion, causing all sorts of problems. All these traffic congestion and delays prevent us from being as efficient at work. Road accidents cause death and injury. Every year, 1.35 million people die in road accidents, and millions suffer damages that can change their lives forever [16].

1.2 Motivation and Objectives:

In the face of the challenges posed by increasing road traffic, vehicular communication provides a new light of hope. Vehicular communication represents a transformative technology that aims to change how vehicles interact with each other and their environment. It is about imagining a scenario where the vehicle communicates transparently with other vehicles, traffic lights, and even the road infrastructure. The vehicle shares real-time information about traffic conditions, road dangers, and the most efficient routes with other vehicles. Congestions are a thing of the past as vehicles coordinate to optimize traffic flow. Moreover, the vehicle's safety systems are in constant communication, reducing the risk of accidents to a minimum.

Recently, significant advances in wireless communication have facilitated the efficient transmission of real-time data over multiple channels, including vehicle-to-pedestrian (V2P), vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) and cellular network (V2N) communications. Implementing vehicle-to-everything (V2X) communication can improve several aspects of transport, including road safety, efficient use of roads, reduced fuel consumption, and improved driving comfort. Today's vehicles are increasingly equipped with many sensors capable of observing and interpreting their environment. These sensors provide signals that enable the vehicle to react accordingly, thus launching the first stages of autonomous driving. However, a vehicle may need to access all the necessary information in a dynamic environment quickly. Cooperation between vehicles via vehicular communication is a promising way of meeting this need.

The next generation of cellular networks, namely the fifth generation (5G) and beyond 5G (B5G), promises to open up a new era of connectivity and interaction for vehicular communication systems in this technologically advanced era. These advanced network paradigms are ready to meet the growing demands of our connected world, designed to respond to a wide range of vehicles while guaranteeing low latency and efficient data rates. Integrating 5G and B5G technologies into vehicle communication systems could transform how vehicles communicate with each other and the complex network of urban infrastructures. This revolutionary technology, introduced by the International Telecommunications Union (ITU) in 2015 as 5G New Radio (NR), is the foundation for advanced vehicular communication.

Millimeter-wave (mmWave) communication has emerged as a critical element of 5G/B5G with the development of autonomous vehicle networks. For V2X communication, particularly in highly dynamic conditions, the enormous bandwidth of these frequencies - 30 GHz to 300 GHz - enables a fast transmission rate and low latency. Nevertheless, it is well known that path loss due to the short propagation distance and signal attenuation produced by surrounding static and/or dynamic barriers is the main difficulty of communication at millimeter wave frequencies. Integrating beamforming with mmWave technology compensates for signal power losses by concentrating transmissions in specific directions, significantly reducing interference. The result is reliable communication connections, even in highly mobile environments, offering a significant gain in beamforming performance. It should be noted that most studies on millimeter-wave vehicular communications in the context of 5G/B5G networks have focused mainly on the beam alignment procedure.

Research in this field can be categorized into three main areas:

1. **Beam Scanning (Extensive Search):** This method thoroughly searches 360 degrees of beam directions to find the optimal pair. However, this process can be

time-consuming and energy-intensive [17], [18].

2. **Vision-Assisted Approaches:** This category includes techniques that utilize data from radar [19], Lidar [20], and cameras [21]. These vision-assisted methods, while effective, may introduce additional costs associated with beam calculation and selection.

3. **Angle-of-Departure/Angle-of-Arrival Prediction:** This approach relies on contextual information, such as the positions of vehicles and base stations, to predict optimal angles for beam alignment.

1.3 Contributions

This thesis is dedicated to advancing the vehicular communications field in the emerging 5G/B5G technology paradigm. We aim to improve the efficiency and performance of communications for connected vehicles with three main contributions.

First, we introduce a new approach designed to tackle the complexities of beam alignment in 5G vehicular networks. This first contribution exploits the power of classical optimization methods, notably the simulated annealing algorithm. We use this algorithm as a fundamental part of our beam management solution, enabling more efficient data transmission and reduced latency between mmBS and moving connected vehicles.

Then, to enable the ability to send data directly to a moving vehicle from an mmBS, we propose a new technique for selecting the appropriate beam Angle of Departure (AoD). Our proposal differs because we propose a deep learning-based hybrid beam alignment by integrating a 1D convolutional neural network with four hidden layers based on BiLSTM. Our proposed method makes use of mmWave channel data to maximize the received signal strength to predict the most effective beam angle. Therefore, when 1D-CNN is combined with BiLSTM, the prediction accuracy is much enhanced, and the probability of mistakes in both the predicted and actual values is significantly reduced. Our suggested CNN-BiLSTM model does well regarding precision, speed, and efficiency. Our proposal avoids the time-consuming computations and iterations required by conventional exhaustive search and beam scanning techniques. To find the optimal beam direction for each data transmission, these methods perform a full-circle search. This innovation is important for vehicular networks, as it improves the signal-to-noise ratio (SINR) and received signal strength of V2I transmissions between autonomous cars and mmBS. It also reduces the computing power of the B5G vehicular millimetre-wave network.

Finally, in the third contribution, we propose a new beam-pair prediction approach based on bidirectional long-term memory (BiLSTM-BPP) for line-of-sight mmWave vehicular networks. This approach aims to predict the optimal beam pairs that establish connections between the vehicle on moving and the mmBS, specifically, the Angle of Departure (AoD) in Azimuth at the mmBS and the Angle of Arrival (AoA) in Azimuth at the vehicle side. By using location information, this approach improves the reliability of data transmission while minimizing the error probabilities and overheads associated with beam search.

1.4 Thesis Structure

In this general introduction, we provide an overview of the motivation for this study, highlighting the key contributions that form the core of this thesis. We also present the structure of this thesis, which consists of seven main sections. The first part, including this general introduction, sets the context by presenting the primary motivation and organization of the thesis. The following chapter focuses on the essential elements of connected autonomous vehicle (CAV) networks. We explain the different types of vehicular communication and the technology behind them, and we explore mmWave technology and the challenges faced in vehicular networks. A good understanding of these fundamentals will form the basis of our study. In the second chapter, we propose a comprehensive taxonomy clarifying the evolution of vehicular networks about beam alignment. This taxonomy classifies existing techniques, from classical optimization approaches to methods exploiting deep learning capabilities. We review several related works in this area, providing a detailed survey of this research field. Finally, we conclude this chapter by posing the problem that will be our study's focus. The third chapter presents the first contribution that we have proposed based on the classical optimization method, notably the simulated annealing algorithm. The fourth chapter details our second contribution based on a hybrid deep-learning model to predict the best beam angle at the mmBS side for efficient communication in B5G vehicular networks. Moreover, the fifth chapter introduces our third contribution, based on the BiLSTM model, to address the challenges posed by our second contribution. This model ensures the suitable beam pair angle prediction at the mmBS and the vehicle side. Finally, the general conclusion summarizes the main findings and conclusions from the previous chapters. It identifies unresolved challenges and potential future research directions in learning-based communication in vehicular networks.

Chapter 2

Background concepts

In recent years, the massive increase in vehicles on our roads has stimulated the rapid development of vehicular networks. These networks represent a central element in the structure of future intelligent transport systems (ITS), offering solutions to the critical challenges of modern urban mobility. The heart of these networks is the innovative concept of vehicular communication, which has the potential to revolutionize the way vehicles interact with each other and with the surrounding infrastructure.

This chapter covers the basic concepts of connected autonomous vehicular networks, types of vehicular communication, and technologies used in vehicular networks. Next, the millimeter wave (mmWave) beamforming system is presented. Finally, we introduce the challenges facing this field.

2.1 Internet of Vehicles

The Internet of Vehicles (IoV) is a subset of the Internet of Things (IoT), a global network that interconnects and enables seamless communication between intelligent objects. It extends these capabilities specifically to vehicles, launching the era of intelligent transport.

The concept of the IoV dates back to the end of the 20th century when it became clear that many accidents were caused by human error at the wheel. To remedy this problem, the idea of deploying interconnected autonomous vehicles gained ground. This paradigm shift has led to the emergence of new concepts, such as interconnected autonomous vehicles and vehicular communication systems. These innovations facilitate cooperation and information sharing between the various nodes that comprise the modern road infrastructure, as depicted in Figure 2.1.

Figure 2.1: Representation of Internet of Vehicles (IoV)

2.1.1 What is an autonomous vehicle?

An autonomous vehicle (AV) can make decisions and move without human intervention. AVs are equipped with various sensors to enable intelligent and efficient navigation, allowing them to avoid collisions and detect static and moving objects in their surroundings. This enables them to operate effectively even in new or unexpected situations, including encounters with dynamic obstacles [22]. In recent years, AVs have gained popularity due to their potential to liberate individuals from the responsibility of driving, thereby allowing them to utilize their time more productively. This shift also has the potential to reduce traffic accidents by minimizing human involvement in driving, and it promises a more enjoyable driving experience compared to conventional vehicles. The Society of Automotive Engineers (SAE) has categorized driving automation into six levels, as depicted in Figure 2.2, ranging from Level 0 (completely manual) to Level 5 (highly automated or fully autonomous) [23].

2.1.2 What is a Connected Vehicle?

A connected vehicle (CV) has advanced technology that enables wireless communication and sharing safety-related messages with other devices, including infrastructure, vehicles, and pedestrians. This communication capability allows connected vehicles to exchange

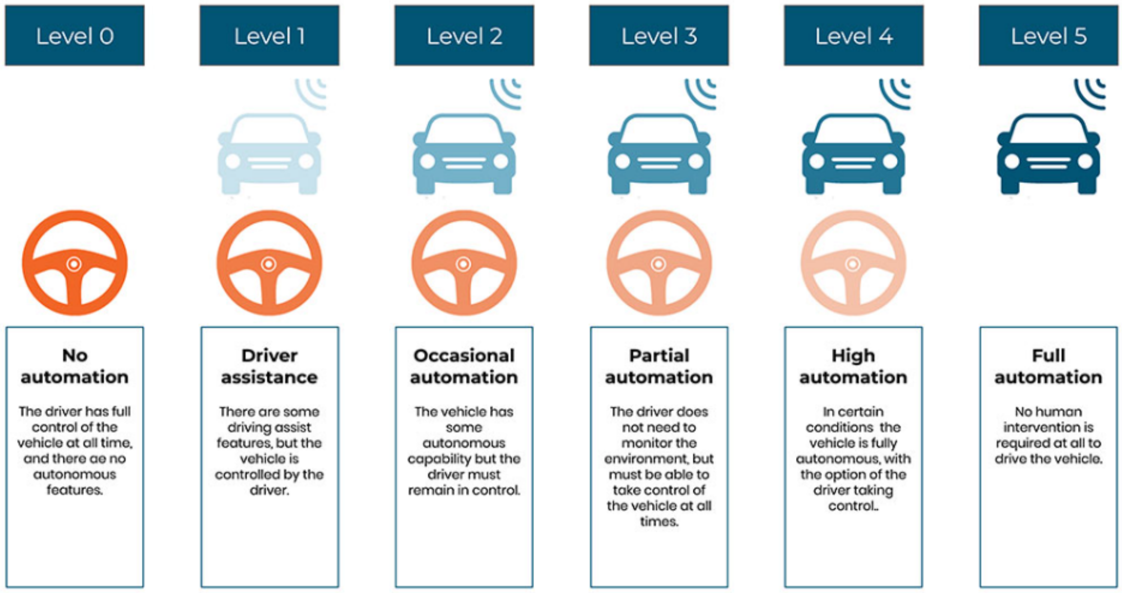

Figure 2.2: The levels of vehicle autonomy [5]

continuous information, including transmitting their precise positions and receiving real-time data that triggers automated responses within the vehicular environment. Consequently, connected vehicles are empowered to make informed decisions, accurately determine their location around the surroundings, and enhance overall safety while driving [24].

2.1.3 Connectivity Types in IoV

In a vehicular network, the connected autonomous vehicle acts as a sensor that captures information from its environment. It exchanges data with nodes that belong to the network via various types of communication technologies. The following subsections present the different types of vehicle communication and introduce how vehicular communication can enhance the vehicle's network. These connectivity types are summarized in Table 2.1.

2.1.3.1 Infrastructure-to-infrastructure (I2I)

I2I communication involves interactions between different components of the road infrastructure. This can include communication between roadside units (RSUs), traffic signs, traffic lights, access points, road sensors, and cellular base stations. I2I communication is a connective tissue that enhances the IoV infrastructure, enabling efficient coordination and information sharing between these critical elements.

Table 2.1: Connectivity Types in IoV

Connectivity Type	Description
Vehicle-to-Vehicle (V2V)	Communication between vehicles on the road
Infrastructure-to-Infrastructure (I2I)	Communication between roadside infrastructure components
Vehicle-to-Infrastructure (V2I)	Communication between vehicles and roadside infrastructure
Vehicle-to-People (V2P)	Communication between vehicles and pedestrians or drivers
Vehicle-to-Everything (V2X)	Comprehensive connectivity involving vehicles, infrastructure, people, and more

2.1.3.2 Vehicle-to-Everything (V2X)

This communication type establishes connections across various components of the transportation ecosystem, including pedestrians, vehicles, infrastructure, and cloud environments. V2X communication catalyzes gathering more data, advancing autonomous driving technologies, and building intelligent transportation systems. It plays a pivotal role in enabling efficient autonomous driving, enhancing transportation efficiency, reducing pollution, lowering accident rates, and improving service quality [25]. V2X encompasses four essential communication types, as Figure 2.3 illustrates.

2.1.3.3 Vehicle-to-Infrastructure (V2I)

V2I communication facilitates interactions between vehicles and intelligent road infrastructure. V2I enables vehicles to make informed decisions in complex scenarios like four-way stops and enhances traffic efficiency by providing real-time information about road conditions or obstacles. This communication mode relies on centralized wireless control [26].

2.1.3.4 Vehicle-to-Vehicle (V2V)

V2V communication, also known as inter-vehicle communication, is exclusive to vehicles. Without centralized coordination, it allows direct message exchange between two vehicles regarding speed, position, road conditions, and safety alerts. V2V communication remains operational even if RSU stations fail or communication ranges are exceeded. It contributes to accident reduction, route optimization, and safety awareness among nearby road users [27].

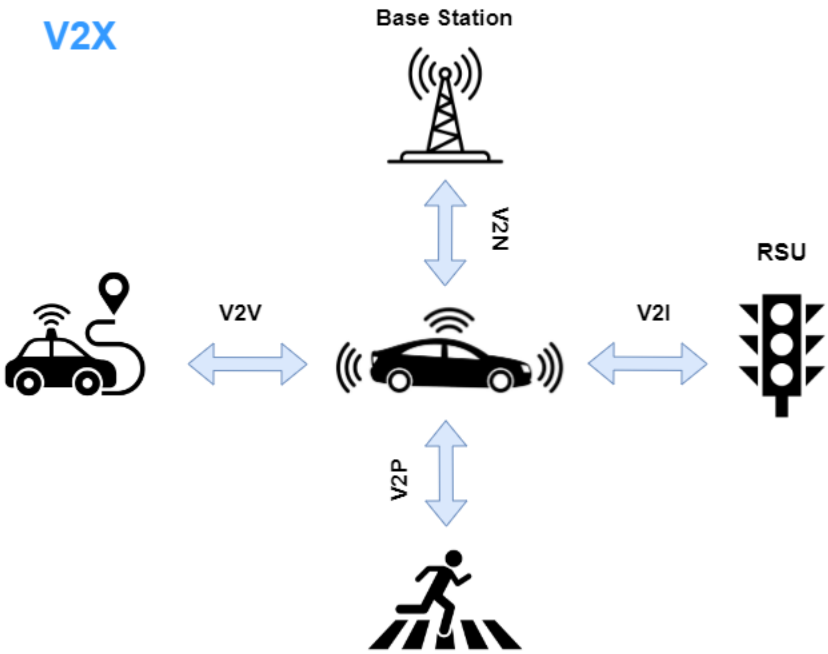

Figure 2.3: Types of V2X communication by IoV

2.1.3.5 Vehicle-To-Pedestrian (V2P)

V2P communication involves interactions between vehicles and non-motorized road users, such as pedestrians and cyclists. These communications aim to minimize collision risks between vehicles and road users using smartphones for communication. The primary goal is to enhance overall road safety for all users.

2.1.3.6 Vehicle-To-Network (V2N)

V2N communication connects vehicles with elements of the cellular communication network, typically Base Stations (BS). It is an alternative to V2I communication in areas lacking roadside equipment (RSU). V2N facilitates information exchange between vehicles, including data about road conditions and accidents. Additionally, V2N enables vehicle internet access, allowing them to connect to remote services. This extends to Vehicle-to-Cloud (V2C) communications [28], which support global road safety management and traffic control applications.

2.1.4 Architecture of IoV

The IoV architecture is a comprehensive framework that integrates various technologies to achieve inter-vehicular connectivity and provide a wide range of services. These services include applications related to road safety, roadside assistance, driving efficiency, remote monitoring, congestion avoidance, maintenance, and system failures. The main elements of the IoV architecture include many onboard sensors, communication infrastructures, and vehicles. The motivation for advancing this technology is to improve road safety, optimize traffic flow, reduce fuel consumption, and minimize travel costs.

The fundamental infrastructure required to implement and deploy autonomous connected vehicles (ACVs) to support intelligent transport systems (ITS) can be described in Figure 2.4. This architecture comprises two main types of nodes:

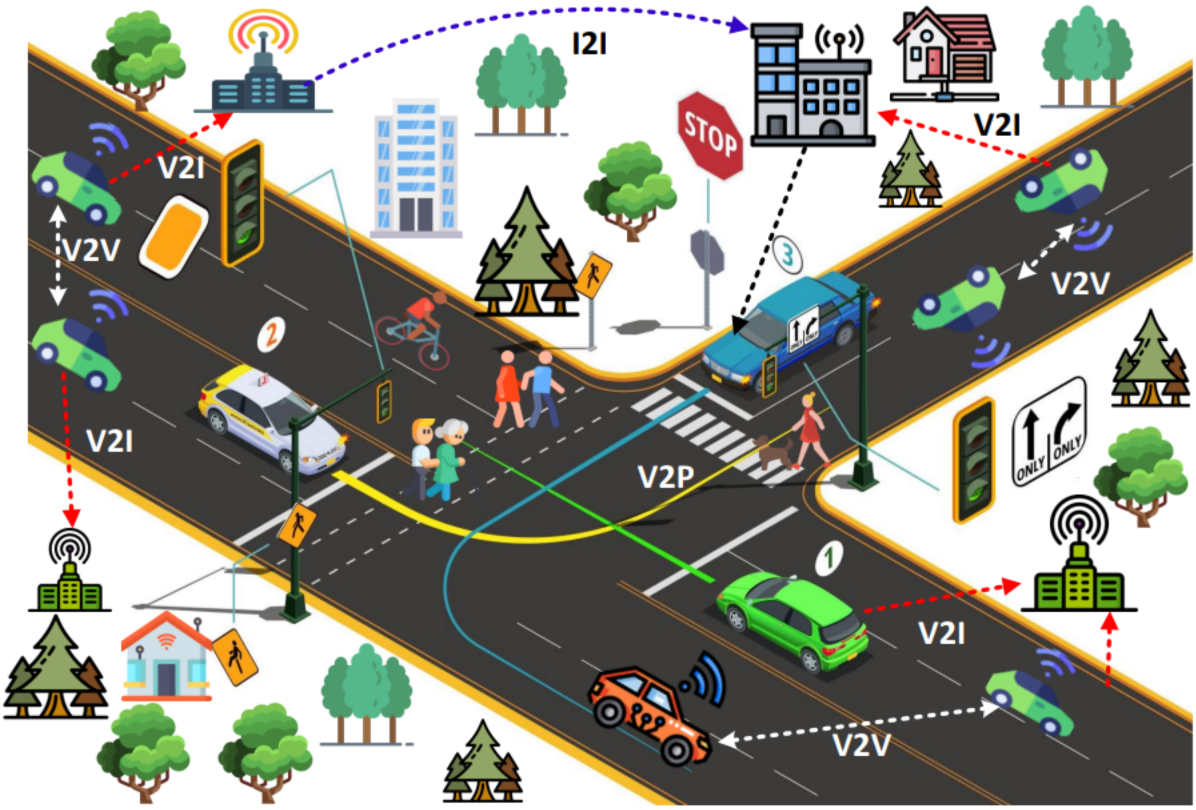

Figure 2.4: Representation of ITS, [6]

- **Vehicles:** Equipped with onboard sensors, these vehicles play a central role in collecting and sharing data. The sensors are responsible for detecting objects and obstacles within their range. The sensors commonly used, their field of detection, and their typical applications are presented in Table 2.2, [6].

- **Communication infrastructure:** This infrastructure, along roads, facilitates communication between vehicles and the wider network. The architecture uses several communication channels, including V2V, I2I, V2I, vehicle-to-person (V2P) and V2X.

Table 2.2: On-Board Sensors: Types, Ranges, and Applications

Sensor Type	**Range**	**Example**	**Applications**
Proximity Sensors	5 meters	Ultrasonic sensor	Detects nearby obstacles, Assists in parking
Short-range sensors	30 meters	Forward camera, Backward camera, Short-range radars	Recognizes traffic signs, Detects blind spots, Alerts oncoming traffic, Assists in lane detection
Medium-Range Sensors	80-160 meters	LiDAR, Medium-range radars	Detects pedestrians, Aids in collision avoidance
Long-Range Sensors	250 meters	Long-range radars	Supports adaptive cruise control, Collects information at high speeds

The general ACV architecture comprises three layers, each dedicated to specific functionalities:

- **Perception layer:** This fundamental layer collects raw data from the vehicle's environment using onboard sensors. The data collected is processed using sensor fusion techniques to calculate local and global location parameters. This layer also generates a map of the environment.

- **Planning/processing layer:** Placed above the perception layer, this layer is essential in route planning. It determines the optimal overall route based on the vehicle's current position, destination, and real-time road and traffic data. Using the environment map generated by the perception layer, this layer calculates trajectory planning and tracking.

- **Control layer:** The control layer provides commands to control the vehicle's actuators, including the steering wheel, accelerator pedal, and brake pedal. It ensures the vehicle operates according to the planned route and follows safety protocols.

In addition to these primary functions, the perception layer shares environmental information with other road users, promoting cooperative driving. Decision-making is an essential function of the planning layer, where high-level control decisions are made, such as controlling servo motors and actuators. The complexity of making critical decisions in real-time requires connectivity between vehicles, infrastructure, and road users, further underlining the importance of interconnectivity in deploying ACVs.

2.1.5 Key Technologies for IoV

Traditional methodologies that have proven effective in real-time may not be suitable for implementing and deploying the various advanced features of ACVs. However, recent sensors, cloud computing, and artificial intelligence innovations offer promising solutions for developing intelligent, connected autonomous vehicles that can provide many benefits. This sub-section explores current technologies that support the deployment of connected autonomous vehicles in the real world.

2.1.5.1 Sensing environment

Unlike traditional vehicular networks focusing primarily on homogeneous or single-type sensors, ACVs use a wide range of heterogeneous sensors. These sensors perform various functions and can be classified into three categories, as shown in Figure 2.5.

- **Detection sensors:** These sensors are generally mounted on the vehicle and are responsible for identifying the various characteristics of the surrounding environment. They also play a role in monitoring the internal state of the vehicle.
- **Ambient sensors:** Ambient sensors are designed to monitor the environment and collect valuable data. The data collected by these sensors is forwarded to the relevant authorities for analysis [29].
- **Backscatter sensors:** These are versatile and can be integrated into various objects. They provide a better perception of the surrounding environment and detect objects like intruders and cyclists.

2.1.5.2 Data Access

ACVs generate significant data through signals emitted by sensors in, on, and around vehicles. This data must be accessible to authorized authorities, other vehicles in the network, and the various infrastructures in the vehicular environment to enable them to make timely decisions. Hosting this data requires resources and high-end servers for temporary storage and archiving.

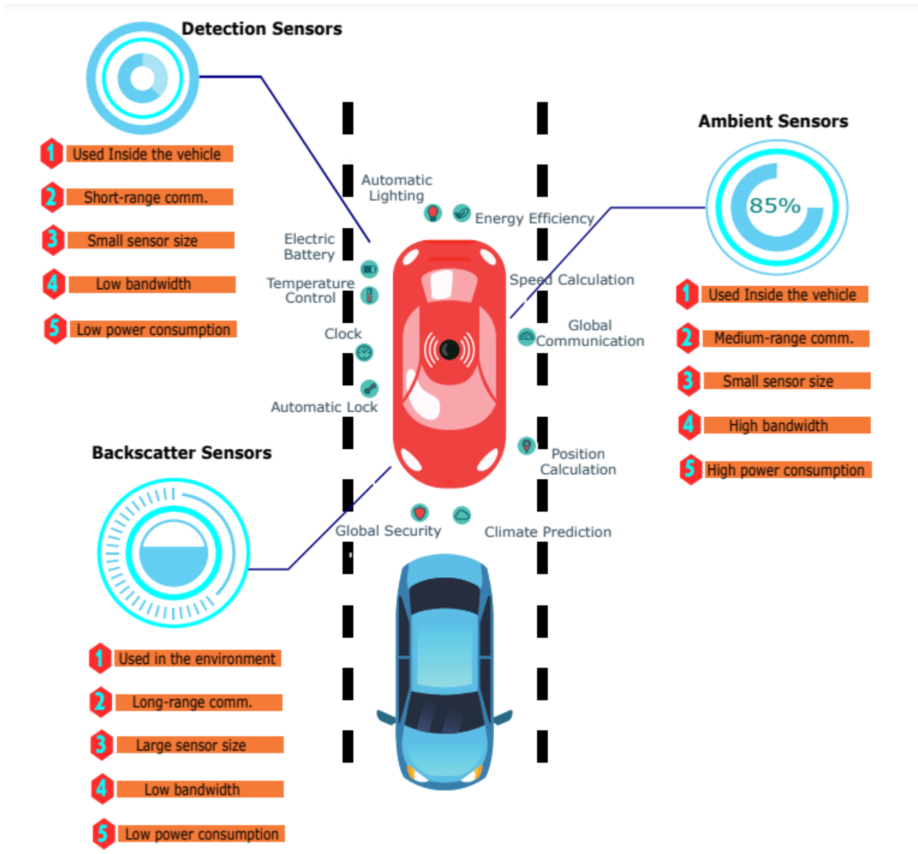

Figure 2.5: Intelligent sensing technology of connected autonomous vehicles [7]

Cloud computing technology has recently made it possible to meet the data access challenge by offering on-demand virtual resources. This enables ACVs to communicate effectively with each other, with the infrastructure, and with all elements of their environment. In addition, fog, edge, and rooftop computing technologies have emerged to support data access, with some ACV fog nodes operating on the principles of fog computing. These nodes provide valuable environmental information and facilitate inter- and intra-vehicular communication. The fog nodes can further process the data collected, and analyses can be performed on the crowd-sourced data from the ACVs. Various optimization algorithms improve the performance of fog nodes.

2.1.5.3 Data Security and Privacy

Security is a significant concern in vehicular communication, mainly when the environment encompasses older and autonomous vehicles. Appropriate security measures are essential to avoid confusion. Recent developments have introduced Physical Layer Security (PLS) as a viable alternative to traditional cryptography. Studies have shown that PLS can improve performance in terms of privacy and enable confusion techniques between source and destination. PLS can also prevent vehicles from broadcasting false data.

Blockchain techniques are increasingly being adopted in various applications to establish trust models for ACVs. These trust models typically involve additional policies and certificates to ensure the security and confidentiality of communications.

2.1.5.4 Vehicular Communication

ACV performance highly depends on the data received from various sensors. To improve performance, the communication bandwidth must support data rates of gigabits per second. Millimetre-wave (mmWave) technology is used for ACVs, enabling high-performance V2X communications.

V2V mmWave links enable vehicles to share information in real-time with neighboring vehicles in their environment. V2I mmWave links have applications in road safety, facilitating data collection from vehicles for decision-making. ACVs also use high-speed mmWave links to download real-time maps and dynamic environmental feeds. Continuous communication between vehicles and their environment is essential to achieving full vehicle autonomy. The following sections will provide a detailed exploration of the enabling communication technologies for autonomous vehicle networks.

2.2 Vehicular Communication Technology

Wireless communication of sensor data plays a crucial role in extending the capabilities of connected vehicles, advancing autonomous driving, and reducing reliance on human drivers. Although effective, traditional technologies such as dedicated short-range communication (DSRC) or fourth-generation cellular connectivity (4G-LTE) often fail to meet the high-bandwidth, low-latency requirements of V2X communication. In response to these challenges, the evolution of vehicular communication technology has led to the emergence of fifth-generation (5G) and beyond 5G (B5G) networks. These advanced technologies, which use mmWave communications, offer promising solutions to autonomous vehicle networks' high bandwidth and low latency requirements.

2.2.1 5G and Beyond 5G Technologies for Vehicular Communication

In the following subsections, we examine the evolution of vehicular communications technology, particularly the evolution of 5G and B5G networks. We discuss why mmWave communications in 5G and B5G networks are emerging as preferable solutions for data exchange in autonomous vehicular networks.

2.2.1.1 5G Technology for Vehicular Communication

With the advent of fifth-generation (5G) mobile communications, vehicular networks have taken a significant step forward, building on advances in Long Term Evolution Advanced (LTE-A) and LTE-A Pro standards. Instead of a radical break with its predecessors, 5G seeks to create a unified vehicle network by combining various existing techniques to improve V2X communication. A fundamental aspect contributing to the success of 5G is its ability to support a wide range of use cases within vehicle networks. This has necessitated the early identification of three critical generic services for new scenarios: Enhanced Mobile BroadBand (eMBB), massive Machine Type Communications (mMTC), and Ultra-Reliable Low-Latency Communication (URLLC), as indicated by the Third Partnership Project (3GPP) [8]. Figure 2.6 visually summarises the importance of eight key performance indicators (KPIs) for these three core 5G services:

- **eMBB** is designed for bandwidth-intensive applications that often require extremely high throughputs over stable/long connections.
- **mMTC** is aimed to support a high number of IoV devices. These devices, often only active briefly to transmit short data payloads, must operate with low power consumption while providing sensing and actuation capabilities.
- **URLLC** is designed for services with high availability, latency, and reliability requirements, and it also deals with high mobility.

The new 5G added new techniques and features to satisfy these different requirements for vehicular communications, which will be described briefly by following:

- **Millimeter waves (mmWave):** mmWaves are high-frequency radio waves in 5G networks that provide greater bandwidth and faster data transmission. They are particularly effective for short-range, high-speed communications in vehicular networks.
- **Device-to-Device (D2D) communications:** D2D communication allows vehicles to communicate directly with each other without going through a centralized network. This reduces latency, improves response times, and enhances safety applications in vehicular networks.

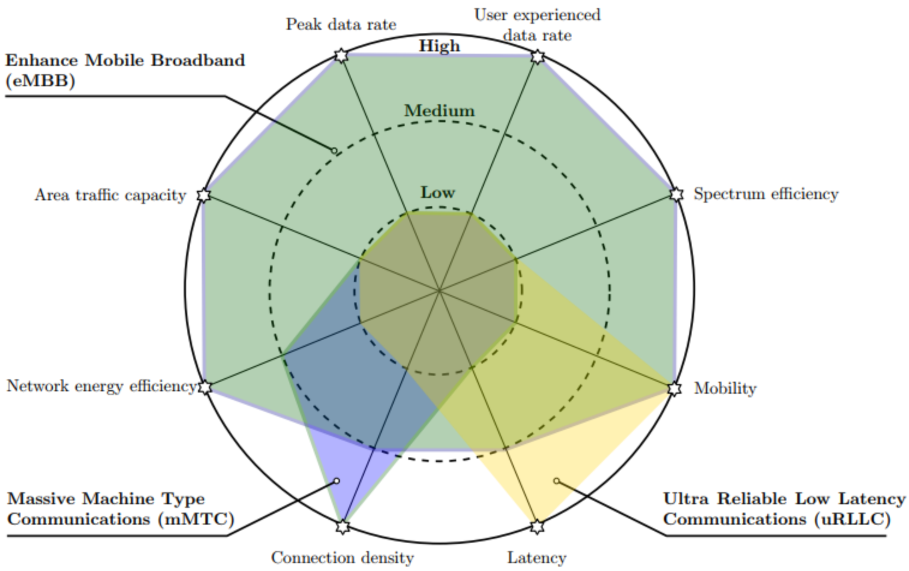

Figure 2.6: Spydergraph of eight critical 5G capabilities for 5G core services [8]

- **Beamforming:** Beamforming technology focuses radio signals on specific devices or areas of the network. By concentrating the signal, Beamforming improves signal strength, reduces interference, and improves communication reliability.

- **Massive Multi-Input-Multi-Output (MIMO):** MIMO technology uses multiple antennas to transmit and receive data simultaneously. It improves signal quality, network capacity, and overall reliability in vehicular networks.

- **Small cell:** Small cell deployments involve placing small, low-power base stations in urban areas. This approach extends network coverage and capacity and ensures seamless communication in densely populated areas.

- **Non-Orthogonal Multiple Access (NOMA):** NOMA is a multiple access technique that allows multiple devices to share the same spectrum of resources efficiently. It optimizes network utilization and supports a higher density of connected devices.

- **Virtualization: Network Function Virtualization (NFV):** NFV is a technology that virtualizes network functions, allowing them to run on a virtualized infrastructure rather than on dedicated hardware. This improves the flexibility, scalability, and cost-effectiveness of network management.

- **Software-Defined Networking (SDN):** SDN centralizes network control by separating the control plane from the data plane. It makes network management more flexible, allowing dynamic adjustments to meet the changing demands of vehicular networks.

- **Network Slicing:** Network slicing creates virtual networks within the 5G infrastructure. Each network slice is customized to meet the specific requirements of different vehicular applications, ensuring efficient resource allocation and quality of service.

According to the Third Generation Partnership Project (3GPP), 5G networks are divided into frequency bands, classified as FR1 (Sub-6GHz) and FR2 (mmWave). While the Sub-6GHz band encompasses the existing LTE spectrum, the mmWave band operates in the frequency range from 30 to 300 GHz. The shorter wavelengths of mmWave allow for higher data transmission rates and more abundant transmission channels, reducing network congestion. However, it is essential to recognize that mmWave signals have limited penetration capabilities and are sensitive to obstructions such as buildings, trees, and adverse weather conditions.

2.2.1.2 Beyond 5G (B5G) Technology for Vehicular Communication

Building on the foundations of 5G, B5G technology is emerging as the next frontier in vehicular communications. B5G technology promises to take V2X communication to unprecedented levels. It explores even higher frequencies, applying advanced beamforming techniques and refining network slicing. The synergy between 5G and the unlimited potential of B5G will revolutionize vehicular networks, paving the way for an era of increased safety and efficiency and fully connected transport systems.

2.2.1.3 B5G Advances in Vehicular Communication

B5G technology brings several advances that should improve vehicular communications based on mmWave. Critical differences between 5G and B5G are summarized in Table 2.3.

- **Frequency range:** One of the critical distinctions between 5G and B5G is their respective frequency ranges. While 5G operates primarily in the sub-6 GHz and mmWave frequency bands, B5G extends further into higher frequency ranges, surpassing traditional mmWave bands. This extension gives B5G access to much greater spectrum resources, potentially increasing data rates and reducing latency in V2X communications.

- **Advanced beamforming:** B5G introduces advances in beamforming techniques compared to 5G. While 5G already exploits beamforming to improve signal quality and reduce interference, B5G goes even further. B5G's improved beamforming capabilities promise more precise signal control, which is particularly beneficial in dynamic vehicular environments where maintaining reliable connections is crucial.

- **Network slicing refinement:** Both 5G and B5G incorporate the concept of network slicing, which allows network resources to be customized for different applications. However, B5G further refines this concept. It offers more granular and adaptive network slicing capabilities, allowing services to be tailored to the specific needs of different vehicular applications. This refined network slicing is essential for efficient resource allocation in vehicular communication's complex and varied world.

- **Expanding use cases:** 5G initially identified three core services: eMBB, mMTC, and URLLC. B5G builds on this foundation by expanding the range of potential use cases in vehicular communications. This expansion reflects the increasing diversity of applications and requirements in modern vehicle networks.

- **Reduced latency:** While 5G has already delivered significant improvements in latency over previous generations, B5G aims to push this limit even further. It seeks ultra-low latency, crucial for real-time communication in autonomous vehicles and safety-critical applications.

- **Improved reliability:** B5G strongly emphasizes improving reliability, particularly in highly mobile vehicle scenarios. It incorporates advanced techniques to ensure robust and reliable communications, even in harsh conditions.

- **Improved security:** As vehicular communication becomes increasingly integrated into safety-critical applications, security becomes even more critical. B5G introduces enhanced security measures to protect against evolving threats and ensure the integrity of communications in vehicular networks.

Table 2.3: Comparison between 5G and B5G

Aspect	**5G**	**B5G**
Frequency Bands	Operates primarily in Sub-6GHz and mmWave bands (FR1 and FR2).	Explores even higher-frequency bands than mmWave.

Bandwidth and Speed	Offers substantial bandwidth and high data speeds.	Promises wider bandwidth and faster data transmission.
Use Cases	Targets eMBB, mMTC, and URLLC.	Further refines eMBB, mMTC, and URLLC for diverse vehicular applications.
Network Slicing	Introduces network slicing for customized service delivery.	Optimizes network slicing for precise vehicular application requirements.
Beamforming	Utilizes beamforming for directional signal transmission.	Advances beamforming techniques for more precise and adaptable connections.
Security	Deploys security measures to protect data and networks.	Requires more robust authentication and encryption mechanisms for advanced applications.
Deployment Status	Currently deployed and continually expanding worldwide.	Pilot projects and trials are underway in the research and development phase.

2.2.2 MmWave-enabled Vehicular Communication

Due to several advantages, mmWave band communication has garnered significant attention in vehicular network research. These include access to a substantial spectrum ranging from 30 to 300 GHz, high security, low latency, and robust resistance to interference and jamming [30]. Figure 2.7 provides a graphical representation of the mmWave frequency band concerning other bands used for wireless communication at microwave frequencies. Notably, these frequencies are nearly ten times larger than the 20 MHz cellular channel employed by LTE [31].

However, it is essential to recognize that V2X communication can encounter challenges when operating at mmWave frequencies, as indicated in Figure 2.8. These challenges stem from the unique characteristics of signal propagation in the microwave band [32] and include [33]:

- **Higher path loss:** mmWave signals experience increased path loss due to factors such as air attenuation, tree signal absorption, and susceptibility to degradation from rain. This leads to more significant propagation attenuation compared to lower frequency bands.

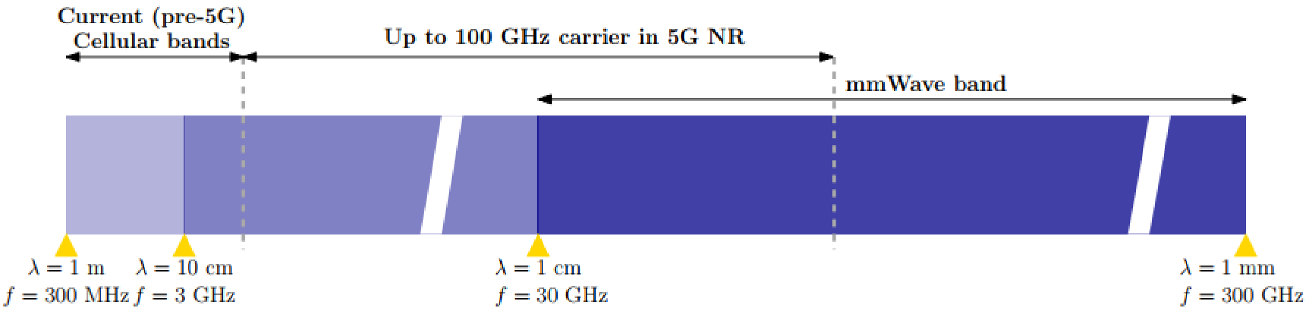

Figure 2.7: Graphical illustration of the mmWave frequency band's placement relative to cellular/wireless operating ranges

- **Higher power consumption:** Higher power consumption is necessary to maintain a signal-to-noise ratio (SNR) equivalent to that of lower frequency bands.
- **Higher penetration losses:** mmWave signals can face obstacles when penetrating walls, buildings, or other structures.

Addressing these critical transmission challenges requires high-quality directional antennas and advanced signal processing techniques like Beamforming (BF).

2.2.3 Beamforming in mmWave Vehicular Communication

In mmWave frequencies, the inherent high path loss poses a significant challenge to achieving robust network performance in vehicular networks. To address this challenge, researchers and academia have turned to beamforming techniques. Beamforming involves sending a signal from a base station to a receiver in a concentrated form, ensuring that only the intended user receives it while rejecting all other signals. This is achieved by adjusting the phase and amplitude of individual antenna elements to focus the antenna's power, typically distributed in all directions (omnidirectional transmission), into a specific direction, as illustrated in Figure 2.9.

1. **Types of Beamforming** Three distinct types of Beamforming have emerged in 5G networks, each characterized by its architecture and hardware implementation:
   - **Analog Beamforming:** Analog beamforming employs a single radio frequency (RF) signal and multiple phase shifters within the antenna components, as depicted in Figure 2.10. Advanced hardware and precoding algorithms regulate the phase of each element, effectively steering the beam. This approach finds widespread use in long-range systems like radar and short-range

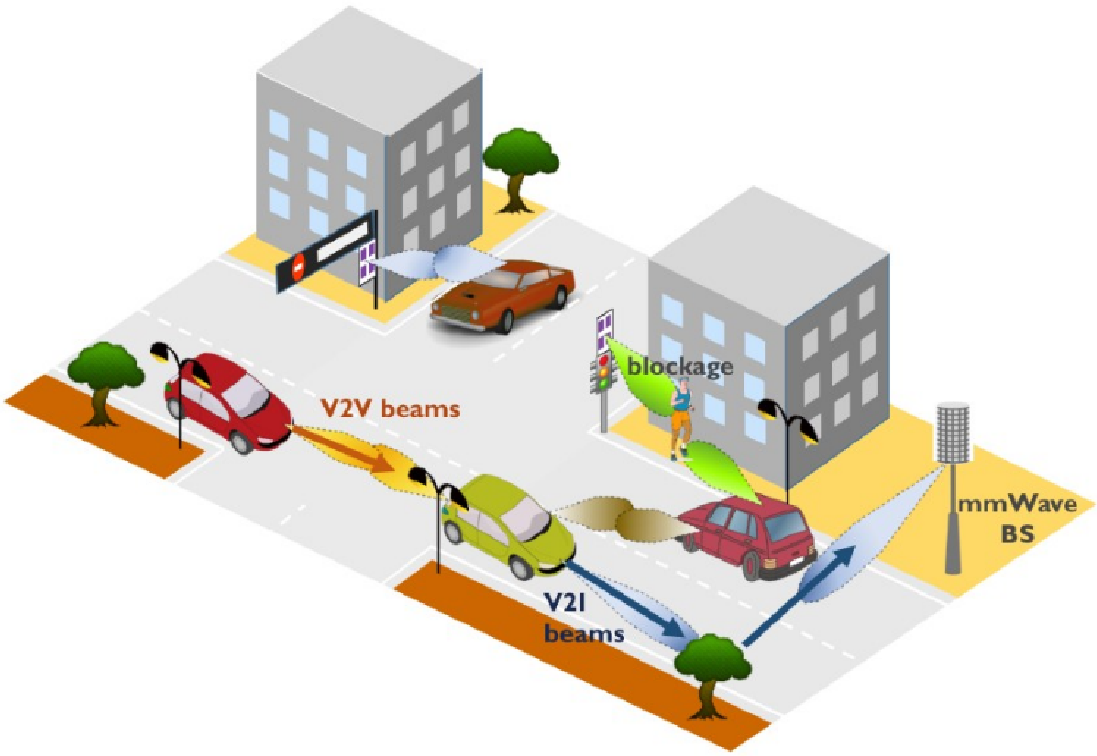

Figure 2.8: mmWave vehicular communication

communication systems like mmWave communication. The advantages of analog Beamforming lie in its simplicity of implementation and cost-effectiveness. However, it comes with a limitation: an RF chain can transmit only a single stream at a time, which limits the potential benefits of spatial multiplexing for Beamforming and MIMO.

- **Digital Beamforming:** Digital Beamforming generates distinct signals for each antenna element within the digital baseband. The number of RF chains equals the number of antenna elements, each with its dedicated RF chain and phase shifter, as illustrated in Figure 2.11. While digital Beamforming allows for multiplexing strategies, it is relatively complex and cost-prohibitive, making it more suitable for base stations rather than mobile devices.
- **Hybrid Beamforming:** Hybrid Beamforming aims to exploit the advantages of both analog and digital beamformers, as shown in Figure 2.12. Baseband digital beamformers handle some beamforming tasks in this approach, while analog RF beamformers handle others. Typically, the number of transmitted signals and RF channels in a beamforming antenna is much smaller than the

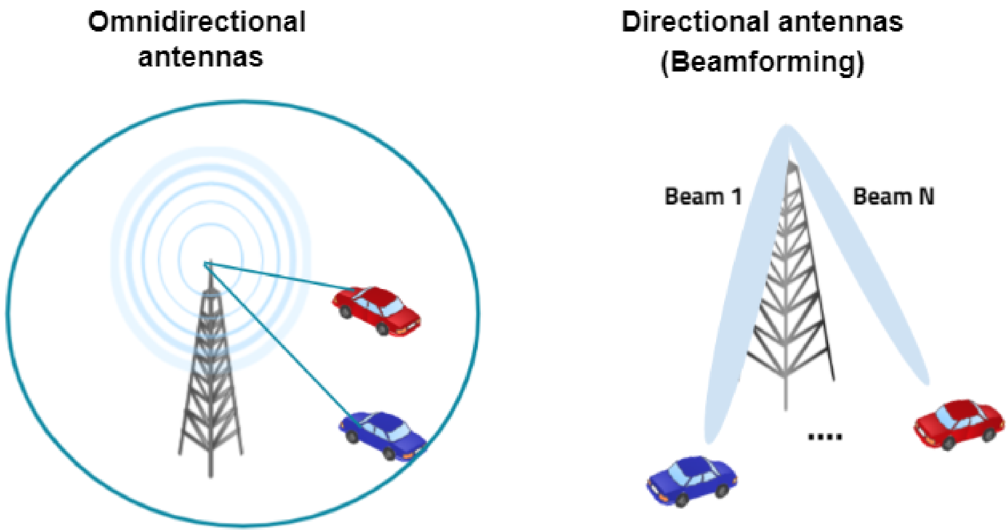

Figure 2.9: Difference between the omnidirectional and directional antennas

total number of antennas, reducing hardware costs and power consumption.

2. **Applications and importance** Applying beamforming techniques in vehicular mmWave communications is paramount in addressing the unique challenges posed by 5G networks in vehicular environments. These techniques play a crucial role in the following areas.

   - **Improving signal quality:** Beamforming dramatically improves the signal quality and reliability of V2X communication, ensuring that critical data and commands are accurately transmitted and received, even in highly mobile scenarios.
   - **Minimized interference:** By accurately directing the signal to the intended receiver, Beamforming reduces interference from other devices and neighboring networks, resulting in more stable, interference-free communication.
   - **Increased range:** Beamforming extends the range of communications in mmWave frequencies, enabling vehicles to exchange data over longer distances, improving road safety and traffic management.
   - **Improving network efficiency:** These techniques maximize the efficiency of vehicular networks by optimizing data transmission, reducing energy consumption, and minimizing latency.
   - **Enabling intelligent transport:** Beamforming is a critical component of intelligent transport systems, autonomous navigation, and the realization

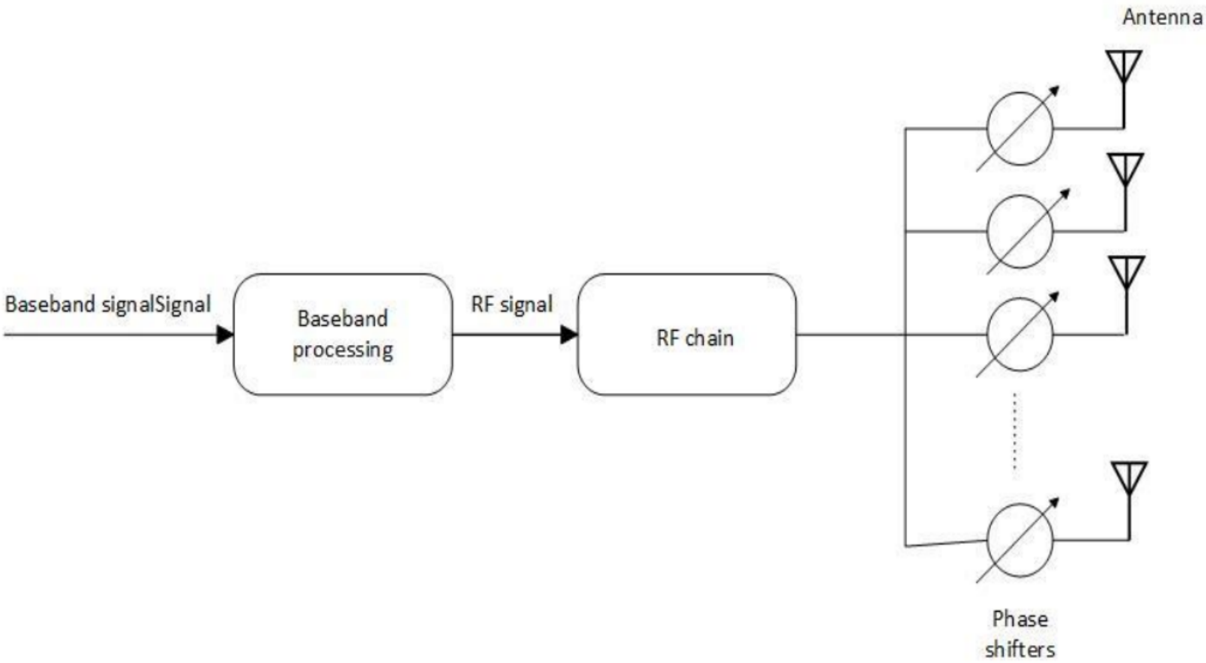

Figure 2.10: Analog beamforming structure [9]

of smart cities. It contributes to safer, more efficient, and better-connected vehicular environments.

Beamforming, which encompasses analog, digital, and hybrid methods, has become indispensable for vehicular mmWave communications. These techniques offer precise control of signal direction, reduced interference, and extended communications range, making them critical to the success of 5G networks in vehicular environments.

However, deploying mmWave communications in vehicular networks comes with challenges that must be overcome to fully exploit the potential of mmWave technology in V2X communications.

2.2.4 Main Challenges in mmWave vehicular Communications

Implementing mmWave communication for V2X (Vehicle-to-Everything) networks poses several significant challenges. According to [34] and [35], these challenges can be categorized as follows:

2.2.4.1 Blockage effects

In vehicular environments, the propagation characteristics of mmWave are susceptible to blockage where pedestrians, trees, or cars can block line-of-sight (LoS) beams. There is a

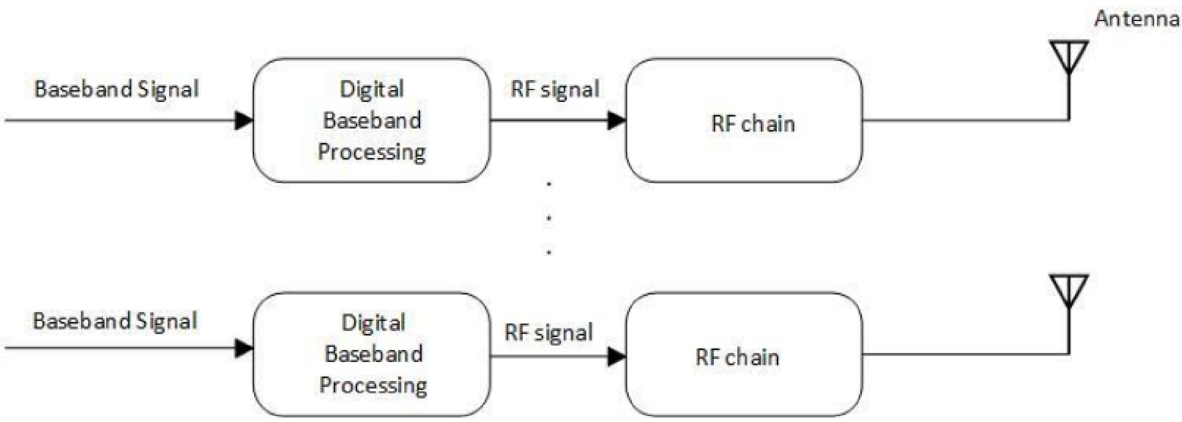

Figure 2.11: Digital beamforming structure [9]

strong dependence of the network performance on the environment, such as the number of moving vehicles, the mobility of reflectors and obstacles, the position of the RSU, or the position of the communication device. Thus, to guarantee consistent service, examining the traffic pattern and determining where the RSU antenna should be located and how the beams should be distributed is necessary.

2.2.4.2 Power consumption

Due to the dramatic increase in data flow requirements, power consumption has become a significant issue for dynamic vehicular networks. Energy efficiency (EE) in mmWave networks can often be improved by choosing a short transmission line between TX and RX. However, it is not clear that choosing a short line will always result in energy savings, as mobility brings many other elements into the system, such as flow delay, dynamic topology, frequent switching, etc. Therefore, methods that can be adapted to the system's specific needs are needed.

2.2.4.3 Effective Authentications

Message authentication is crucial for mmWave networks to deliver trustworthy services. However, mobility causes frequent handover across mmWave small cells/HetNets, necessitating multiple authentications between various small cells/tiers/networks, which imposes high communication costs and excessive delay [36]. Consequently, more effective authentication mechanisms are needed, and numerous prototypes have been created. To improve authentication accuracy while decreasing latency, Duan et al. [37] presented a software-defined-networking-enabled (SDN-enabled) rapid authentication technique that uses weighted security context transfer. In [38], we propose and investigate a cooperative

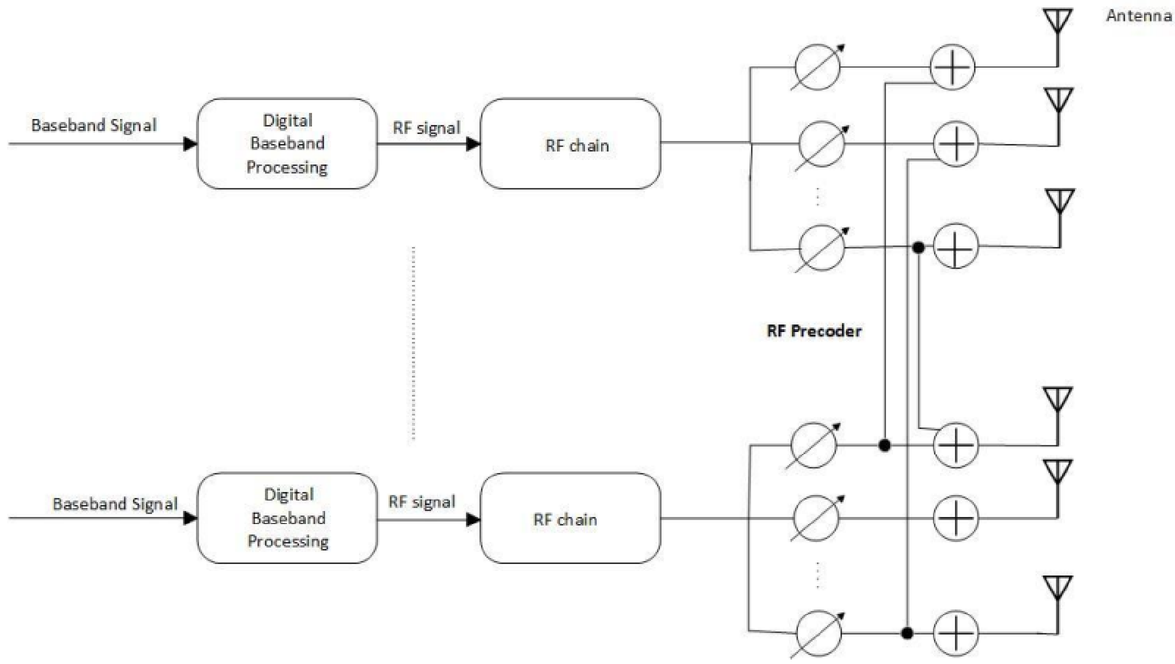

Figure 2.12: Hybrid beamforming structure [9]

message authentication scheme for a V2X communication, where the fleet, rather than individual vehicles, serves as the authentication units. Future attack defence and EE quality improvements may benefit from using intelligence and programmability to optimize handover authentication further.

2.2.4.4 Beam Alignment (BA)

High-gain directional antennas are required to overcome the challenges associated with propagation signals at mmWave frequencies. These antennas need BA from the mmWave devices to adjust the directions of the transmit and receive angles. BA is changing the send and receive beams to achieve optimal performance. It is an essential procedure vehicular networks use to adapt to a changing environment. For BA existing approaches, the most straightforward is to search for all possible antenna beams and choose the one with the highest SNR to ensure V2X communication. However, this method is inefficient, and the overhead grows with the number of antenna combinations (and thus the number of antenna elements). The beam search space for a single connection with N beams per antenna and no omnidirectional reception is N^2. In the case of omnidirectional reception, the complexity remains linear.

In summary, mmWave communication has immense potential to revolutionize vehicle networks but faces multiple challenges. These challenges highlight the complexity of establishing seamless V2X communication within mmWave vehicle networks. Resolving these issues is essential to ensure the reliability and sustainability of millimeter-wave vehicular communications. It represents a significant step forward in improving intelligent transport systems broadly.

In the following chapter, we will comprehensively explore proposed solutions and emerging technologies to face the critical problems of BA in V2X communications. This exploration will provide valuable insights into overcoming these obstacles, thereby propelling the evolution of V2X communication.

Chapter 3

Vehicular Communication Based On mmWave Beam Alignment: A Literature Review

3.1 Introduction

Vehicular networks continue to develop, and the search for efficient communication and seamless connectivity is paramount. Among this field's many challenges and innovations, beam alignment (BA) is emerging as a critical technology. It could revolutionize V2X communication and pave the way for autonomous navigation. BA is the art of precisely directing wireless signals, aligning them for optimal communication between vehicles, infrastructure, and the environment. This technology is the basis for reliable V2X communication, where a split-second connection can make the difference between a smooth journey and a road accident.

In this chapter, we propose a comprehensive taxonomy, as depicted in Figure 3.1, to address the evolution of vehicular networks in BA. It classifies existing techniques, ranging from classical optimization approaches to innovative approaches exploiting the power of deep learning.

3.2 Classical-Based Beam Alignment Approaches

This section examines classical-based BA approaches that enable V2X communication in 5G/B5G networks. Based on signal processing and optimization, the above methods have consistently produced reliable and interference-resistant connections in the literature. We can divide this category into traditional optimization and deep learning approaches.

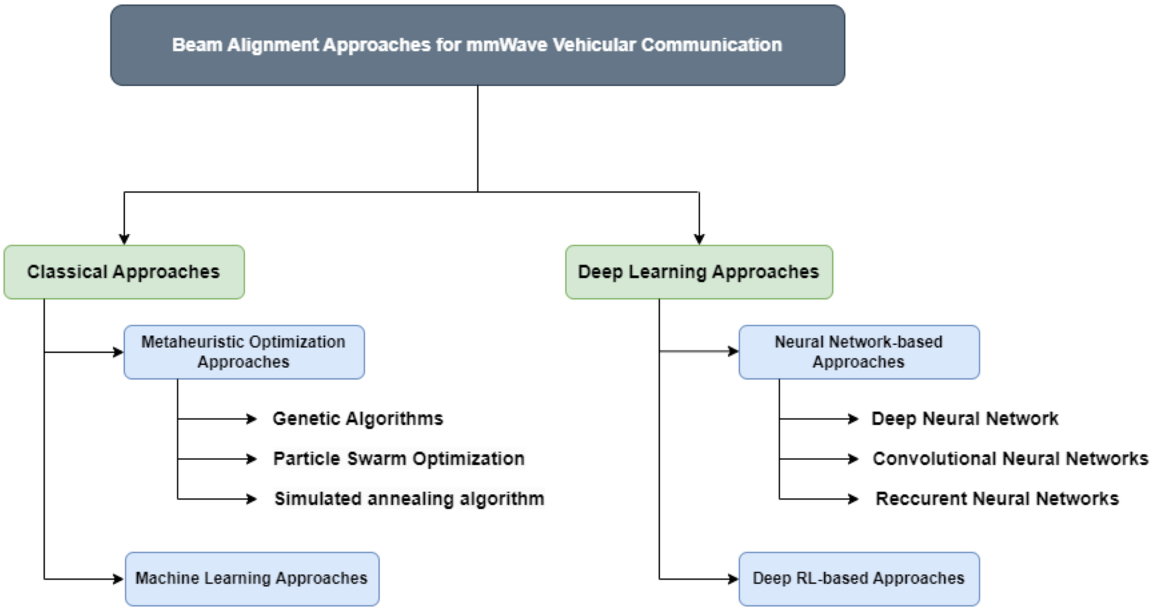

Figure 3.1: The proposed taxonomy of BA approaches for mmWave vehicular communication

3.2.1 Meta-heuristic Optimization Approaches

In vehicular communications optimization, various approaches have been explored to address the complex challenges of improving signal quality, minimizing interference, and extending communications range. Traditional optimization techniques have long been at the forefront of these efforts, providing proven methods for fine-tuning parameters and improving communication efficiency. However, as the requirements of modern vehicular networks become more complex and dynamic, new approaches inspired by nature's problem-solving mechanisms have gained prominence. Genetic algorithms (GA), particle swarm optimisation (PSO) and simulated annealing techniques are the leading candidates in this field. These innovative optimization strategies are inspired by biology and collective behavior, offering unique advantages for adapting to vehicular communication networks' constantly changing, highly mobile environment.

3.2.1.1 Genetic Algorithms for Beam Alignments

Genetic algorithms (GAs) represent a powerful class of optimization techniques inspired by natural selection and the principles of genetic inheritance. These algorithms have been widely applied to solve complex problems due to their simplicity of implementation, low operating costs, and easy parallelization.

GAs work iteratively, generating new candidate solutions (beamforming configurations) and evaluating their suitability based on predefined criteria. Over successive generations, GAs select the most promising solutions, recombine their characteristics through crossover, and introduce diversity through mutation, thus evolving the population towards increasingly efficient beamforming strategies, as shown in Figure 3.2. This ability to adapt and explore a vast solutions space makes GAs well-suited to vehicular scenarios' dynamic and highly mobile nature. Numerous research studies have used this method to solve problems related to V2X communication.

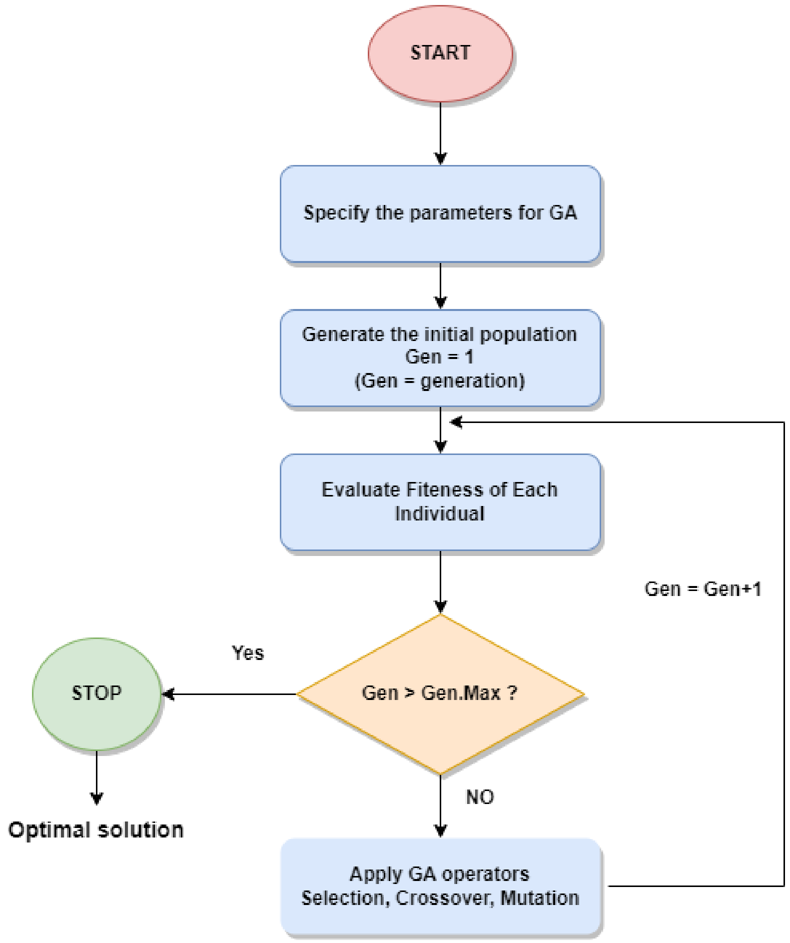

Figure 3.2: Flowchart of Genetic Algorithm (GA)

In [39], the authors proposed a novel approach that uses GAs as a required optimization tool to address the challenges associated with the initial access phase in 5G millimeter-wave (mmWave) communications. The proposed method begins with utilizing GAs to optimize beamforming configurations dynamically during the initial access process. Then, GAs adaptively adjust parameters, such as beam direction and power allocation, to maximize the likelihood of successful communication establishment. This intelligent optimization process considers various factors, including signal propagation characteristics and the dynamic nature of mmWave channels. Through an iterative and evolutionary approach, the system fine-tunes beamforming settings to locate and synchronize with base stations efficiently. The simulation results show that the suggested approach outperforms the method discussed in the references [40], [41], [42], achieving comparable outcomes to Exhaustive Search (ES). However, one potential limitation is the computational complexity of using GAs for real-time optimization, which can require substantial processing power.

On the other side, to tackle the challenge of the initial access procedure of connecting a moving vehicle (VE) and a stationary base station (RSU) through bidirectional communication, I Rasheed [43] proposed an innovative beam refinement technique for 5G mmWave Vehicle-to-everything (V2X) communications. This approach utilizes an Improved Genetic Algorithm (IGA) to discover the optimal BA where the RSU and Vehicle are equipped with multiple-input multiple-output (MIMO) antenna systems. The IGA employed in this research incorporates crucial improvements in the selection process, elitism, crossover operations, and mutation procedures. A series of comprehensive analyses are used to evaluate the effectiveness of the proposed technology. These evaluations include critical factors such as capacity, codebook size, probability of failure, and total transmitted power. In particular, the study performs an extensive comparative analysis, contrasting the proposed approach with the most advanced previous work in this domain. The main performance metrics are closely examined, including capacity achieved, outage probability, and total transmitted power utilization. Nevertheless, like many optimization algorithms, GAs are sensitive to parameter tuning. Efficient parameter tuning can be complex, and sub-optimal tuning can lead to reduced performance.

3.2.1.2 Particle Swarm Optimization for Beam Alignment

After introducing Genetic Algorithms (GAs) as one of the optimization techniques for BA in vehicular communications, we discuss another powerful method known as Particle Swarm Optimization (PSO). PSO is a nature-inspired optimization algorithm inspired by the collective behavior of swarms in nature, such as flocks of birds and schools of fish. In PSO, particles in a swarm have positions and velocities representing potential solutions to the optimization problem. These particles iteratively adjust their positions and velocities based on their own experience and the collective knowledge of the swarm, as shown in Figure 3.3. This adaptive and iterative approach is used to refine beamforming configurations, improve signal quality, reduce interference, and optimize communication performance. The PSO technique finds applications in vehicular communication systems because it can address the vehicular communication scenario's dynamic and highly mobile nature.

Various studies have effectively utilized this technique to ensure efficient vehicular communications. The authors in [44] presented an innovative beamforming strategy for V2V

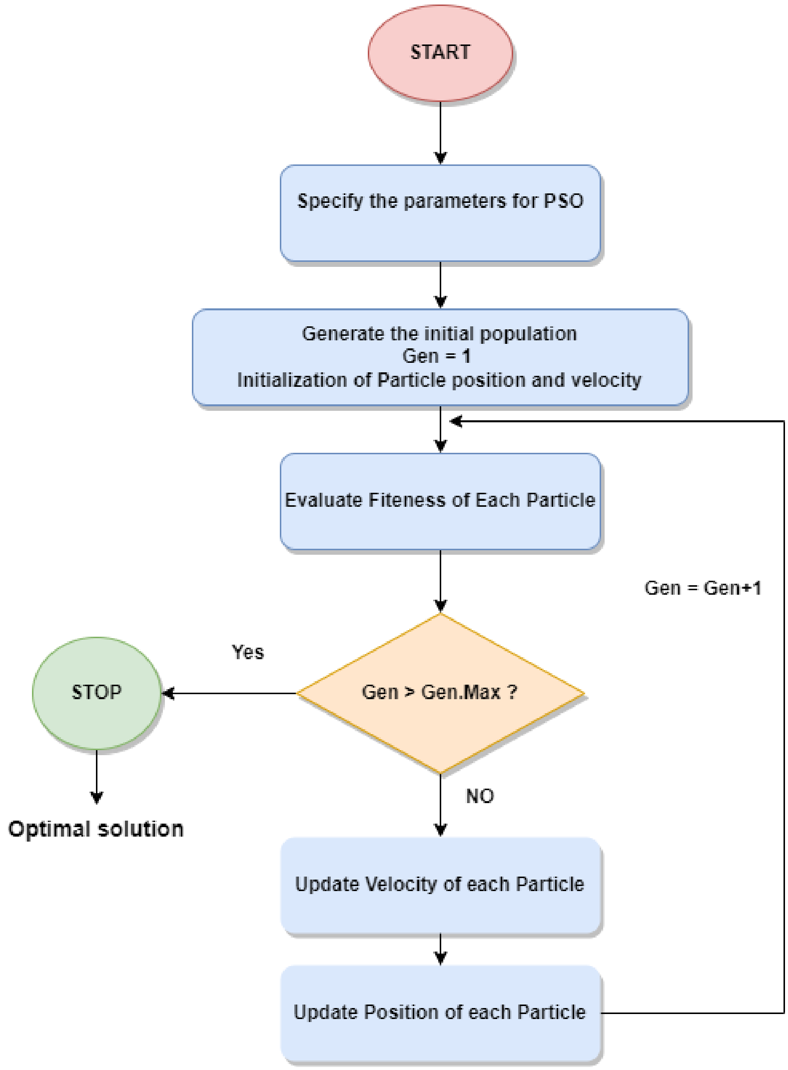

Figure 3.3: Flowchart of Particle Swarm Optimization (PSO)

communications in urban intersections. The main objective is to optimize the antenna array configuration using an algorithm based on PSO to maximize the power received in all intersection streets. The proposed approach consistently outperforms the conventional isotropic antenna scheme in various simulated scenarios, including those that have yet to be explicitly trained. Simulation results demonstrate that beamforming extends the achievable connectivity range by an average of approximately 14 meters in all street directions. This extended range translates directly into improved road safety by giving vehicles a longer awareness window, giving them the extra reaction time crucial to avoiding accidents. However, further analysis of the computational complexity associated with implementing the algorithms is required in this work. This means the proposed method may have computational requirements that must be better understood and mitigated for practical use.

Although traditional optimization approaches have provided fundamental solutions for BA in vehicular communications, they have limitations. These methods often rely on predefined models and assumptions that may not capture the complexity of real-world vehicle dynamics. In addition, they may struggle to adapt quickly to changing conditions, which could undermine their effectiveness in highly mobile 5G networks.

3.2.1.3 Simulated Annealing for Beam Alignment

Another notable meta-heuristic optimization approach used in BA for vehicular communications is Simulated Annealing (SA). SA is a probabilistic optimization technique inspired by the annealing process in metallurgy. It is well-suited for addressing complex optimization problems where finding the global optimum is challenging due to multiple local optima. In SA, the optimization process starts with an initial solution and iterative explores the solution space by probabilistic accepting worse solutions early in the search. As the search progresses, the probability of taking worse solutions decreases, allowing SA to gradually converge toward an optimal or near-optimal solution, as presented in Figure 3.4.

In vehicular communications, SA can be applied to dynamically adjust beamforming configurations, optimize signal quality, and minimize interference. This adaptability makes SA suitable for the dynamic and highly mobile nature of 5G vehicular networks. While SA has demonstrated effectiveness in various optimization problems, its application to BA in vehicular communications is an area of ongoing research. Researchers are exploring how SA can be tailored to address the specific challenges posed by vehicular networks, including rapid changes in network topology and environmental conditions.

Several research works have applied the SA algorithm in recent years. For example, in a study by Li et al. [45], a new approach was proposed that combines the Rosenbrock optimization algorithm with SA techniques to improve beamforming mmWave vehicular communication systems. In this approach, the beamforming process begins with an initial set of candidate beamforming parameters generated by the Rosenbrock algorithm. These parameters include beam direction, beam width, and transmit power settings. To guide the optimization process, the study defines an objective function that quantifies the quality of the communication link, considering factors such as signal strength, interference, and other relevant parameters. SA is then introduced to refine these beamforming parameters. SA is essential as a global optimization mechanism, effectively extending the solution to space exploration. It makes it possible to escape local optima by occasionally accepting parameter changes that may initially degrade the objective function. This behavior mirrors the annealing process in metallurgy. In addition, to improve the efficiency

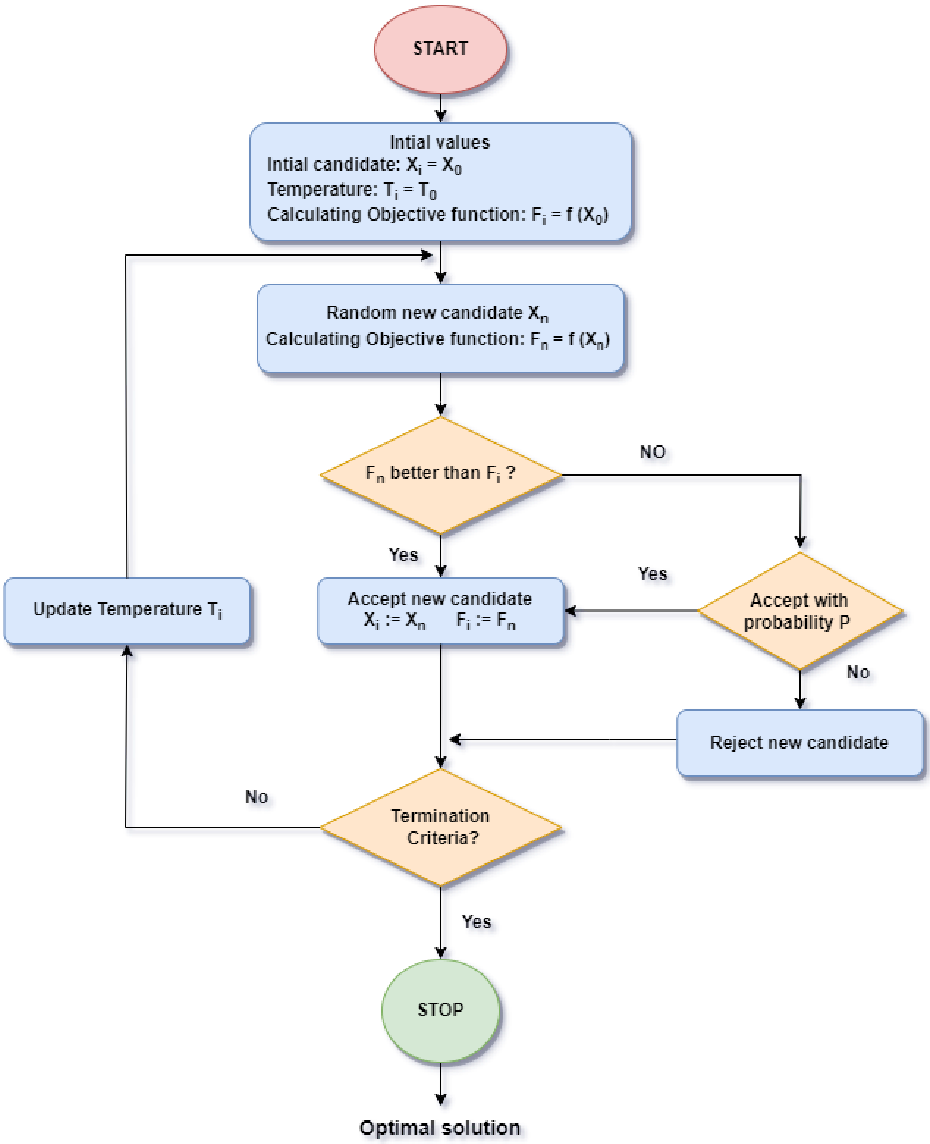

Figure 3.4: Flowchart of Simulated Annealing Algorithm (SA)

of the Rosenbrock algorithm, the study incorporates a tabu table mechanism. This table stores previously explored solutions, thus avoiding redundant revisits and enhancing the efficiency of the optimization process.

The proposed method has been rigorously evaluated using simulations in realistic millimeter-wave communication scenarios. The results of these simulations highlight the effectiveness of the tabu-table enhanced Rosenbrock algorithm, combined with simulated annealing, in achieving accurate and efficient beamforming. In particular, its ability to adapt to changing channel conditions and mitigate blocking effects makes it a promising solution for optimizing millimeter-wave communication links. Nevertheless, Integrating SA and the Tabu Table Enhanced Rosenbrock Algorithm may provide computational overhead.

To tackle the challenges posed by metaheuristic optimization techniques, we are turning to the promising field of machine learning. Machine learning, known for its adaptability to complex and dynamic environments, offers a compelling alternative. The following section will examine how machine-learning approaches provide innovative solutions to overcome these limitations, opening up a new era of adaptive BA in vehicular communication.

3.2.2 Machine Learning-Based Optimization for Beam Alingnment

Machine learning, a subset of artificial intelligence, enables computers to learn from data and enhance their performance on specific tasks over time without explicit programming. It revolves around the idea that machines can automatically detect patterns, make decisions, and refine their behavior based on experience. Machine learning encompasses various techniques, from supervised learning, where models are trained on labeled data, to unsupervised learning, which uncovers hidden patterns in unstructured data, and reinforcement learning, which allows machines to learn through interaction with their environment. It has diverse applications, including image recognition, natural language processing, and optimization, making it a trans-formative force across industries and domains. As shown in Figure 3.5, the machine learning process can be divided into two distinct steps. The initial step is the training phase, during which a model is built using a subset of the available data. Then, in the evaluation phase, a battery of tests is performed using a separate dataset to measure the disparities between the generated model and real-world conditions.

In the search for precision and adaptability in BA for vehicular networks, the integration of machine learning techniques has emerged as a transformative research path. By recognizing vehicular communication's dynamic and the high mobility limitation imposed on V2X scenarios, machine learning opens the way to intelligent adaptation and optimization. These approaches exploit the power of data-driven decision-making to revolutionize BA and ensure reliable and efficient communication in an ever-changing vehicular network environment. These methodologies, from supervised learning to reinforcement learning, represent a paradigm shift in the approach to BA between the base station (transmitter) and vehicles (receiver) in 5G vehicular networks and beyond.

Several studies based on ML approaches were proposed in the literature to ensure BA between the entities of the vehicular networks, as summarised in Table 3.1.

Asadi et al. introduced a novel online learning method called 'Fast Machine Learning'

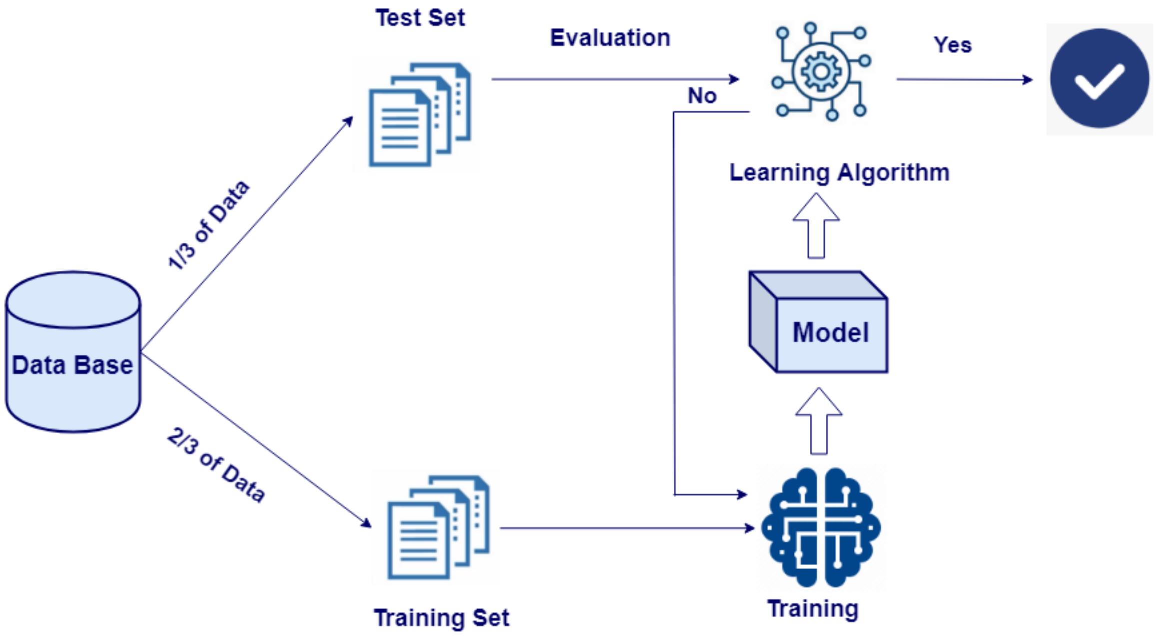

Figure 3.5: Process of machine Learning

(FML) to manage beams in mmWave base stations (mmBs), as described in their publication [46]. The proposed method is influenced by the classical reinforcement learning technique known as the multi-armed bandit problem (MAB) [14]. The FML algorithm enables mmBs to independently and efficiently select the most suitable beams, effectively adapting to changing environmental conditions and overcoming network congestion obstacles. This technological development is crucial in improving the efficiency of 5G cellular network communications, especially in V2X communications. When used with mmWave frequency bands, the FML method facilitates the selection of beam directions that exhibit enhanced bandwidth performance compared to traditional approaches [47]. Nevertheless, it is essential to note that this approach does face the challenge of longer execution times as it adapts to varying traffic dynamics and congestion scenarios.

To address the challenges posed by mobile obstacles, also called dynamic obstacles, in road environments, the authors of [48] introduced an effective method for achieving rapid mmWave alignment between vehicles and infrastructure. This method relies on the vehicle's position and a repository of past beam data (beam history), which is stored in a database on Roadside Units (RSUs). This historical data is employed to rank the most promising beam direction angles. The authors of this study utilized a classification technique based on a Learning-to-Rank (LtR) approach [49], a popular machine learning method. Initially, the vehicle sends a training request to the RSU, including its positional information. Subsequently, the RSU generates a list of beam pairs through LtR. Following this, beam training is executed, guided by the historical beam data, to determine and relay the optimal angular beam direction to the vehicle. This enables high-speed millimeter-wave communication. It is important to note that it is recommended to incorporate additional contextual data, such as vehicle speed and orientation, for improved system modeling, as the LtR approach benefits from a more comprehensive set of details.

Many of the existing solutions for BA are grounded in supervised learning methods, which require collecting all data in advance. In [50], the authors introduced a multi-armed bandit framework to develop a real-time and efficient BA and enhancement algorithm based on vehicle positions. In contrast to offline learning, this method allows the database to continuously update as new observations are collected while the vehicle is in motion. In this research, the authors combined the upper confidence bound (UCB) algorithm to select the best beam pair and a modified version of Hierarchical Optimistic optimization (HOO) to refine the chosen beam pair. The numerical outcomes of this study revealed that, over time, the beamforming gain could be improved by approximately 1.5 dB compared to previous works [51] and [52]. Nevertheless, it is worth noting that the capacity of the MAB framework is limited when it comes to extracting and utilizing contextual information for beam training purposes.

For V2V communication in the mmWave vehicular network, a novel approach was introduced by the authors of [53], departing from previous works such as [54] and [55], which were based on conventional methods of selecting an appropriate analog beam to facilitate simultaneous V2V transmissions. In this innovative method, the authors have exploited the power of a support vector machine (SVM) to optimize the beam selection process to maximize the average sum rate (ASR) in V2V communication scenarios over MmWave. According to the simulation results, this machine learning-based approach has several advantages over traditional solutions based on channel estimation, including reduced complexity and superior ASR performance during simultaneous V2V transmissions. However, it is essential to note that the Support Vector Machine (SVM) technique may not be the most reliable choice when dealing with large databases due to its high computational and substantial memory requirements for managing large datasets.

In [56], the authors introduced a novel machine-learning model that significantly reduces search times and maintains a remarkable accuracy rate of more than 95% for BA in mmWave networks. This new algorithm is designed to predict the optimal base station (BS) and identify the most promising candidate beams (called "optimal beams") using only the user's location information, which significantly reduces the search time. Experimental evaluation has shown a remarkable reduction in search space, approximately four times for base station selection and more than ten times for beam selection. However, it is essential to note that this study does not analyze energy consumption.

Table 3.1: Machine Learning-Based Beam Alignment in Vehicular Networks

Study	**Machine Learning Technique**	**Key Contributions**	**Advantages**	**Limitations**
Arash et al. [46], 2018	MAB	Introduced FML to select the most suitable beams	Efficient adaptation to changing conditions, enhanced bandwidth performance.	Longer execution times, especially in dynamic scenarios.
Vutha et al. [48], 2017	LtR	Proposed a method for rapid mmWave alignment using vehicle position and historical beam data.	High-speed communication, LtR approach for ranking beam directions.	Recommended additional contextual data for better vehicular system modeling.
Vutha et al. [50], 2019	MAB + UCB	Developed a real-time and efficient BA framework.	Continuous database updates, improved beamforming gain.	Limited capacity for extracting and using contextual information.
Yang et al. [53], 2020	SVM	Optimizing beam selection, improving average sum rate (ASR) in V2V mmWave scenarios.	Reduced complexity, superior ASR performance.	High computational and memory requirements for large datasets.
Yuqiang et al. [56], 2021	Machine-learning model	Reducing BA search times with over 95% accuracy.	Remarkable reduction in search space, especially for base station and beam selection.	Energy consumption analysis not conducted.

In conclusion, machine learning techniques have become powerful tools for improving BA in mmWave vehicular networks. These approaches have demonstrated their ability to reduce search times and improve alignment accuracy. However, they face challenges regarding data requirements, adaptability to dynamic environments, and computational complexity, particularly in resource-limited scenarios. In addition, the interpretability of machine learning models remains an issue, limiting their transparency in decision-making processes. We are now turning our attention to deep learning approaches to address these challenges and fully exploit the potential of BA in mmWave vehicular networks. In the following sections, we examine how deep learning architectures, such as deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), are giving a new form to BA, enabling more efficient and adaptive solutions in this dynamic communication environment.

3.3 Deep learning-based Beam Alignment Approaches

Deep learning represents a new generation of innovations in mmWave BA. As a subset of machine learning, deep learning uses multi-layer neural networks to autonomously extract complex patterns and representations from data. This part of the thesis examines deep learning-based alignment approaches, exploring proposed research, applications, and their potential to develop mmWave communication in vehicular networks. These approaches can be classified into two major categories: neural network-based and deep reinforcement learning-based.

3.3.1 Neural Network-Based Approaches for Beam Alignment

In mmWave communications, where high-speed, low-latency data transfer is becoming demanding for precise BA, Neural Networks (NNs) are emerging as a revolutionary force. These neural networks, inspired by the complex workings of the human brain, offer a distinct solution to the complexities of mmWave BA procedure. Unlike conventional methods that rely on predefined algorithms, neural networks can autonomously extract complex patterns from data. This adaptability allows them to excel in tasks such as optimizing beam angles, predicting ideal configurations, and dynamically monitoring changes in the vehicular environment. NNs effectively transform BA into an intelligent, data-driven process. They can analyze various factors, including user positions, channel conditions, and environmental variables, enabling real-time decisions about beam selection, orientation, and adaptation. The result is a faster and more accurate beam alignment process, which is essential for improving the potential of in-vehicle mmWave communications, particularly for 5G networks.

For a more comprehensive view of neural networks and their impact on vehicular communications, we will classify them according to their architectural designs into three categories: DNN, CNN, and RNN. This categorization will provide a clear distinction between the different NN structures, and we will complement this overview with overviews of existing research in each category.

3.3.1.1 Deep Neural Network (DNN) for Beam Alignment

Deep neural networks (DNNs) have become a transformative tool for optimizing the alignment of communication beams in vehicular networks. DNNs are based on a fundamental architectural element, the fully connected layer (FCL), often called the dense layer. This fully connected layer forms the basis of many neural network architectures, including deep neural networks, and plays a crucial role in achieving BA in vehicular communication scenarios.

In Figure 3.6, we can visualize the FCL as a layer with multiple neurons (circles) where each neuron is connected to every neuron in the previous and subsequent layers. These connections are represented by arrows, signifying the flow of information. The FCL performs weighted summations of the inputs of the prior layer, applies an activation function, and passes the results as output to the next layer. This dense connectivity allows FCLs to learn complex relationships within the data. It makes them essential for various tasks, including pattern recognition, feature extraction, and decision-making in BA for vehicular communication.

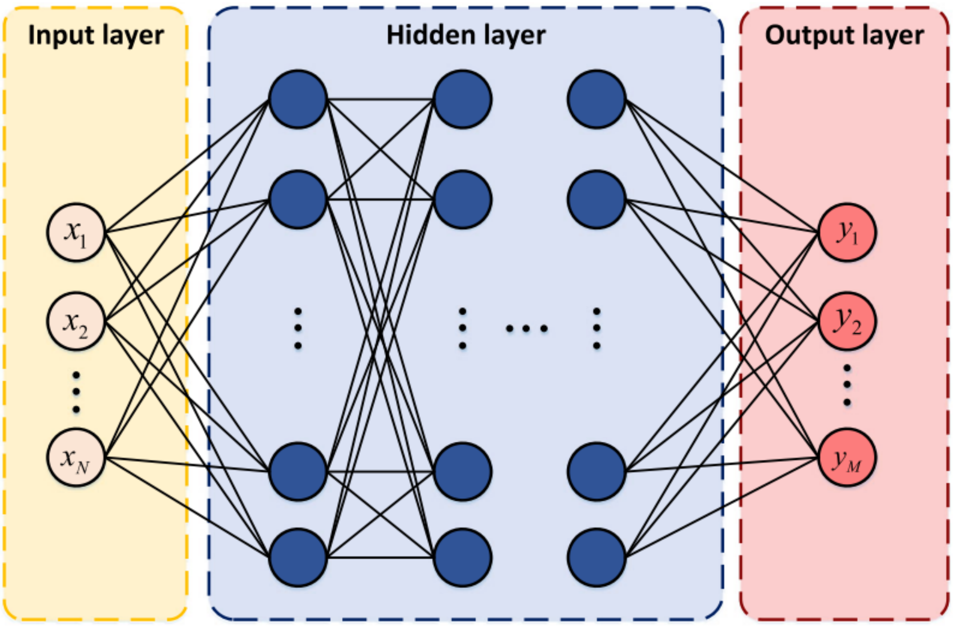

Figure 3.6: Schematic representation of a Fully Connected Layer

According to [57], a one-layer NN can model any relationship between input features and output results. However, it is well known that a deeper model is more efficient than a one-layer NN regarding the complexity required to meet a specific performance criterion. This efficiency comes from the ability of a deeper model to deliver better results with less complexity.

Here are some studies where the DNN architecture has been applied to ensure BA in vehicular networks. In [58], the researchers developed a DNN using a fingerprinting database. This database contains information about beam pairs (transmit and receive), received signal strength (RSS), and supplementary data like vehicle location. The DNN-based approach predicts the optimal beamforming vectors, significantly reducing the initial setup time for MmWave V2X communication. However, it is essential to note that training this model necessitates an exhaustive fingerprint database encompassing various traffic scenarios. Furthermore, if the environment undergoes significant changes, the model's performance may degrade post-training as it relies on the original database for accurate predictions.

Additionally, Sajad et al. [59] introduced a DNN-based approach that relies on orientation information. This approach incorporates details such as the AoA, AoD, and the receiver's position to predict a concise list of optimal beam pairs, effectively reducing the overhead associated with beam alignment. The obtained results of this approach illustrated that employing a multi-class labelled classifier outperforms the conventional technique in terms of both performance and accuracy [60]. Nevertheless, this approach necessitates data for each training sample, a requirement that can be prohibitively costly and impractical for outdoor mobile communication scenarios.

To enhance the speed and precision of the initial access (IA) process in mmWave networks, as compared to the conventional beam sweeping (CBS) method, Tarun et al. [61] designed a DNN for IA (DeepIA). This network was trained to select the optimal beams for data transfer and minimize the time required for IA by evaluating RSS across various beams. The outcomes of this study revealed that DeepIA could predict the ideal beam with an impressive accuracy of approximately 100% in LOS communications. In contrast, the accuracy of CBS in beam prediction dropped to around 24% under the same LOS conditions. The RSS signals utilized as input to the DNN, which is transmitted by the vehicle, could potentially be vulnerable to attacks during data transmission, potentially affecting the performance of the beamforming process.

Beam management and interference coordination are two further applications for the DNN model, both employed in dense MmWave networks. In [62], the authors introduced an innovative model-based DNN approach to optimize critical parameters such as beam direction, transmit power, and beam width for the position of each network node. They developed a beamforming technique to communicate directly between mobile users and base stations. The results of their study demonstrated that the suggested DNN consumes less computing time and decreases computational complexity while giving a percentage of total throughput equivalent to previous approaches. This method may work better over longer distances outdoors, but it is ideal for closer quarters.

3.3.1.2 Convolutional Neural Networks (CNNs) for Beam Alignment

CNNs are one of the successful Deep Learning models. It should be noted that while DNNs excel at learning complex relationships in data and making accurate predictions, CNNs are particularly good at extracting spatial features from multivariate datasets. CNNs are at the forefront of mmWave communication, where precise spatial information is essential for efficient beam selection.

CNNs use a set of filters that can be learned to analyze the spatial information contained in the received signal data and extract the high-level features from the given input raw. In addition to their spatial data expertise, CNNs can adapt to sequential data. This is particularly useful in mmWave vehicular communication, where data is transmitted in a time-sequential manner. Using 1D cross-correlation operations enables CNNs to handle sequential data efficiently.

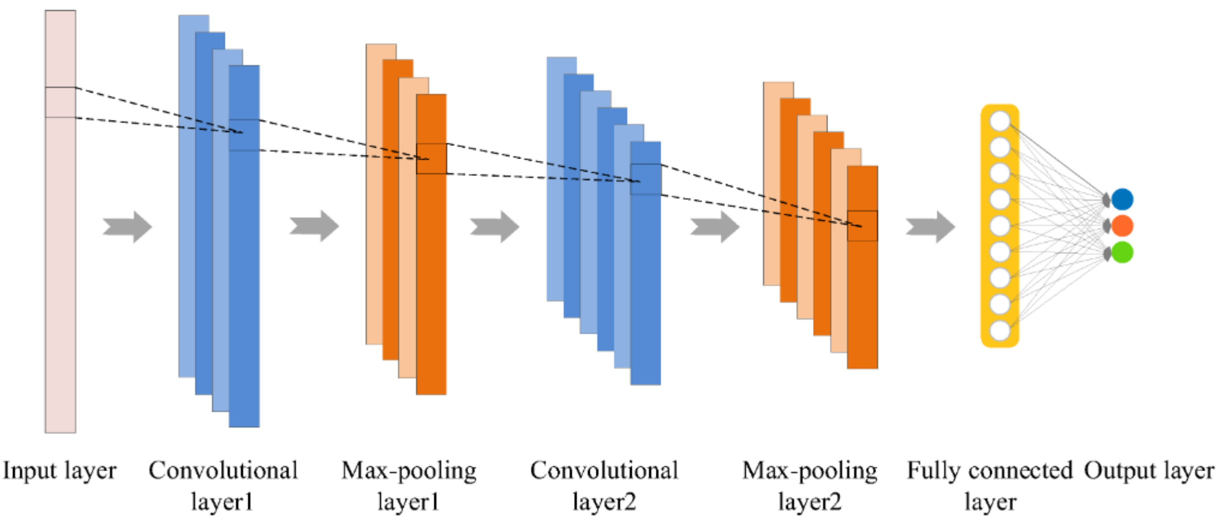

Figure 3.7: The structure of 1D CNN architecture

According to Figure 3.7, the architecture of a 1D CNN consists of several layers, including convolutional, pooling, and fully connected layers, which we present below. These layers work together to process spatial information sequentially, making CNNs well-suited to beam alignment in mmWave vehicular communications.

- **Convolutional Layer:** In this layer, the input feature matrix is locally convolved using convolution kernels that have already been constructed based on the stride value. A corresponding feature matrix is generated after the convolution operation on the input feature matrix. For the 1D CNN, the convolution kernel is one-dimensional [63], and the convolution operation can be expressed as follows [64]:

$$x_k^l = \sum_{i=1}^{N_{l-1}} conv1D(w_{ik}^{l-1}, S_i^{l-1}) + b_k^l \tag{3.1}$$

  The variables x_k^l and b_k^l represent the input and bias of the k_{th} neuron in the l_{th} layer. The variable w_{ik}^{l-1} denotes the convolution kernel between the i_{th} neuron in the $l-1$ layer and the k_{th} neuron in the l_{th} layer. The variable S_i^{l-1} represents the output of the i_{th} neuron in the $l-1$ layer. N_{l-1} denotes the number of neurons in the $l-1$ layer. Lastly, $conv1D(*)$ refers to the one-dimensional convolution operation.

- **Pooling Layer:** The main objective of the pooling layer is to reduce network parameters and computational complexity by changing the size of the feature matrix while preserving the essential features. Pooling operations are mainly of two types: average pooling and maximum pooling.

- **Batch Normalization:** is a critical step to normalize each layer's input, ensuring a consistent Gaussian distribution. This step enhances learning stability, accelerates convergence, and mitigates issues related to vanishing gradients during training.

CNNs have performed exceptionally in various vehicular communication tasks, including channel estimation [65], beam management [66], and millimeter-wave Channel State Information (CSI) acquisition [67]. Table 3.2 summarises selected studies employing CNN-based architectures for BA. This table provides insights into their objectives, methodologies, performance metrics, and limitations, shedding light on the effectiveness and challenges of CNN-based approaches.

Table 3.2: Summary of Proposed CNN-Based Beam Alignment Studies

Reference	Objective	Methodology	Performance Metrics	Limitations
Radwa et al. [68], 2021	Improving V2X communications reliability	1D CNN	Achievable data rate, packet delivery ratio, packet loss rate, and average end-to-end delay	Limited to specific V2X scenarios
Lulu et al. [69], 2022	Adapting narrow mmWave beams in real time	CNN	Alignment probability	Consider only V2I communication
Michele et al. [66], 2021	Establishing and maintaining reliable links in dynamic V2I communications	CNN	Accuracy and Latency	Automated data collection and labelling tools should be developed
Peitho et al. [65], 2019	Improving estimation performance for 5G vehicular networks	Spatial-Frequency CNN and Spatial Pilot-Reduced CNN	Minimum mean squared error (MMSE)	The performance loss and its impact on the quality of the channel estimate are not discussed.
Ahmet et al. [67], 2020	Improving beam selection efficiency for V2I communications	LIDAR pre-processing and 2D-CNN	throughput ratio and Accuracy	It is recommended to employ data rebalancing techniques to ensure that no single vehicle's data dominates the training process.

3.3.1.3 Reccurent Neural Networks (RNN) for Beam Alignment

Recurrent Neural Networks (RNNs) have been successfully applied in various domains, including beam alignment in vehicular communication. RNNs have played a key role in beam alignment, where accurate spatial information is crucial for effective communication. RNNs excel at processing sequential data and have been used to capture the temporal dynamics of changing radio environments in real time. However, standard RNNs often struggle to capture long-range dependencies effectively. This limitation has led to adopting more advanced architectures, such as Long Term Memory Networks (LSTMs) and Bidirectional LSTM Networks (BiLSTMs).

- **Long Term Memory Networks (LSTMs):** The LSTM network model was initially proposed and subsequently improved in [70] and [71], respectively, to address a significant issue in recurrent neural networks (RNNs) known as gradient instability. RNNs often suffered from the vanishing or exploding gradient problem, which made it challenging to learn long-term dependencies effectively. LSTM introduced a critical innovation to RNNs: the cell state. This component stores information over time and facilitates data transfer between LSTM units, thus preventing gradient-related issues. Figure 3.8 illustrates the architecture of an LSTM, which includes three essential gates: the forget gate (f_t), the input gate (i_t), and the output gate (O_t). These gates play a crucial role in controlling the flow of information within the cell state. At each time step t of the LSTM, a set of vectors comprising the forget gate f_t, input gate i_t, output gate O_t, and the hidden state h_t are calculated using the following formulas:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{3.2}$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{3.3}$$

$$\tilde{C}_t = tanh(W_C.[h_{t-1}, x_t] + b_c) \tag{3.4}$$

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \tag{3.5}$$

$$O_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{3.6}$$

$$h_t = o_t tanh C_t \tag{3.7}$$

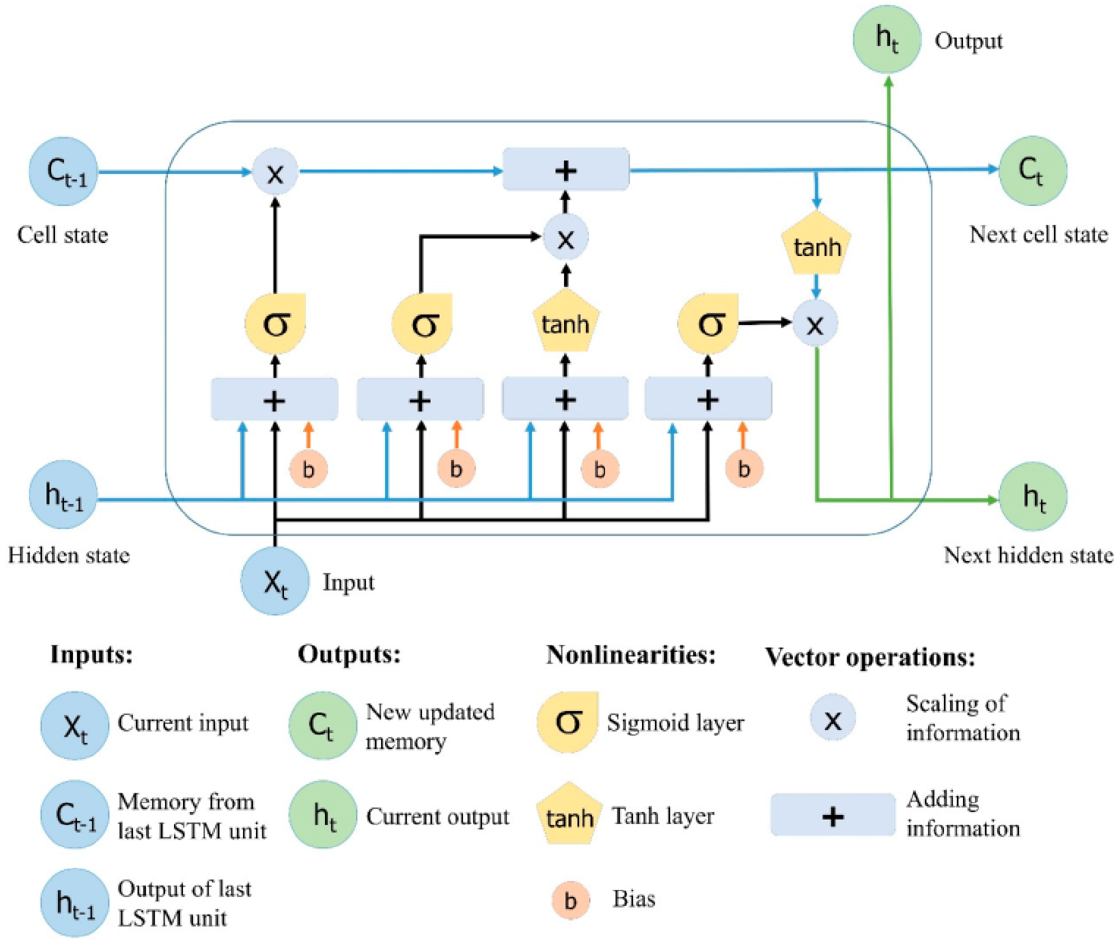

Figure 3.8: The architecture of LSTM, image source [10]

- **Bidirectional LSTM (BiLSTM):** consists of LSTM units organized into two hidden layers to effectively incorporate information from past and future contexts. This bidirectional approach enables the network to capture dependencies in both forward and backward directions, allowing the network to capture dependencies in both directions and then combine the results in the same output layer. It is particularly suitable for tasks where historical and future information is crucial, as in the beam alignment process. The hidden layer in a Bi-LSTM can be computed using the following function [72]:

$$h_t = \sigma(\overset{t}{\underset{h}{\rightarrow}} + \overset{t}{\underset{h}{\leftarrow}}) \tag{3.8}$$

Here, the symbol $\rightarrow$ represents the forward direction, and $\leftarrow$ represents the backward direction. The architecture of a BiLSTM is illustrated in Figure 3.9.

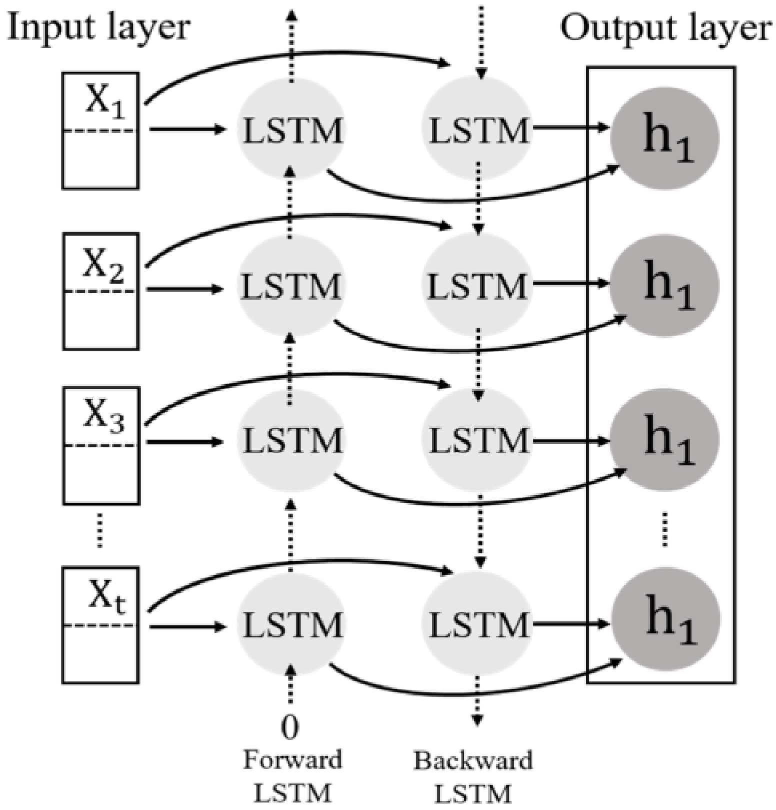

Figure 3.9: The architecture of BiLSTM neural network, image source [11]

The high isotropic attenuation and channel loss associated with mmWave frequencies pose inherent difficulties in achieving accurate beamforming. These difficulties are compounded in dynamic and highly mobile environments, where reliable and continuous tracking of the base station (BS) and the vehicle on moving angles becomes challenging. To address these challenges, the authors of [73] on beam alignment at the base station. They introduce an adaptive method based on RNN, specifically the LSTM model, to efficiently track and predict the angle of departure (AoD). In addition, they propose a refined frame structure strategically designed to reduce the overhead of beam alignment, thereby increasing communication rates. Through a series of numerical experiments conducted in a complex, non-linear mobility scenario, this method demonstrates remarkable efficiency in tracking the departure angle. It significantly increases communication rates compared to conventional techniques such as particle filtering [74]. However, RNNs may need lots of labeled training data to generalize, where data collection can be resource-intensive and time-consuming in highly dynamic and vast mmWave vehicular environments.

In conclusion, NNs have emerged as formidable tools for aligning vehicular communication beams. We have explored the power of CNNs for spatial feature extraction and RNNs, including LSTM and BiLSTM, for processing sequential data for more dynamic beam alignment. These methods have shown great promise for improving beam selection accuracy, reducing latency, and adapting to changing vehicle environments. In addition to approaches based on neural networks, another powerful paradigm is gaining ground in vehicular communication: Deep Reinforcement Learning (DRL), which will be presented in the following subsection.

3.3.2 Deep Reinforcement-Learning Approaches for Beam Alignment

Reinforcement Learning, often known as RL, is a machine learning that focuses on agents learning how to interact with an environment to maximize a reward signal. RL functions in a situation that involves sequential decision-making, in which an agent makes actions in an environment to accomplish specific objectives. In mathematical terms, RL may be represented as a Markov Decision Process (MDP), which is comprised of the following four essential parts, as depicted in Figure 3.11:

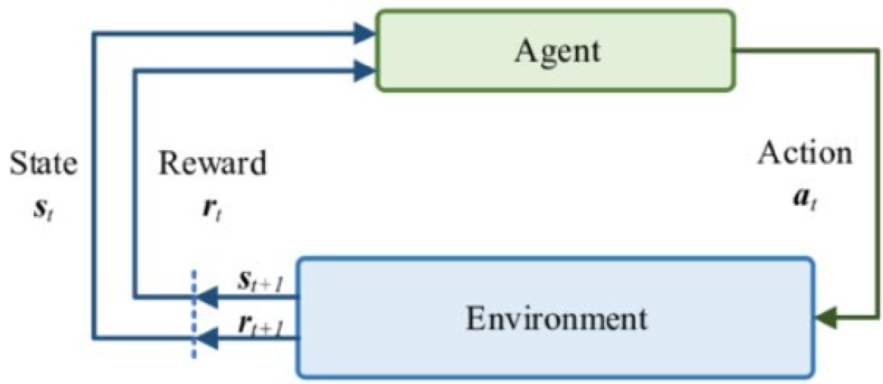

Figure 3.10: The representation of Reinforcement Learning model

- **State (S):** This represents all possible environment configurations the agent can perceive.
- **Action (A):** These are the choices or decisions that the agent can make while interacting with the environment.
- **Transition Function (T):** This function describes how the environment evolves from one state to another based on the agent's actions. Given the current state and action, it provides the probabilities of transitioning to different states.

- **Reward Function (R):** This function defines the immediate feedback or reward the agent receives after each action in a particular state. The goal of the agent is to maximize the cumulative reward over time.

The RL agent learns a policy, a strategy that maps states to actions and tries to choose actions that lead to the highest expected cumulative reward. Different methods like Q-learning and policy gradients are used to train RL agents.

Deep reinforcement learning (DRL) incorporates neural networks to approximate policy or value functions [75]. These neural networks allow DRL agents to handle high-dimensional input spaces, as presented in Figure, making them suitable for training agents capable of learning to make decisions in complex environments, such as beam alignment in dynamic vehicle scenarios. Notable examples of DRL algorithms include Deep Q-Networks (DQN) [76], Proximal Policy Optimization (PPO) [77], and Trust Region Policy Optimization (TRPO) [78].

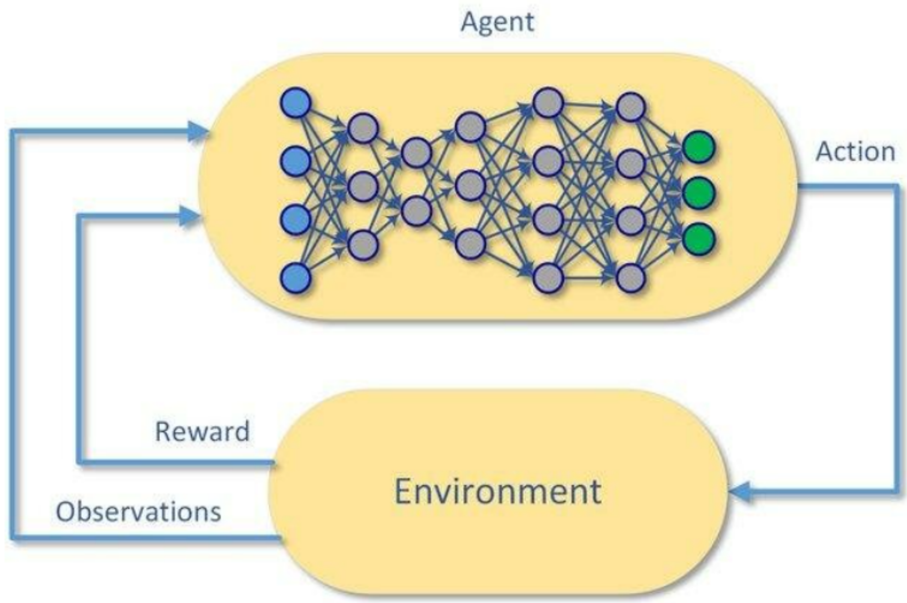

Figure 3.11: The representation of Deep Reinforcement Learning model, captured from [12]

Due to their ability to learn optimal control policies in complex and dynamic contexts, DRL-based techniques have recently attracted much interest in vehicular communication systems [79]. Several applications of vehicular networks, including route planning [80], platooning [81], and cooperative driving [82], have benefited from DRL. The optimization of communication networks in V2V and V2X situations using beamforming has been suggested using techniques based on DRL [83]. These approaches often use deep neural networks (DNNs) to build approximations of the best policy for making beamforming and resource allocation choices in real time [84].

To tackle the challenges of dynamic blockage in mmWave V2X networks, the authors of [85] developed an online DRL framework to identify dynamic blockage during the transmission phase and allow appropriate switching choices to increase system dependability. To evaluate the effectiveness of the proposed framework, the authors performed extensive evaluations using ray-tracing-based channel data. The simulation results are promising, showing a 28.9% reduction in violation probability compared to conventional baseline algorithms. However, it is recommended that this approach be extended to multi-user scenarios rather than using the case of a single user.

In [86], the authors proposed a novel technique for blind beam alignment in mmWave communication using deep reinforcement learning. The method relies on individual vehicles' unique radio frequency (RF) fingerprints, which are transmitted to the base station via omnidirectional transmission. It also uses the SINR values to predict the optimal base station for each vehicle and determine the appropriate beam-forming parameters, such as azimuth and elevation angles, to be used. This system intelligently selects the most suitable beam angle parameters for each transmission. In particular, this proposal has resulted in a four-fold increase in data throughput compared with conventional methods such as the beam scanning technique [87] or Vanilla's Deep Deterministic Policy Gradient (DDPG) approach described in [88]. However, this system does not consider the precise positioning of vehicles, which could improve the accuracy of the proposed beam alignment method.

Multiple Input Multiple Output (MIMO) is the basis of beamforming in mmWave vehicular networks and plays a crucial role in using multiple antennas to transmit data efficiently. However, high-speed applications over mmWave face data transmission and latency problems. Pulok T et al. [89] present a new DRL-based approach designed for coordinated beamforming in mmWave vehicular networks to address these challenges. This approach involves multiple base stations collaborating to collectively serve a single vehicle's needs. The solution is based on a DRL model proposed to predict sub-optimal beamforming vectors from a set of potential candidates in the beamforming codebook. The resulting system architecture ensures reliable coverage for highly mobile mmWave applications and minimizes training overheads and latency. This study's numerical results demonstrate the proposed algorithm's effectiveness, significantly improving the total throughput capacity achievable in massive and highly mobile mmWave vehicular MIMO scenarios while keeping training overheads and latency to a minimum. However, in real-world scenarios, mmWave vehicular signals are susceptible to interference from other devices, obstacles, and environmental conditions, impacting the performance of coordinated beamforming systems.

In conclusion, this chapter has provided an overview of different approaches to BA in mmWave vehicular communication systems. We have explored the capabilities of deep learning models, in particular, CNNs for spatial feature extraction and RNNs, including LSTM and BiLSTM, for processing sequential data in dynamic beam alignment. While conventional beam alignment methods have their merits, they often face limitations in highly dynamic and unpredictable vehicular environments.

In the following chapters, we will present our proposed methods for addressing the limitations and difficulties outlined in previous studies. Our innovative approaches rely on classical and deep learning methods to improve beam alignment performance, thus ensuring reliable and high-speed V2X communications in highly mobile mmWave vehicular scenarios.

Chapter 4

Simulated Annealing-based Beam Management for 5G Vehicular Networks

4.1 Introduction

Despite significant advances in fifth-generation (5G) vehicular networks, data transmission continues to be limited by signal attenuation, mainly when vehicles are in motion. This limitation is caused by the constraints inherent in 5G connectivity, primarily associated with waves, which can only travel short distances and are likely to be disrupted by physical obstacles such as buildings, trees, and walls. These obstacles block, disrupt, or weaken certain parts of the transmitted signal.

In this chapter, we present our initial contribution to this field. We propose a new approach based on the classical optimization method, using, in particular, the simulated annealing algorithm for beam management in 5G vehicular networks.

Our first contribution was published in a short paper at the IEEE 22nd International Conference on High-Performance Switching and Routing (HPSR), 2021. The published paper is entitled *Simulated annealing-based beam management for 5G vehicular networks*, [1]. Please visit this link for more information.

4.2 Our Proposed Method

The beam management process aims to communicate effectively between the vehicle and the BS, allowing the two to align their antennas for high-speed, low-power transmission.

[1] https://ieeexplore.ieee.org/document/9481825

However, the signal attenuation problem makes this process challenging to implement since it is easily disrupted by environmental factors that can block the signal and swiftly break the communication link between the BS and the linked car [90].

We propose a new model, SABM-5GVNet (Simulated Annealing-based Beam Management for 5G Vehicular Networks), to tackle this challenge. SABM-5GVNet dynamically identifies the best beam angle for every vehicle's location within the communication link between the vehicle and the BS.

Our contribution focuses on the communication scenario between a stationary mmWave base station and moving automobiles in a 5G vehicular network, as shown in Figure 4.1. We integrate beamforming technology (directed signal transmission) into the mmWave base station. Our proposal enables the base station to adjust the beam direction dynamically based on the connected vehicle's location, unlike a conventional BS that transmits and receives data using fixed beam radiation patterns.

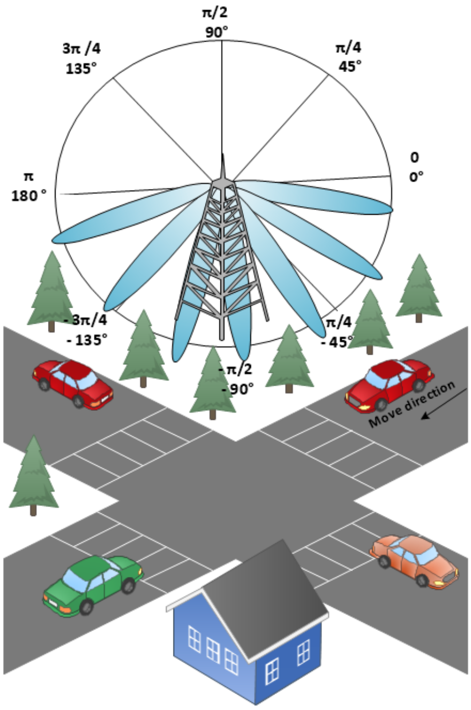

Figure 4.1: mmWave communication in 5G vehicular network

We propose a SA algorithm to find the optimal direction beam $\alpha \in [0, 2\pi]$ for each location along the vehicle's route $Pv = (Xv, Yv) \in \mathbb{R}^2$, which improves system performance by maximizing the signal-to-interference-and-noise ratio (SINR). The proposed SA procedure for beam angle optimization is depicted in Figure 4.2.

- First, we initiate the process by generating the initial solution, denoted by S_0. At this stage, we also set a high initial temperature represented by $T = T_0$ (represent-

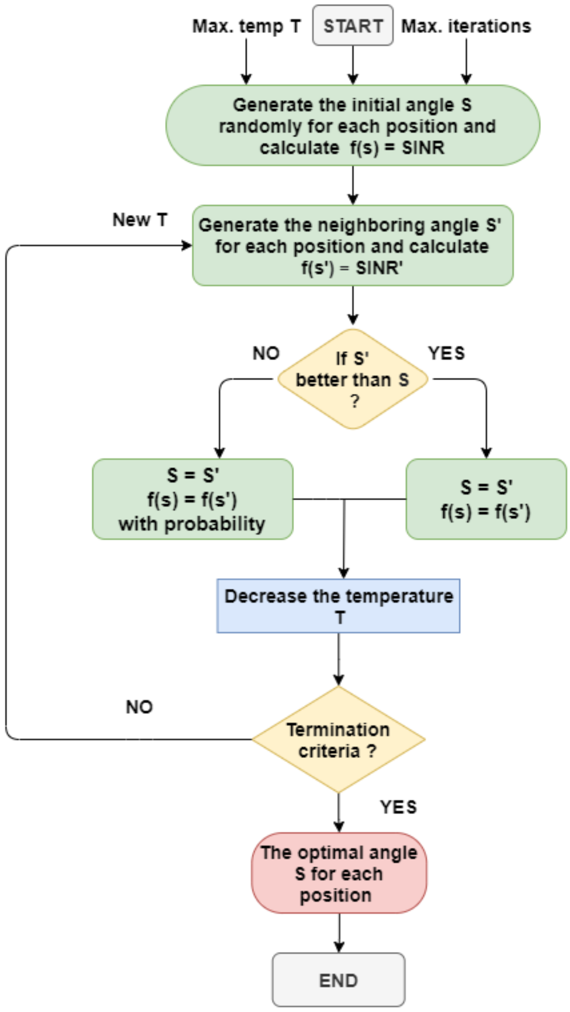

Figure 4.2: The proposed SABM-5GVNet algorithm

ing a time-varying global parameter chosen by the user). During this phase, we randomly introduce a search for the angular orientation α, associated with its SINR value previously stored in a database. This search is performed for each specific position $P_v = (x, y)$ in the environment. The output of this step is an array of pairs: $[(p_0, \alpha_0), (p_1, \alpha_1), ..., (p_n, \alpha_n)]$.

- For each generating solution, it is necessary to:
  - ◇ Using the objective function, the SINR value corresponding to each pair (p_v, α) is calculated, giving an initial energy level of $E = E_0$. Note that the energy level acts as the objective function in this context.
  - ◇ A linear reduction rule is established using a user-specified β value: T is updated as $T = T - \beta$ at each iteration.

- ◇ The suggested neighborhood function is employed to identify the neighboring solution S' from the current solution S.

- During each iteration, we generate a new neighboring solution, denoted as S', by introducing a random number, n, drawn from the interval $[a, b]$ and adding it to the angle α of the current solution, S. This process yields a new angle, α', for S', resulting in a new SINR value, $f(S')$.

- We calculate the change in system energy, represented by the objective function, as $\Delta_E = f(S') - f(S)$. Depending on the value of Δ_E, we classify it into two categories:

  - ◇ If $\Delta_E > 0$: indicates that the generated solution S' is superior to the existing one, we accept S', which guarantees an improved SINR. This newly accepted solution replaces the original S, denoted as $S \leftarrow S'$.
  - ◇ Conversely, if $\Delta_E < 0$, S' is conditionally accepted with a probability determined by the following equation 4.1. This approach makes exploring part of the solution space possible to avoid being trapped in a local optimum.

$$P = e^{-\Delta_E/T} \tag{4.1}$$

- The SA algorithm continues its iterations until it meets the specified stopping criterion.

The best angle for each location will be determined when the process is finished.

4.3 Experiments and Results

This section describes the experimental research study performed to evaluate our suggested SABM-5GVNeT. After that, we explain the findings obtained after comparing a SABM-5GVNeT to the traditional scheme used to choose the beam angle.

4.3.1 Parameter Settings and Simulation Setup

Table 4.1: Simulation parameters for SABM-5GVNeT

Parameters	Value
Transmitter Power	30 dBm
Bandwidth	200 Mb/s
Carrier frequency	30 GHz
BS Antenna Model	3GPP
BS Height	10 m
BS Gain	4.97 dBm
Velocity vehicle	20 m/s
Scenario	UMI
Simulated time	10 s

We have selected an Urban Micro-cell (UMi) scenario with a radius of $R = 200m$ for our proposal. This scenario considers a single mmWave base station (BS) operating at a carrier frequency of $f = 30GHz$ and a bandwidth of $B = 200MHz$. The BS is at coordinates $p_{bs} = (0, 0)$. Communication is established between the mmWave BS and a mobile vehicle, which initiates the starting position $p_{v_s} = (+60, -20)$. This vehicle maintains a constant velocity of $v = 20m/s$ and reaches its final destination at $p_{v_f} = (+60, +180)$. To evaluate the effectiveness of our proposed solution in real-world scenarios, we have introduced a residential building structure between the mmBS and the vehicle, simulating the presence of obstacles during communication.

4.3.2 Database creation and a simulation scenario

- To initiate the experiment, we projected a transmission (Tx) beam from the mmBS towards various vehicle locations within the environment. This beam was directed along different angles, $\alpha \in [-180, 180]$

- Each beam angle's performance was determined and stored in a database by calculating the SINR of the received signal, as reported in 3GPP TR 38.900 [91].

- Then, we designed and implemented our proposed simulated annealing algorithm in the millimeter-wave base station to autonomously determine the optimum beam angle for each vehicle position. This algorithm selected a new beam direction at 40-

meter intervals along the vehicle path. It should be noted that this specific spacing between two positions was set as an empirical value.

- For our simulated annealing implementation, we defined the parameters as follows:
  - ◇ The number of iterations was set to 300, constituting the termination criterion.
  - ◇ The maximum temperature was set at 2000, based on empirical considerations.
  - ◇ According to the proposed methodology, we allowed the selection of a sub-optimal neighboring solution if the calculated probability, denoted by P, exceeded the threshold value of 0.8. This threshold was determined experimentally.
  - ◇ The β parameter, used for linear temperature reduction, was set to 50.

4.3.3 The obtained Results

After completing the initial step of SABM-5GVNet, which consists of randomly generating the initial solution, we acquired the following initial angles for different positions of the vehicle along its trajectory: [[$p_{v_1} = (60, -20)$, $\alpha_1 = 53°$], [$p_{v_2} = (60, 20)$, $\alpha_2 = 88°$], [$p_{v_3} = (60, 60)$, $\alpha_3 = 76°$], [$p_{v_4} = (60, 100)$, $\alpha_4 = 7°$], [$p_{v_5} = (60, 140)$, $\alpha_5 =$ -176°], [$p_{v_6} = (60, 180)$, $\alpha_6 =$ -83°]].

After this, the neighborhood function is executed. In this step, we propose to select the neighborhood angle by incorporating a randomly generated number in the interval [-2, +2], for example, 53° - 2 = 51°. As a result, 51° becomes the new angle for the new solution. This process is repeated 300 times according to SABM-5GVNet. Finally, we reach the optimal solution that ensures efficient communication and maximizes the received signal strength between the base station and the vehicle. The optimal solution generated by our proposed algorithm is shown in green in Figure 4.3.

4.3.3.1 Discussion of results

We performed a comparative analysis between our results and a conventional approach to demonstrate the influence of angle optimization on 5G vehicular communication performance. In the traditional method, the BS selects the beam angle based on a fixed orientation model, as shown in the red graph in Figure 4.3. Our observations show that, for each position, the SINR of the received signal obtained with our proposal is higher than that of the traditional approach.

This improvement highlights the dynamic beam management capabilities of the optimal solution generated by the proposed SABM-5GVNET algorithm. It ensures the quality

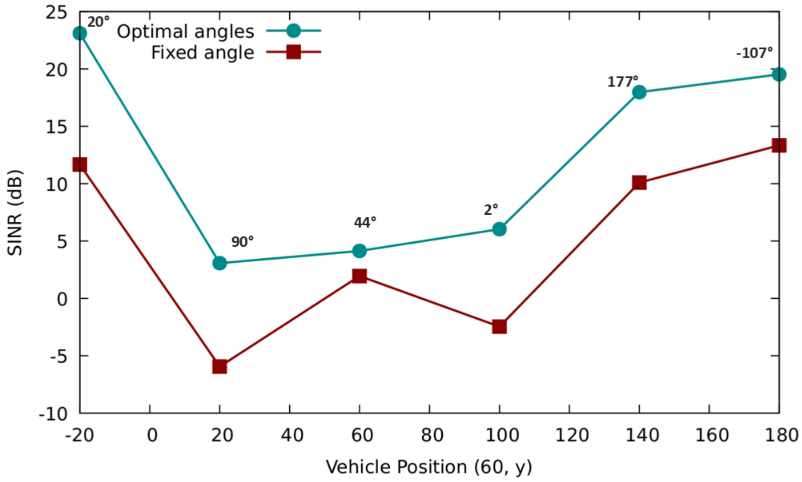

Figure 4.3: Impact of angle optimization on the SINR

of non-line-of-sight (NLOS) connectivity, as the mmBS configures the beam direction at each position in the environment by selecting the optimal angle. This strategy facilitates rapid data transmission to the connected vehicle. Therefore, our proposal improves data throughput and ensures low latency for data transmission between the mmBS and the mobile vehicle in 5G networks.

4.4 Conclusion

This chapter presented a new beam management solution for 5G vehicular networks, the Simulated Annealing-based Beam Management for 5G Vehicular Networks (SABM-5GVNET) algorithm. First, we collected performance data for different beam angles at different vehicle positions in the environment. Then, we used these data to determine the optimal beam angle that maximizes the SINR for each vehicle position along its route. The main objective of our proposal is to improve the data transmission rate and minimize the latency between the mmBS and the connected vehicle, thereby improving the overall performance of the traffic flow. Our results indicate that SABM-5GVNET performs significantly better than the traditional method regarding data transmission efficiency. Nonetheless, our proposed simulated annealing algorithm can be computationally intensive, especially when dealing with many beam angles and vehicle positions.

The next chapter presents our second contribution based on a deep-learning method for the BA procedure. We aim to deal with the limitations of SABM-5GVNET and to improve the 5G vehicular networks, particularly V2X communication. This new approach should make communication more intelligent and contribute to autonomous vehicular navigation.

Chapter 5

A Novel mmWave Beam Alignment Approach for Beyond 5G Autonomous Vehicle Networks

5.1 Introduction

With the rapid evolution of vehicle networks towards B5G (Beyond 5G), the demand for high-speed, ultra-low latency data transmission between entities in the vehicle network has exploded. The vision of fully AV has highlighted the critical need for efficient and continuous signal transmission.

This chapter presents our second contribution, based on a deep-learning model for B5G vehicular communications. Autonomous vehicle navigation, which relies on a constant stream of data to make real-time decisions, dramatically illustrates the urgency of ensuring reliable, lightning-fast data exchange. This need goes beyond mere convenience; it has become an imperative requirement.

Our second contribution was published in IEEE Transaction Vehicular Technology (TVT), 2023. The published paper is entitled *A Novel mmWave Beam Alignment Approach for Beyond 5G Autonomous Vehicle Networks*, [1]. Please visit this link for more information.

5.2 System and Channel Model

This section comprehensively overviews the implemented mmWave system and the channel model used.

[1] https://ieeexplore.ieee.org/abstract/document/10246397/

5.2.1 System Model

This study focuses on the downlink data transmission (DL) within a B5G MIMO system operating within the high-frequency mmWave spectrum, illustrated in Figure 5.1. In this scenario, we have a BS, the transmitter, equipped with a uniform planar array (UPA) consisting of N_t antennas. On the receiving end, there are k vehicles, each equipped with a single antenna configured omnidirectionally. For tracking the location of each mobile vehicle, we rely on GPS Cartesian coordinates, ensuring precise positioning. Simultaneously, we assume that the base station's position is readily available and known to all vehicles.

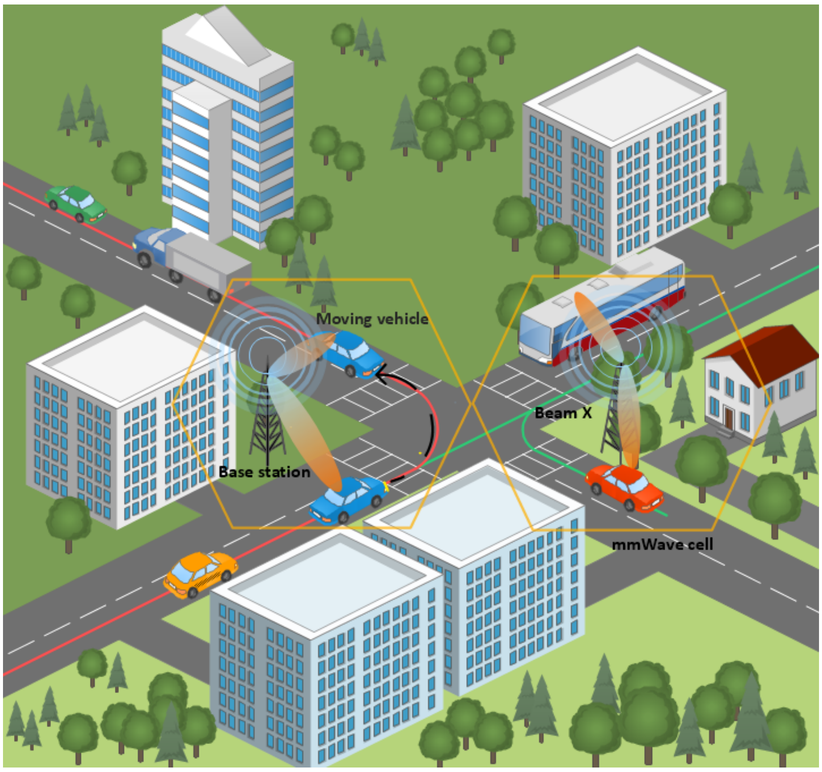

Figure 5.1: Example of beam alignment in a B5G vehicular network

5.2.2 Channel Model

Using the ray-tracing methodology, we create the mmWave channel that connects the mmBS to the mobile vehicle at each location in the vehicular environment. This ray-tracing tool provides the essential characteristics of the channel, including azimuth and elevation departure angles, phase information, time of arrival (ToA), received signal strength, and the number of distinct line-of-sight (LOS) and non-line-of-sight (NLOS) paths (L) that exist between a vehicle and a BS.

Signal propagation between a mmBS and a vehicle is defined by the channel matrix $\mathbf{H} \in \mathbb{C}^{N_t 1}$, which covers L_p paths. In vehicular communication scenarios, the Doppler effect, which refers to the shift in signal frequency due to the relative motion between the mmBS and the vehicle, is significant. We can model this phenomenon by introducing a time-varying complex gain factor for each path in the $\mathbf{H}$ channel matrix. This factor presents a time difference that depends on the signal frequency, the speed of the vehicle, and the direction of arrival of the signal. By accounting for the Doppler effect, the resulting fitted channel matrix $\mathbf{H}$ [?] provides a more accurate representation of the channel characteristics in vehicular communication scenarios. This can be expressed as follows:

$$\mathbf{H}(t, f) = \sum_{l=0}^{L_p-1} \alpha_l(t, f)\mathbf{a}(\phi_l^{AoD}, \theta_l^{ZoD}), \tag{5.1}$$

Here, $\mathbf{H}(t, f)$ represents the channel matrix at time t and frequency f, while $\alpha_l(t, f)$ represents the complex gain factor of path l at time t and frequency f. The expression ϕ_l^{AoD} denotes the departure angles in azimuth (AoD), and θ_l^{ZoD} denotes the departure angle at zenith (elevation) (ZoD). The orientation vector $\mathbf{a}(\phi_l^{AoD}, \theta l^{ZoD})$ is an array $Nt1$, responsible for steering beam direction. The beam steering includes the phase differences of the signal coming in at each antenna, mainly determined by the azimuth angle, as expressed by the following equation [92] :

$$\mathbf{a}(\phi_l) = \frac{1}{\sqrt{N_t}}[1, e^{j\frac{2\pi}{\lambda}d\sin\phi_l}, ..., e^{j(N_t-1)\frac{2\pi}{\lambda}d\sin\phi_l}]^T, \tag{5.2}$$

The carrier wavelength, denoted by λ, and the distance between the antennas in mmWave communication, represented by d, may be determined using the formula provided by [93].

$$d = \lambda/2. \tag{5.3}$$

In the base station, we implement analog beamforming, which employs a single shared RF chain for N_t antennas. Each antenna branch includes a phase shifter and a power amplifier (PA) for antenna control. The beamforming vector w, which encapsulates the phase shifters, can be expressed as:

$$w = [e^{j\beta_1}, ..., e^{j\beta_{N_t}}]^T, \tag{5.4}$$

Here, β represents the phase corresponding to the nth phase shifter linked to the nth antenna element.

For each beam direction, the complex gain factor can be written as:

$$\alpha_{l,k}(t) = \alpha_{l,k} \cdot e^{j2\pi f_d k T_s t}, \tag{5.5}$$

f_d signifies the Doppler shift frequency, while k denotes the sample index at time t, and T_s represents the sampling interval. To incorporate the frequency index f into the complex gain factor, we can adjust the Doppler shift frequency f_d as demonstrated below:

$$f_d = \frac{2v_r}{\lambda}, \tag{5.6}$$

Here, $2v_r$ represents the velocity of the vehicle. Subsequently, we can formulate the received mmWave signal y_k at vehicle k as follows:

$$y_k(t, f) = h_k^H(t, f) w_k(f) x_k(t) + n_k(t, f), \tag{5.7}$$

The vector $h_k^H(t, f) \in \mathbb{C}^{N_t 1}$ represents the channel for vehicle k at time t and frequency f. The beam applied by the mmBS to transmit the signal to vehicle k is denoted as $w_k(f)$, and $x_k(t)$ represents the transmitted signal from the mmBS antennas to vehicle k. The term $n_k(t, f)$ refers to the additive white Gaussian noise (AWGN) with zero mean and variance $\sigma_{n,k}^2$ at time t and frequency f. The optimal beam, denoted as $\hat{b}$, may be formally defined in the following manner:

$$\hat{b} = \arg\max_b \left\| \mathbf{H} w_b \right\|, \tag{5.8}$$

where $\mathbf{H}$ is the channel matrix and $0 \leq b \geq N_t - 1$ is the beam index.

5.3 Our Proposed Beam Alignment Approach

In this part, we will detail the critical components of the suggested beam angle prediction technique that we have developed and explain why a hybrid model is required to align mmWave beams in B5G networks for AVs to navigate successfully. Figures 5.2 and 5.3 represent the three major stages of our proposed solution.

5.3.1 Data pre-processing

The initial data pre-processing phase involves collecting all the data generated during the environmental simulation. Next, we carried out a normalization process using the z-score method. This step was essential because the parameters involved had distinct ranges of values with varying scales. The z-score normalization procedure transforms the feature

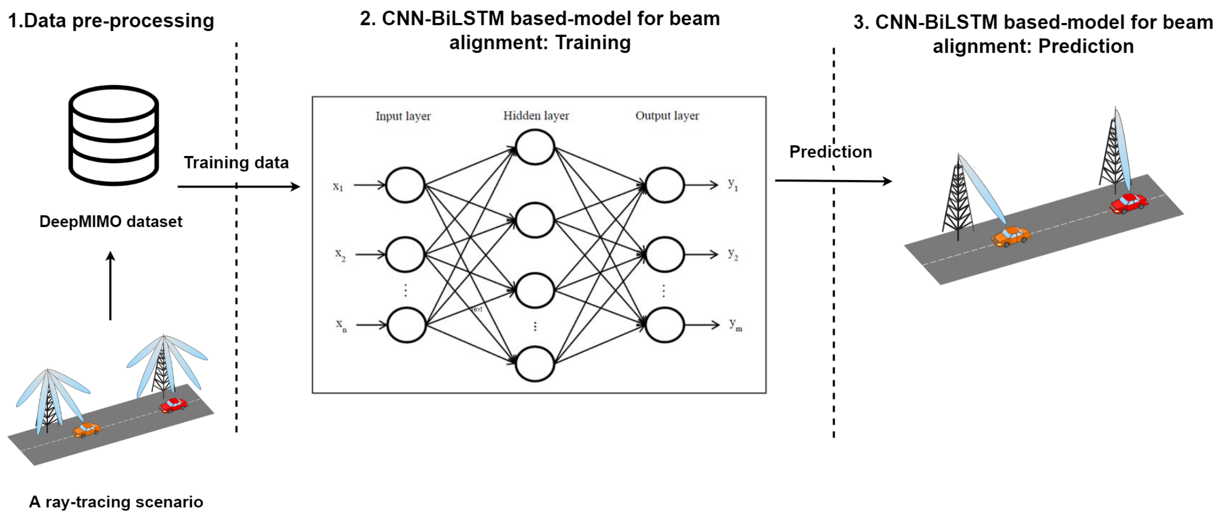

Figure 5.2: The overall structure of the proposed beam alignment approach.

values into a normalized range between 0 and 1. This is done by subtracting the mean (μ) of each feature and then dividing it by the standard deviation (σ), as shown in the following equation:

$$\text{Normalized data} = (X - \mu)/\sigma, \tag{5.9}$$

Here, X represents the initial dataset, mu is the mean of the data, and $sigma$ is the standard deviation of the data. This process centers each feature by giving it a mean value of 0 and a standard deviation of 1. This normalization improves the performance of our model, speeds up data convergence, and simplifies model learning. After normalization, the dataset is divided into training and test subsets. The training data is then divided into training and validation datasets for model development and evaluation.

5.3.2 Training step

Our research introduces an original hybrid model that combines one-dimensional CNN and BiLSTM architectures to determine the optimal beam angle for each vehicle's position. As illustrated in figure 5.4, our proposed model consists of four main layers. Table 5.1 presents a detailed analysis of the structure of the proposed model, and we will describe each block of our model as follows:

5.3.2.1 Input layer

We have chosen five parameters of the mmWave channel as inputs to our model. These parameters include the vehicle position coordinates (loc_x and loc_Y), the received signal

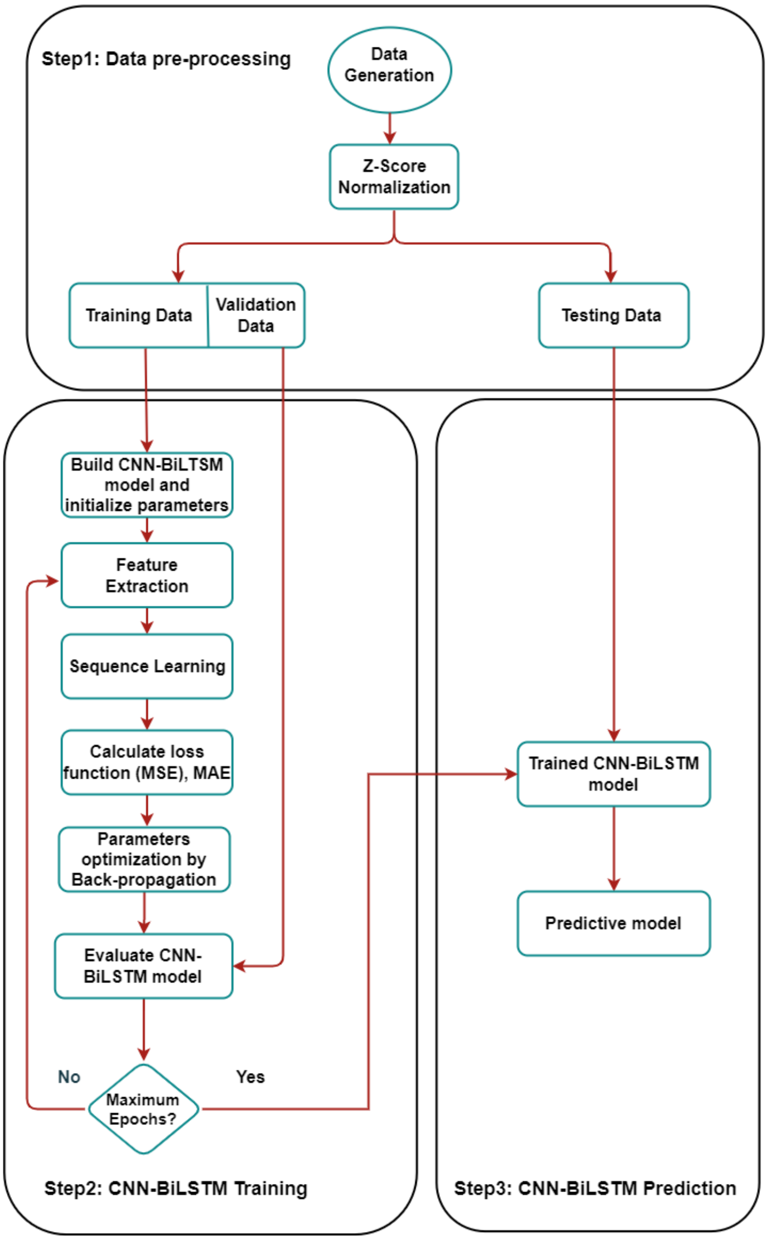

Figure 5.3: Diagram of the proposed model

power, the phase, and the elevation angle of the mmBS departure. To comply with the requirements of the CNN layer, we structure the input vector in a three-dimensional format, incorporating the number of samples, time steps, and features.

5.3.2.2 Feature extraction layers

In our feature extraction layers, we incorporated a single 1D convolution layer (Conv1D), initiated with 128 filters, each with a size of two. To introduce non-linearity and solve problems such as gradient vanishing and neuron death [94], we used the Rectified Linear Unit (ReLU) activation function, represented by the equation below:

$$relu(x) = max(o, x). \tag{5.10}$$

By applying multiple convolution kernels to the input data, we generate a range of convolved features that are generally more informative than the original input features. This significantly increases the accuracy of the model in predicting angles.

After the Conv1D layer, we introduce a pooling layer, more precisely, the maximum pooling layer. This layer has a dual purpose: it minimizes the computational complexity of the model by reducing the Conv1D output; simultaneously, it compresses the data and extracts the principal features.

We normalize the output data using a Batch Normalisation (BN) layer to optimize our model further and speed up the training process. This step serves as a regularisation strategy. In this layer, features are normalized to align their mean closer to zero and with optimal distributions. The batch normalization process is calculated as follows:

$$\mu = \frac{1}{N_{batch}} \sum_{i=0}^{N} x_i, \tag{5.11}$$

$$\sigma^2 = \frac{1}{N_{batch}} \sum_{i=0}^{N} (x_i - \mu)^2, \tag{5.12}$$

$$\hat{x}_i = \frac{x_i - \mu}{\sqrt{\sigma^2 + \varepsilon}}, \tag{5.13}$$

$$y_i = \gamma \hat{x}_i + \beta, \tag{5.14}$$

In this equation, the i^{th} observation value in the mini-batch is represented by x_i, while y_i represents the corresponding output. The size of the mini-batch is indicated by N_{batch}. In this context, μ and γ indicate the samples' mean and standard deviation values in the mini-lot. Our approach incorporates a scaling parameter, γ, which is fixed as a constant close to zero, and a bias parameter, β, to ensure numerical stability.

It is important to note that during the convolution operations, no features are lost. This is achieved by selecting the padding type "same". It should be noted that the feature extraction layer serves as a preliminary step in preparing the Bi-LSTM input. Unlike traditional pre-processing methods, Conv1D, in this context, treats each feature individually, considering its content.

5.3.2.3 Sequence Learning layers

This block of layers consists of four BiLSTM layers, three dropout layers, and a flattened layer. BiLSTM was chosen as the beam angle prediction model because of its ability to preserve dependency relationships in the input data, both in the forward and reverse directions. Although it excels in prediction accuracy, it requires a more significant amount of input data to exploit its three gates effectively and converge toward stability.

First, the normalized input data are sequentially processed by a Bidirectional Long Short-Term Memory (BiLSTM) network, which consists of four layers. Each BiLSTM layer has various neurons, starting with 256 neurons in the first layer, 128 neurons in the second layer, 64 neurons in the third layer, and 32 neurons in the fourth layer. The BiLSTM network employs two activation functions: hyperbolic tangent (tanh) and sigmoid [95]. The forward LSTM processes the data from left to right, while the input data is inverted and passed to the reverse LSTM, which operates from right to left. These activations are mathematically defined as follows:

$$tanh(x) = (e^x - e^{-x})/(e^x + e^{-x}). \tag{5.15}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}}. \tag{5.16}$$

After each BiLSTM layer, a dropout layer is incorporated with a probability of dropout set at 0.4. This strategic addition mitigates overfitting and improves the model's predictive performance model's predictive performance, mainly when dealing with test data.

Finally, a flattened layer transforms the output data into a one-dimensional format to align it with the model's requirements.

5.3.2.4 Prediction layers

The prediction layer block consists of three fully interconnected layers, ending with the output layer comprising 64, 32, and one neuron, respectively. These fully combined layers perform linear transformations on the values derived from the previous block. Finally, they predict the optimal beam departure angle (azimuth angle) of the mmBS. This prediction allows our system to achieve precise beam alignment between the mmBS and the AV at every position.

Table 5.1: Structure of the proposed model

Block	**Layer**	**Number of neurons**
Feature extraction layers	Conv1D	128*2*1
	MaxPooling	128*2
Sequence learning layers	BiLSTM1	256
	BiLSTM2	128
	BiLSTM3	64
	BiLSTM4	32
	Flatten	-
Prediction layers	FC1	64
	FC2	32
	FC3	1

5.3.3 Prediction step

The ability of our model to predict the optimal beam angle direction relies on minimizing the loss function during the learning phase. Our research has shown that reducing the loss function using mean square error (MSE) aligns with data rate optimization of V2X transmission in millimeter-wave B5G vehicular networks. This optimization allows our proposal to maximize the data rate transmission and reduce the overhead caused by beam sweeping, thus reducing network congestion. In the next section, we will explore the influence of the loss function on our proposed system's performance, particularly its role in beam alignment within a 5G autonomous vehicle network.

5.4 Simulation results

In this section, we evaluate the effectiveness of our model designed for beam alignment in 5G autonomous vehicular networks. We start by describing the scenario we used and

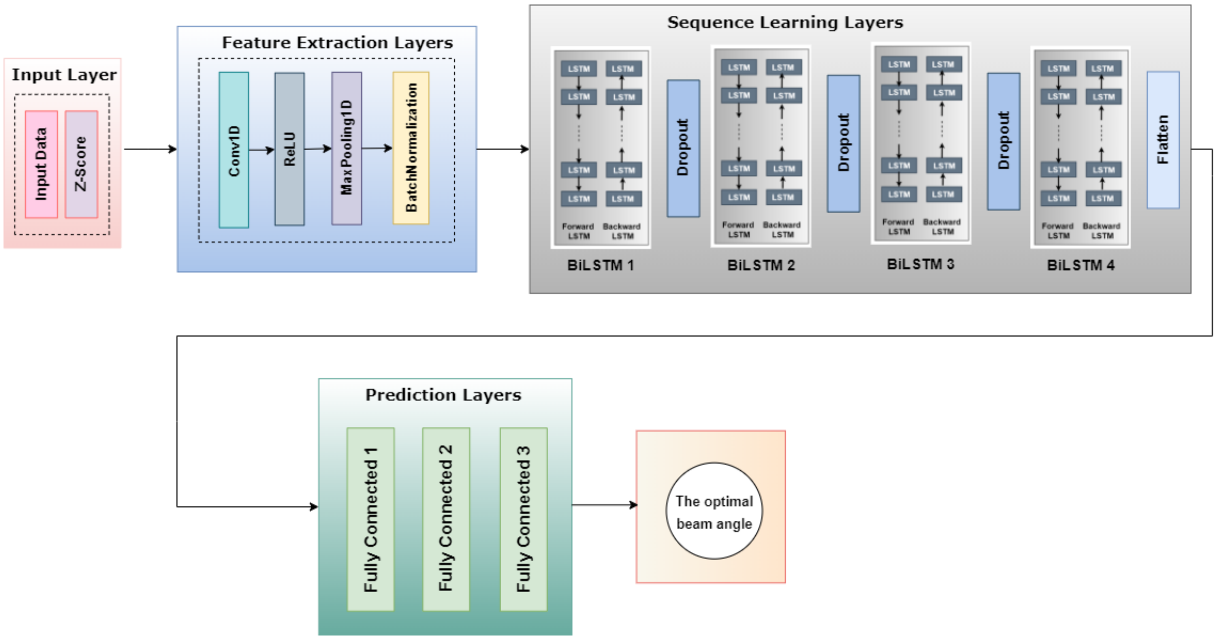

Figure 5.4: The proposed architecture of the proposed model for beam alignment in B5G vehicular networks.

the dataset on which our simulations are based. We will then look at the results and conclusions obtained from these simulations.

5.4.1 Simulation Setup

This study used the available DeepMIMO dataset [13], a well-established resource frequently used in deep learning applications for massive mmWave MIMO systems. This dataset was generated using 3D ray tracing techniques in the commercial Remcom Wireless Insite simulator. Our simulations focus on the "O1_60" scenario, designed for outdoor vehicular communication, as shown in Figure 5.5.

Initially, for data collection in scenario O1_60, we ran the deepMIMO generation scripts accessible via [96]. This process was carried out in the MATLAB environment, following the specified parameters and system configuration, as shown in table 5.2. In this scenario, all vehicles maintain LoS communication with the mmBS and operate at a carrier frequency of 60 GHz.

The resulting dataset includes channel matrices calculated using formula 5.8 and beam information about the communications between the vehicles and the mmBS. We extracted critical features from this data to serve as input and output for the proposed model. These characteristics include the AoD in azimuth and elevation from the mmBS, received signal strength, path phase, signal propagation delay, and vehicle location.

As indicated in the simulation parameters in Table 5.2, we strategically positioned

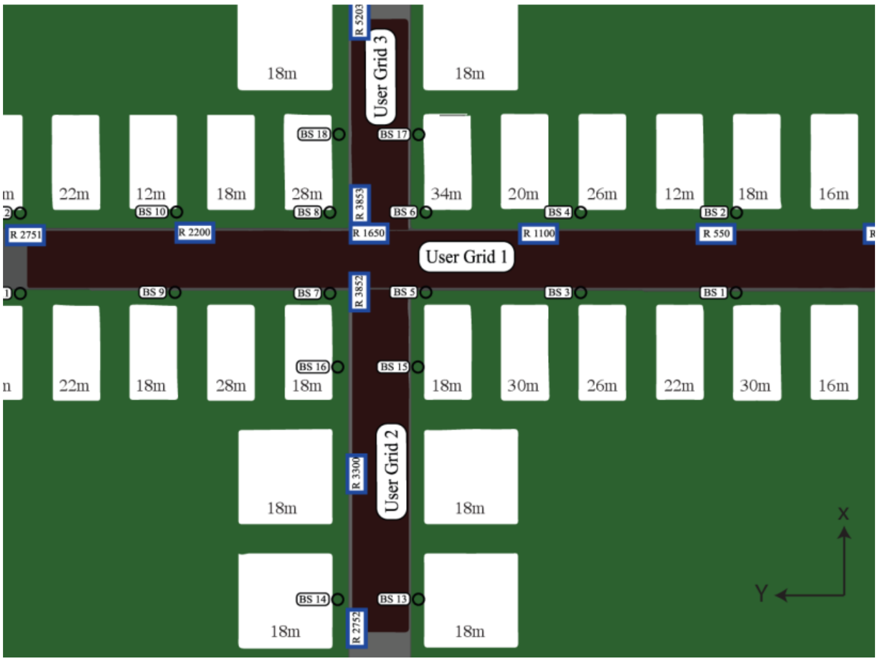

Figure 5.5: Simulation environment, [13].

four mmWave base stations (BS1, BS2, BS3, BS4) on the roadside, each at a height of 8 meters. These base stations adopted the system model described in Section 4.2.1, with uniform planar arrays (UPAs) arranged in a 16-column, 4-row configuration. These UPAs collectively housed M = 64 antennas, with a spacing of 0.5 meters between antennas.

The grid of vehicle positions extended from row number #1000 to row number #1650, with each row accommodating 181 separate positions. This arrangement generated 10^7 vehicle positions evenly distributed along the road in the scenario. It should be noted that the vehicles in this scenario traveled at 60 km/h, approximately equivalent to 16.67 m/s.

In our CNN-BiLSTM model, we divide the dataset into training (60%), validation (20%) and test (20%) subsets. Before training the model, we use the z-score normalization technique on the characteristics of the input data, including vehicle location, path phase, received signal strength, and base station elevation angle. Next, we use the proposed architecture.

The training process consists of training the CNN-LSTM model for 250 epochs, each with 64 batches. We use the RMSprop optimizer with a specified learning rate of 0.0001 to facilitate training. We use Python 3.8 and the Keras libraries to implement our model, with TensorFlow as the backend. Table 5.3 summarises the hyperparameters used in the training process.

Table 5.2: System hyperparameters and configuration for data generation

Parameters	**Values**
Scenario name	O1_60
Active BSs	4
Active users	1000 to 1650
BS UPA dimensions	64 antenna elements
Antenna spacing **(m)**	0.5
Bandwidth (GHz)	0.5
OFDM subcarriers	1024
OFDM sampling factor	1
Transmit power of BS	30dBm
Model system	Intel(R) Core(TM) i7-8565U CPU
Processor	@ 1.80GHz
RAM	16GB
Graphics card	NVIDIA GeForce MX150

Table 5.3: CNN-BiLSTM training hyper-parameters

Parameters	**Values**
Optimizer	RMSprop
Learning rate	0.0001
Batch size	64
Dropout	0.4
Epoch	250
Data size	200.000
Data split	60:20:20

5.4.2 Evaluation Metrics

In this subsection, we present the three main regression model evaluation measures that will be used to evaluate the communication performance of our proposed model. The definitions of these measures, namely MSE (Mean Squared Error), MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error), are as follows:

5.4.2.1 MSE

The Mean Squared Error (MSE) is employed as a loss function (or cost function) during the training of our proposed deep learning model to minimize prediction errors. It computes the average squared difference between the actual and predicted data values.

For the actual base station angle of departure value denoted as θi and its predicted counterpart $\hat{\theta} i$, where 'n' represents the total number of samples in the training set, the MSE is determined as follows:

$$MSE = \frac{1}{n}\sum_{1}^{n}(\theta_i - \hat{\theta}_i)^2, \tag{5.17}$$

5.4.2.2 RMSE

The Root Mean Squared Error (RMSE) quantifies the difference between the model's predicted and actual values extracted from the database. Its calculation is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(\theta_i - \hat{\theta}_i)^2}, \tag{5.18}$$

5.4.2.3 MAE

The mean absolute error (MAE) signifies the absolute difference between the actual and predicted values, and it can calculated as follows:

$$MAE = \frac{1}{n}\sum_{1}^{n}|\theta_i - \hat{\theta}_i|. \tag{5.19}$$

We implemented several traditional beamforming techniques based on regression models in our study, including K-Nearest Neighbors (KNN) [97], Support Vector Regression (SVR) [98], CNN-LSTM [99], and Bi-LSTM [100]. These models were used to evaluate the performance of our proposed CNN-BiLSTM model, and our model outperformed these traditional approaches. We use mean square error (MSE), mean absolute error (MAE), and root mean square error (RMSE) as metrics to quantify the accuracy of the regression on the optimal beam angle. These measures are evaluated during the learning and testing phases. Lower values of RMSE and RMSE mean better prediction accuracy, indicating that the predicted values are closely aligned with the actual values.

5.4.3 The Obtained Results

To demonstrate the effectiveness of our proposed hybrid solution for enhancing communication between mobile vehicles and the mmWave base station, we evaluated the training loss (MSE) and MAE values at each epoch using the training dataset. These evaluations were performed exclusively on the training data. As shown in Figures 5.6 and 5.7, the curves show rapid initial convergence, with both MSE and MAE converging after a minimal number of epochs. At the last epoch of the training phase, the MSE value is 0.0507, while the MAE value is 0.2486. In particular, the validation curves for the loss function and the MAE metric closely mirror the learning curves during convergence. This indicates that the CNN-BiLSTM model did not suffer from overfitting.

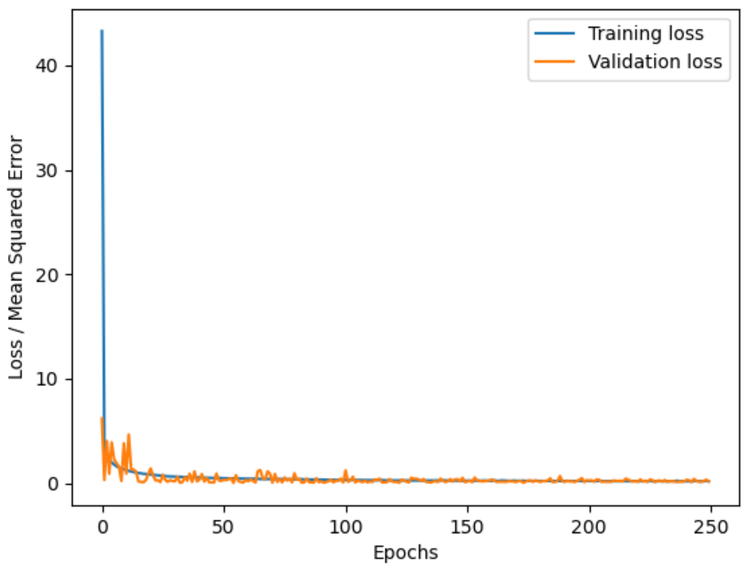

Figure 5.6: Training and validation loss (MSE) for the proposed model.

Visualizing the projected values generated by the CNN-BiLSTM model compared with the actual values of the test set provides a further means of evaluating the accuracy of our approach. If we look at figure 6.5, we see a remarkable similarity between the predicted and actual values. Based on this analysis, we can confidently state that our proposed CNN-BiLSTM model has been effectively trained. Its results are convincing and reliable, justifying its use to predict optimal angles in B5G vehicle networks.

These results are closely related to the choice of input data used in training the proposed model. As shown in Figure 5.9, we used the Pearson correlation matrix to explain and illustrate the linear relationships between the input and output variables. Examination of the matrix indicates that variables such as ($AoDAzi$, $AoDElev$), ($AoDAzi$,

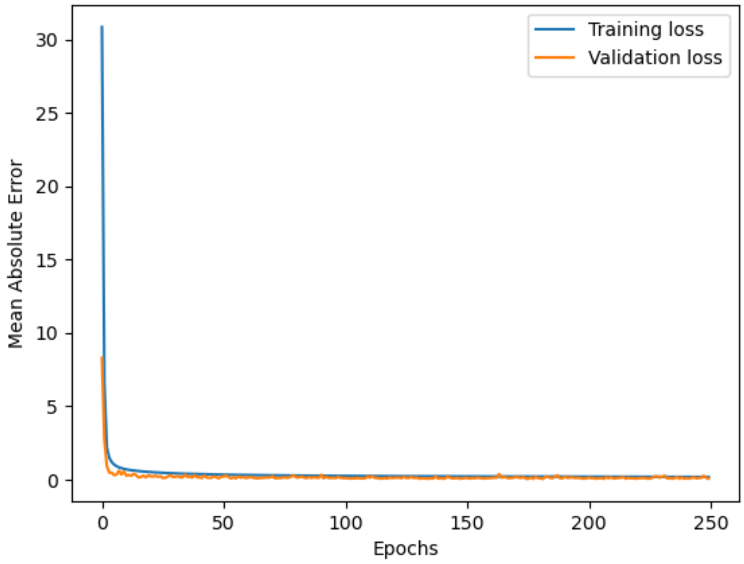

Figure 5.7: Training and validation (MAE) for the proposed model.

Power), and (*AoDAzi*, *Locx*) have exceptionally high positive correlations with each other. On the other hand, the variables (*AoDAzi*, *Locy*) show a significant negative correlation.

A comparative analysis was performed to validate and evaluate the performance of the proposed CNN-BiLSTM model compared to conventional beamforming approaches. Specifically, we conducted these experiments using the same scenario characteristics. As shown in Figure 5.10 and summarised in Table 5.4, we present the results obtained from the test data for each model.

First, we evaluated the beam alignment process for the beam alignment process by using two machine learning-based methods, the K-Nearest Neighbors (KNN) regressor and Support Vector Regression (SVR). The results indicate that the KNN model produced values of 0.0826, 0.168, and 0.287 for MSE, MAE, and RMSE, respectively. Subsequently, the SVR presented MSE, MAE, and RMSE values of 0.0787, 0.165 and 0.256, respectively.

In contrast, using the hybrid CNN-LSTM model, we obtained MSE, MAE, and RMSE values of 0.0225, 0.0945, and 0.1500, respectively. In addition, applying the Bi-LSTM model yielded values of 0.0319, 0.1716, and 0.179 for the same measures, respectively.

The results of the CNN-LSTM and Bi-LSTM models were so promising that we decided to combine the CNN and Bi-LSTM models. We thus obtained the lowest possible values for MSE, MAE, and RMSE, with values of 0.0107, 0.0765, and 0.103, respectively.

Based on the above results, our proposed hybrid model emerges as the most effective approach for predicting the optimal departure angle based on the location of each vehicle,

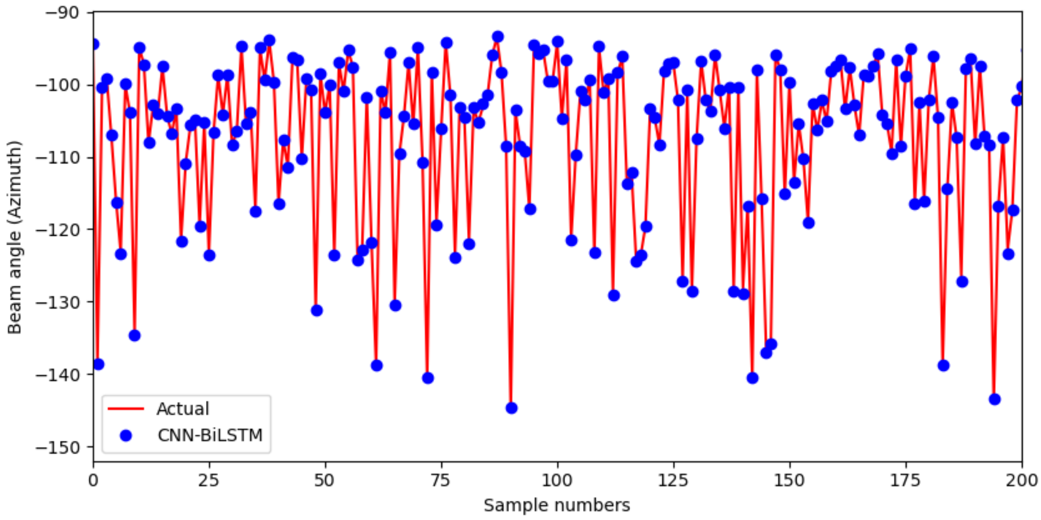

Figure 5.8: Predicted values VS the actual values.

Table 5.4: A Comparative Study of Our Proposed Model Against Traditional Beam Alignment Solutions Using Evaluation Metrics (MSE, MAE, and RMSE)

Method	Models	Error metrics		
		MSE	MAE	RMSE
Cheng et. al [97]	KNN Regressor	0.0826	0.168	0.287
Li et. al [98]	SVR	0.0787	0.165	0.256
Liu et. al [99]	CNN-LSTM	0.0225	0.0945	0.1500
Aldalbahi et. al [100]	BiLSTM	0.0319	0.1716	0.179
Proposed model	**CNN-BiLSTM**	**0.0107**	**0.0765**	**0.103**

outperforming conventional machine learning methods. The improvement in prediction accuracy and overall model performance is directly reflected in lower MSE, MAE, and RMSE values.

Based on these observations, we can confidently state that our hybrid CNN-BiLSTM model can dynamically configure the beam angle direction and select the optimal departure angle of the millimeter-wave base station based on the vehicle position with minimum error probability, maximum received signal strength and shortest beam search time.

In addition, it should be noted that the CNN-BiLSTM model excels in accuracy, computational efficiency, and time complexity. Unlike conventional exhaustive search and beam scanning techniques, which require a 360-degree search for each data transmission

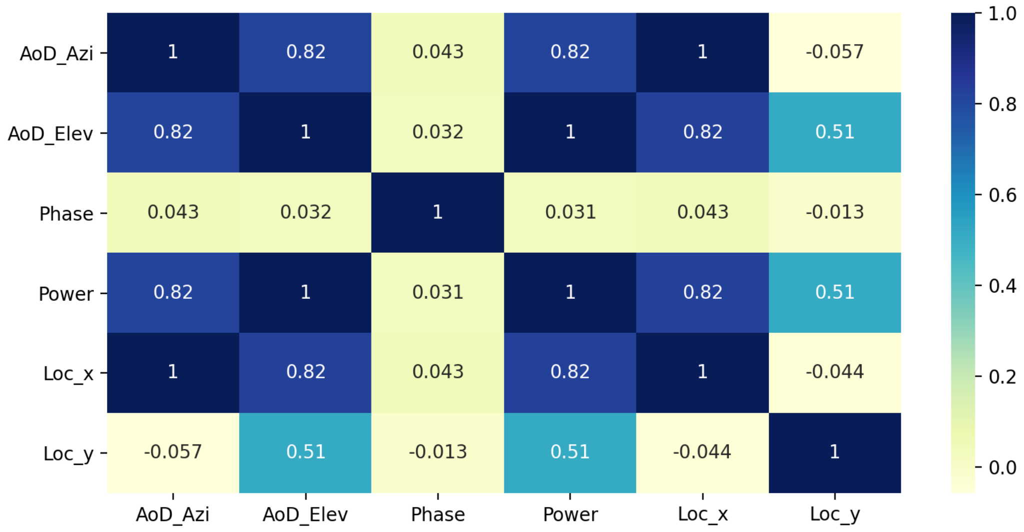

Figure 5.9: Heatmap of the Pearson correlation matrix.

to determine the ideal beam direction, our model eliminates the need for such time-consuming calculations and iterations.

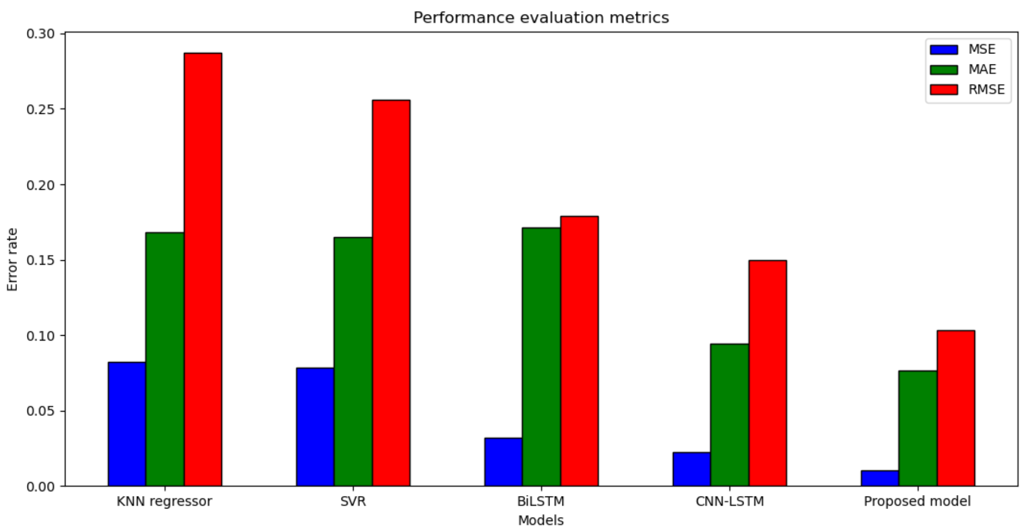

Figure 5.10: Values obtained by different regression models for the beam alignment procedure in B5G vehicular networks.

This enhancement is significant for 5G vehicular networks, as it ensures a higher SINR value and higher received signal power during V2I transmissions between autonomous vehicles and millimeter-wave base stations. It also reduces the computational load within the B5G vehicular mmWave network.

5.4.4 Complexity analysis of CNN-BiLSTM

5.4.4.1 Analysing computational complexity

This subsection conducts a comparative analysis of the computational complexity between our proposed beam alignment model and traditional beam search methods in vehicular environments. Traditional exhaustive search methods examine all potential beam angles, covering 360° for azimuth and elevation angles, to select the optimal beam that maximizes received signal power or minimizes interference. However, the computational complexity of these methods is influenced by the number of antennas and the angular resolution of the search, leading to a computational complexity expressed as $\mathcal{O}(N^2)$. Here, N^2 represents the total number of possible combinations of transmit and receive beams. As the number of candidate beams increases, the complexity of exhaustive search increases quadratically, making it impractical for densely populated vehicular environments and large antenna arrays.

In contrast, our proposed hybrid CNN-BiLSTM beam alignment model offers significantly lower computational complexity. The 1D-CNN component of the model has a complexity of $\mathcal{O}(N * F)$, where N is the number of input samples, and K is the kernel size of the 1D-CNN filter. It is important to note that this complexity is independent of the number of candidate beams or the angular resolution of the search.

To estimate the overall computational complexity of the proposed model, we need to aggregate the complexities of the 1D-CNN and BiLSTM components. The complexity of the 1D-CNN component is expressed as $\mathcal{O}(T * O * K * F)$, where T is the number of input channel parameters, O is the number of output features, K is the size of the convolution kernel, and F is the number of filters in the layer. For the complexity of the BiLSTM component, we use the following formula: $\mathcal{O}(2 * n * snh * (4 * n_i + 4 * n_h + 3 + n_o))$. Here, n indicates the number of time steps. The term snh quantifies the number of operations required to compute the output of a single LSTM cell, where s represents the length of the sequence, h the number of hidden units, n_i the size of the input at each time step, n_h the number of hidden units in each LSTM layer, and n_o the size of the output at each time step.

The BiLSTM layer comprises two LSTM layers, one processing the input sequence in the forward direction and the other in the reverse direction. The output of each LSTM layer is concatenated to produce the final BiLSTM output sequence, which is then sent to a fully connected layer for further processing. As a result, the total complexity of the proposed model can be estimated as the sum of the complexities of the 1D-CNN and BiLSTM components, expressed as $\mathcal{O}(TOKF + 2nsnh(4n_i + 4n_h + 3 + n_o))$.

Table 5.5: Computational Complexity Analysis

Component	Complexity
1D-CNN	$\mathcal{O}(T * O * K * F)$
BiLSTM	$\mathcal{O}(2 * n * snh * (4 * n_i + 4 * n_h + 3 + n_o))$
CNN-BiLSTM	$\mathcal{O}(TOKF + 2nsnh(4n_i + 4n_h + 3 + n_o))$

5.4.4.2 Analysing the complexity of time

A model's efficiency, particularly in learning and prediction time, is intrinsically linked to its time complexity. A model's complexity level is crucial in its computational effectiveness, influencing various facets of its practical applicability. When the complexity of a model reaches a certain threshold, it can pose problems in terms of validating concepts, improving model performance or accurately predicting the optimal beam angle.

Table 5.6 and Figure 5.11 give an overview of the learning and testing times, expressed in seconds (s), for conventional beam alignment-based regression models and our new CNN-BiLSTM model using the deepMIMO dataset. It should be noted that all benchmark solutions employing deep learning models were run over 250 epochs.

Our results highlight that classical machine learning techniques such as SVR and KNN have faster learning phases but more extended testing periods. This can be attributed to the fact that these machine-learning methods rely on simple mathematical formulas and distance calculations, unlike deep-learning approaches, which depend on complex neural networks. , leading to faster training times. In addition, SVR and KNN operate as non-parametric models, which avoids the need to estimate many parameters. This starkly contrasts deep learning models such as CNN-LSTM, BiLSTM, and CNN-BiLSTM, which contain many trainable parameters, contributing to longer training times.

Nevertheless, the testing phase for SVR and KNN exceeds that of deep learning models. This longer testing time can be attributed to the inherent nature of instance-based machine learning algorithms, in which they must explore the dataset in detail to determine the optimal prediction angle for each new vehicle position. This search can be time-consuming, mainly when dealing with large datasets like the deepMIMO dataset.

Concerning beam alignment using deep learning techniques, it is evident that our CNN-BiLSTM approach excels in reduced learning and testing times compared to CNN-LSTM and BiLSTM models. This efficiency can be attributed to the architectural advantages of CNN-BiLSTM, which allow local features to be extracted in parallel by the convolutional layers while allowing the BiLSTM layers to process these features simultaneously in the forward and backward directions.

In contrast, the LSTM layers of BiLSTM and CNN-LSTM operate sequentially, incurring time costs at each time step. As a result, these sequential operations lengthen learning and testing times compared with our CNN-BiLSTM architecture.

In addition, our proposed CNN-BiLSTM model takes pride in a reduced number of trainable parameters, namely 1.65 million, compared with 2.66 million for CNN-LSTM and 5.55 million for BiLSTM. This reduction considerably reduces the model's computational complexity, speeding up the learning and testing phases. Our results show that our approach achieves impressive accuracy with a reduced set of parameters, confirming its superiority regarding prediction accuracy and computational efficiency for vehicular networks. This combination not only improves prediction accuracy but also reduces computational costs.

Table 5.6: Comparative execution time analysis of various beam alignment models using the DeepMIMO dataset

Models	**Training time**	**Testing time**
KNN regressor [97]	8553.39	130.84
SVR [98]	1949.24	802.24
CNN-LSTM [99]	64230.47	35.89
BiLSTM [100]	182512.74	67.18
Proposed model	**33674.46**	**11.67**

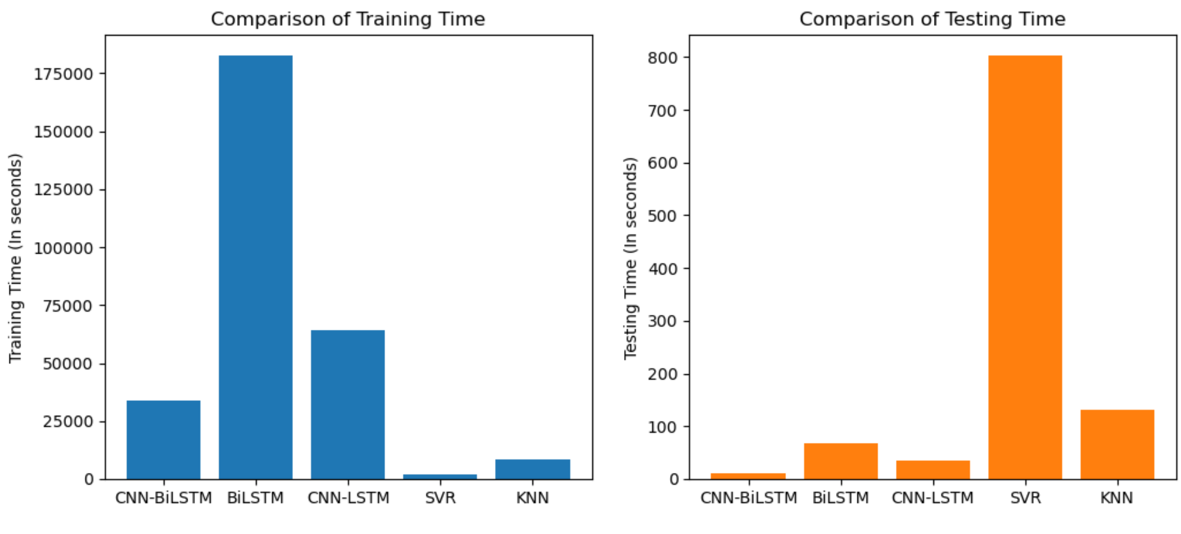

Figure 5.11: Temporal complexity of each regression model.

5.4.5 The expected benefits of the proposed CNN-BiLSTM model

5.4.5.1 Capturing Spatial and Temporal Dependencies

The CNN-BiLSTM model that has been suggested combines the advantages of both CNN and BiLSTM layers. As a result, it can recognize both the spatial and the temporal dependencies in the vehicular wireless channel. To begin, the CNN layers that are a part of our CNN-BiLSTM model do an excellent job of capturing the spatial dependencies in the vehicular wireless channel. These layers can automatically learn and extract spatial features and patterns by applying convolutional filters to the Channel State Information (CSI) matrices. Because of this spatial awareness, our model can better grasp the spatial properties of the vehicular channel. Consequently, our model can provide more accurate predictions about the best beam angles. On the other hand, methods like KNN, SVR, BiLSTM, and CNN-LSTM may have difficulty properly using spatial information or capturing complicated spatial correlations [101].

Furthermore, the BiLSTM layers that are included in our model make it possible to capture temporal dependencies. This is important when considering the fluid nature of the B5G vehicular environment. These layers can ingest information from settings in the past as well as contexts in the future since they include recurring bidirectional connections. Due to the presence of this feature, our model can successfully simulate temporal dynamics and dependencies in the data. In contrast, SVR, KNN, BiLSTM, and CNN-LSTM may need more advanced approaches to sufficiently model temporal dependencies or capture long-term dependencies owing to the constraints they have in sequence modeling [102], [103], [104]. These models may require more sophisticated techniques to effectively model temporal or capture long-term dependencies. Our CNN-BiLSTM model is distinguished from other approaches by its features, which lead to its better performance in capturing both the spatial and temporal components of the vehicular wireless channel. This performance sets it apart from other techniques.

5.4.5.2 Efficient Prediction

Our CNN-BiLSTM model uses the parallel processing capabilities of the CNN layers. This enables fast, real-time prediction of beam alignment, which is essential in dynamic traffic situations. Algorithms such as KNN, on the other hand, require an exhaustive search of the entire training data set, resulting in longer prediction times. Similarly, SVR involves the solution of a computationally demanding quadratic optimization problem. In addition, due to their sequential structure, CNN-LSTM and BiLSTM may have a more significant potential to increase computational complexity.

Our CNN-BiLSTM model, which uses parallel processing, offers considerable advantages in terms of speed and efficiency, making it particularly suitable for beam alignment tasks in dynamic vehicle environments.

5.4.5.3 Improved Generalization

Our model incorporates CNN and BiLSTM layers, enabling excellent feature extraction and modeling of complex interactions in vehicular communication. These capabilities are made possible by merging these two types of models. This attribute enhances the flexibility of the model and its ability to generalize successfully over a wide range of channel conditions and traffic situations that may occur within a network of vehicles. On the other hand, techniques such as KNN, SVR, CNN-LSTM, and Bi-LSTM may have difficulty capturing complex patterns. They may not generalize these models to dynamic vehicular communication scenarios successfully [105].

5.4.5.4 Robustness in the Face of Noisy Channel Conditions

Using the parallel processing capabilities of CNN layers, our CNN-BiLSTM model can provide accurate beam alignment predictions quickly and in real-time, essential in highly dynamic automotive situations. Methods like KNN, on the other hand, need a thorough search of the training dataset, which increases the time it takes to make a forecast. Similarly, SVR is a computationally demanding optimization issue using quadratic functions. The sequential structure of CNN-LSTM and BiLSTM may also be more resource-intensive.

Our CNN-BiLSTM model uses parallel processing to substantially benefit speed and efficiency, making it ideal for beam alignment problems in dynamic vehicular environments.

5.4.5.5 Adaptability to Dynamic Vehicular Environments:

The dynamic and frequent changes seen in B5G vehicular communication scenarios are captured by the CNN-BiLSTM model we have proposed. Our model displays extraordinary flexibility to changing channel conditions, traffic patterns, and mobility situations specifically because it incorporates spatial and temporal relationships. This flexibility is essential in mobile situations, characterized by fast variations in the wireless channel due to factors such as the movement of vehicles, impediments, and interference. Our CNN-BiLSTM model, characterized by its capacity to capture and represent these dynamic components adequately, not only improves performance but also presents itself as a potentially helpful option for beam alignment procedure. Because of its capacity to successfully deal with these dynamics, it can produce improved results, making it an appealing option for tackling beamforming issues in vehicular communication.

5.5 Conclusion

In conclusion, this chapter presents a new approach to beam alignment, which focuses on selecting the optimal beam angle (AoD) from the millimeter-wave base station for efficient data transmission to moving vehicles. Our study focuses on an outdoor vehicular communication scenario, generating the DeepMIMO dataset with specified parameters. The proposed CNN-BiLSTM model is then trained to quickly and accurately determine the optimal beam direction at the mmWave base station, adapting to frequent changes in vehicle position.

The main objective of our approach is to speed up the selection of the optimal angle in a dynamic vehicle environment, achieving lower error rates and shorter beam search times. A comparative analysis with various machine learning algorithms, including the KNN, SVR, Bi-LSTM, and CNN-LSTM regressors, using MSE, MAE, and RMSE measurements, shows our hybrid solution's superior accuracy and reduced computational cost. In particular, our model achieves values of 0.0107, 0.0765, and 0.103 for these measures.

Collectively, these results highlight the potential of our hybrid solution to predict the optimal beam angle of the mmWave base station with exceptional accuracy while reducing computational costs. This translates into reduced beam search times and minimized network overheads, representing a significant advance in beam alignment methods.

In the next chapter, we will focus on developing a new system that promises to revolutionize beam alignment for millimeter-wave V2X data communication. This approach will address beam alignment requirements on the mmWave base station and dynamic vehicle sides. This new approach aims to improve vehicular communication, paving the way for better connectivity and data transmission between vehicles and mmWave base stations.

Chapter 6

Deep Learning-Based Beam Pair Angle Prediction for Beyond 5G Millimeter-Wave Vehicular communication

6.1 Introduction

In today's world, mmWave communication has become an essential component of Beyond fifth-generation (B5G) systems for autonomous vehicular networks [30]. The enormous bandwidth of these frequencies, which range from 30 GHz to 300 GHz, allows V2X communication to have both a high transmission rate and low latency, which is mainly in demand in high dynamic range situations [106]. However, it is well known that the most significant challenge associated with communication at the millimeter wave frequency is the path loss due to short-range propagation distance and the signal attenuation due to surrounding static and dynamic obstacles. Many antenna components should be used with beamforming technology to align the beams on the mmBS and the AV sides. This will help to overcome the disadvantage. This will result in a high overall beamforming gain and a reliable communication connection in a high mobility environment [107].

This chapter presents our third contribution, based on new deep learning to predict the optimal beam pairs that establish connections between the vehicle on moving and the mmBS, specifically, the AoD in Azimuth at the mmBS and the AoA in Azimuth at the vehicle side.

Our third contribution was published in a paper at the IEEE Global Communications Conference (GLOBECOM) in 2022. The published paper is entitled *Deep Learning-Based*

Beam Pair Angle Prediction for Beyond 5G Millimeter-Wave Vehicular communication, [1]. Please visit this link for more information.

6.2 System Model

This section presents the mmWave MIMO system and a channel model used in our study. This includes aspects such as *the received signal power (RSP), AoD, and AoA.*

We are considering a downlink massive MIMO mmWave vehicular communication system in which multiple mmBSs are equipped with $N_A := N_A^h N_A^v$ antennas. Here, N_A^h arrays are arranged horizontally, and N_A^v arrays are arranged vertically. A similar setup is assumed for autonomous vehicles, equipped with $M_A := M_A^h M_A^v$, where M_A^h arrays are positioned horizontally, and M_A^v arrays are positioned vertically. The mmBS and AV employ antennas configured in uniform planar arrays (UPAs). At time instant k, the signal received in the downlink, denoted as $y_k \in \mathbb{C}$, at the vehicle, is expressed as follows:

$$y_k = f_k^H \mathbf{H}_k s_k + \mathrm{z}_k, \tag{6.1}$$

Here, $f_k \in \mathbb{C}^{M_A 1}$ denotes the receive beamforming vector, $_k \in \mathbb{C}^{N_A} 1$ represents the transmit beamforming vector, $\mathbf{H} \in \mathbb{C}^{N_A M_A}$ represents the channel matrix and $z_n \in \mathbb{C}$ corresponds to the additive white Gaussian noise (AWGN) with zero mean and a variance of σ^2. In the context of mmWave vehicular networks, the mmWave MIMO channel matrix for the transmission from the mmBS to the AV is expressed as follows:

$$\mathbf{H} = \sqrt{\frac{N_A M_A}{L}} \sum_{l=1}^{L} \beta_l \alpha_{\mathbf{r}}(\theta_l) \alpha_{\mathbf{t}}^{\mathbf{H}}(\varphi_l), \tag{6.2}$$

Here, L represents the number of multi-paths, and β_l represents the complex gain associated with the lth path. θ_l and φ_l represent, respectively, the AoD and the AoA for the lth path. These angles, AoD and AoA, are in the range [-180°, 180°]. In addition, α_r and $\alpha_t^{\mathbf{H}}$ are used to denote the steering vectors at the vehicle and mmBS, respectively, and are defined as follows:

$$\alpha_{\mathbf{r}}(\theta_l) = \frac{1}{\sqrt{M_A}} [1, e^{j\frac{2\pi d}{\lambda} cos\theta_l}, ..., e^{j\pi(M_A-1)\frac{2\pi d}{\lambda} cos\theta_l}]^T \tag{6.3}$$

$$\alpha_{\mathbf{t}}(\varphi_l) = \frac{1}{\sqrt{N_A}} [1, e^{j\frac{2\pi d}{\lambda} cos\varphi_l}, ..., e^{j\pi(N_A-1)\frac{2\pi d}{\lambda} cos\varphi_l}]^T \tag{6.4}$$

In this context, *ambda* represents the wavelength of the carrier, and d represents the

[1] https://ieeexplore.ieee.org/document/10001428

spacing between two consecutive antennas. In mmWave communications, this spacing is generally configured as $\lambda/2$.

6.3 Proposed Deep Learning-Based Beam Pair Selection

We present a new beam-pair prediction approach based on bidirectional long-term memory (BiLSTM-BPP) for LoS mmWave vehicular networks. By using location information, this approach improves the reliability of data transmission while minimizing the error probabilities and overheads associated with beam search. The schematic representation of this process is shown in Figure 6.1. In the following, we describe the main steps of the beam pair prediction approach using the proposed BiLSTM-BPP model, including database generation, data processing, and beam pair prediction, as shown in Algorithm 18.

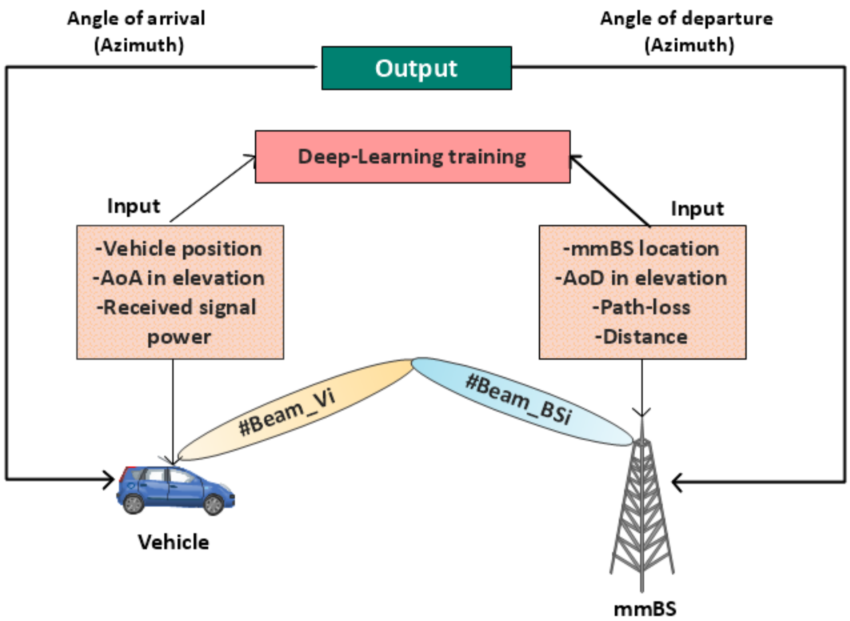

Figure 6.1: Deep-Learning Beam Pair Prediction scheme

6.3.1 Data Generation and Processing

Our study is based on the DeepMIMO (version 2) dataset, known for its high utility in mmWave and Massive MIMO research applications. A 3D ray-tracing scenario simulator, Wireless InSite (WI), created by Remcom, manages this dataset. It should be noted that the dataset generation follows the procedures described in Algorithm 1-Part 1. By tracing the paths meticulously in this simulation, we obtain the complete DeepMIMO datasets. These data sets include a multitude of essential parameters, including AoD in azimuth and elevation, AoA in azimuth and elevation, phase, received signal strength, path loss, time of arrival, delay spread, mmBS location, vehicle location and distance between mmBS and vehicle.

After generating the channels in the dataset through environmental simulations, we acquire contextual information about the channels specific to vehicular communication. Subsequently, these features serve as inputs to our novel BiLSTM-BPP. This model is designed to determine the optimal (AoA) and (AoD) for each vehicle position in B5G mmWave vehicle networks.

To facilitate the training of BiLSTM-BPP, we use 60% of the dataset. This division splits the entire database into three distinct sets: the training set, the validation set, and the test set, according to a proportional distribution of 6:2:2. It should be noted, however, that before introducing the data into the model, we carry out a normalization. This step is essential because of variations in the units of the characteristics. Using Z-Score normalization, we calculate each feature's mean (μ) and standard deviation (σ). We then normalize the data by subtracting the mean of each feature and dividing it by the standard deviation, ensuring that all values fall between 0 and 1. This normalization process is succinctly expressed as follows:

$$X_{norm} = (X - \mu)/\sigma, \tag{6.5}$$

where X is the value of the input feature.

6.3.2 The proposed model for Beam Pair Prediction

In our study, we address the issue of beam misalignment as a regression problem and use a supervised learning method to train our novel model. The input parameters of our BiLSTM-BPP model include azimuthal AoD and AoA, received signal power, path loss, vehicle location, mmBS location, and distance between mmBS and the vehicle.

Using the BiLSTM architecture, our model executes two identical computational passes: one in the forward direction and one in the reverse direction. This dual processing capability allows the model to retain past and future information, incorporating complete data on the environmental context. As a result, our model can make precise predictions about the optimal beam angle for the vehicle's current position. This bidirectional processing approach significantly improves the predictive accuracy of our model.

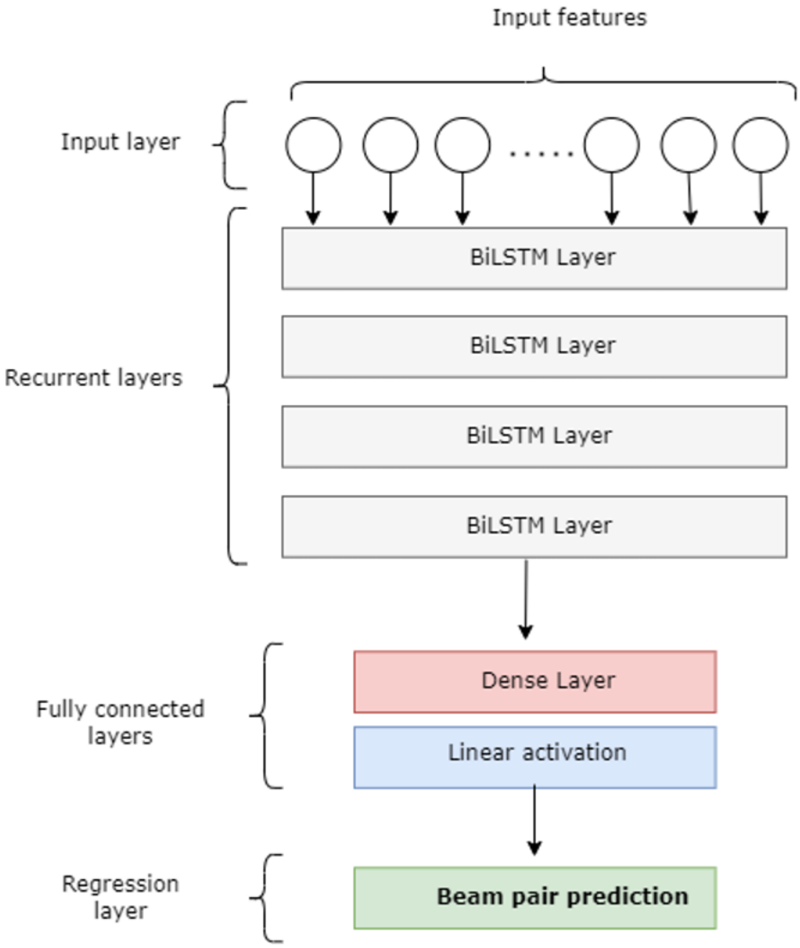

Figure 6.2: The proposed BiLSTM-BPP architecture

Our proposed approach follows the procedure described in 18 and operates according to the architecture shown in Figure 6.2. Our system aims to achieve optimal results through multiple iterations. The architecture comprises a single input layer with nine input features, followed by four layers of BiLSTM. These BiLSTM layers have varying hidden layer sizes of 256, 128, 64, and 50 neurons, respectively, followed by a batch normalization layer. The output is then flattened and passed through a fully connected (FC) layer of 32 neurons, which uses a Rectified Linear Unit (ReLU) activation function, where $ReLU(x) = \max(x, 0)$. This layer is followed by another FC layer with two outputs and a linear activation function. We opted for a linear activation function because it preserves the input values without alteration and returns the calculated values directly.

Algorithm 1 Position and Deep-Learning Based Beam Pair Selection Approach

Part 1: DeepMIMO Dataset Generation
1. Begin by selecting the outdoor vehicular scenario.
2. Define the parameters for the DeepMIMO dataset.

while The vehicle is in motion **do**
  3. Generate the channel matrix between the base station (BS) and the vehicle.
  4. Choose the strongest communication path between the BS and the vehicle.
  5. Save the relevant channel information for the selected path.

end while

Part 2: The Proposed Beam Pair Prediction Method

Input: Parameters such as AoA and AoD in elevation, Received Signal Power, Vehicle Location, BS Location, Distance, and Path-loss.

Output: Predicted AoA and AoD in azimuth.

Initialization
1. Begin by preprocessing the input data, which includes normalization.
2. Construct the proposed model.
3. Train the proposed model using the available data.
4. Apply the trained model to testing data and evaluate its performance.
5. Generate the predicted beam pair angles (AOA/AOD).
6. Calculate the MSE to measure the dissimilarity between actual and predicted angle values.

=0

6.4 Simulations and Numerical Results

In this section, we describe the details of our experimental setup, followed by a detailed analysis of the results obtained in predicting beam pair angles using the proposed model.

6.4.1 Simulation Setup

To validate the proposed approach, we conducted experiments in an outdoor vehicular communication scenario to evaluate the performance of our beam pair prediction method. Our evaluation was based on the DeepMIMO dataset [13], which was generated using a 3D ray-tracing simulator called Wireless InSite [108]. Specifically, we used the LOS scenario "O1 60", operating at a frequency of 60 GHz, in which all vehicles had LoS communication with the mmBS. Using the DeepMIMO generator script [13], we generated a substantial dataset comprising approximately $S^{LOS} \approx 7310^3$ LOS samples. Table 6.1 describes the data generation parameters. In our configuration, we chose four base stations (mmBS3, mmBS4, mmBS5, mmBS6), each equipped with a UPA containing $N_A = 64$ antennas. The vehicles were equipped with a single antenna $M_A = 1$, and their positions extended from line #1000 to line #1500, each consisting of 181 data points.

Table 6.1: Hyper-parameters for data-generation.

Parameters	**Values**
Name of scenario	O1_60
Active mmBS	3,4,5,6
Active users	1000 to 1500
Number of mmBS antennas (x, y, z)	(1, 64, 1)
Number of vehicle antennas (x, y, z)	(1, 1, 1)
Bandwidth (GHz)	0.5
Antenna spacing	0.5
Number of OFDM sub-carriers	1024
OFDM sampling factor	1
OFDM limit	64
Number of paths	1

The main objective of our model training is to minimize the loss function, which is quantified using the root mean square error (RMSE) metric. This loss function measures the disparity between the predicted values generated by the our model and the actual θ_i values at each time step. As shown in table 6.2, we used Adam's optimizer [109] with a learning rate 0.0001 to facilitate this minimization process. The choice of the loss function, MSE, is common in regression problems. Through multiple iterations and model configurations, we have refined our approach to predict beam pair angles efficiently. In our study, we evaluate the performance of the proposed method by quantifying the probability of error between the expected angle values and the ground truth values. It is important to note that minimizing the loss function (MSE) simultaneously maximizes the received signal power, improving our approach's overall efficiency.

Table 6.2: BiLSTM-BPP training hyper-parameters.

Parameters	**Values**
Optimizer	Adam
Learning rate	0.0001
Loss function	MSE
Batch size	1024
Epoch	250
Data size	300.000
Data split	60:20:20

6.4.2 The Obtained Results

Evaluating the performance of our proposed model during the training phase required tracking two key metrics, namely MSE and MAE, as illustrated in Figures 6.3 and 6.4. Over the 250 epochs, these parameters showed a clear trend. They reached a point where the curves began to flatten and eventually converged. During this convergence, the MSE reached a minimum value of 0.0268, while the MAE reached 0.1036. These values are very satisfactory for a beam pair prediction model, indicating the efficiency of the model.

Furthermore, the closeness of the validation and learning curves for the MSE and MAE is remarkable. This proximity suggests that the proposed BiLSTM-BPP model has successfully avoided overfitting, as its performance on the unseen (validation) data closely mirrors its performance on the training dataset.

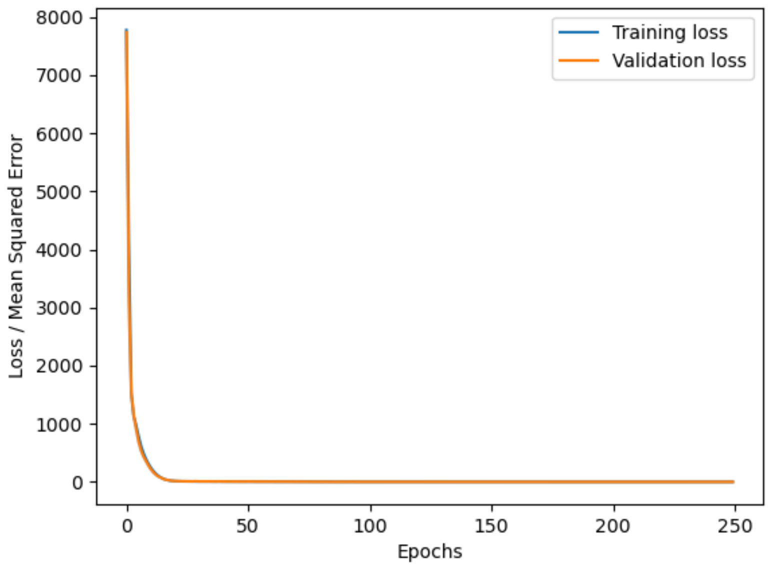

Figure 6.3: Training and validation loss (MSE) plot

To evaluate the performance of our model, we have generated graphs that compare the predicted angle values obtained from our proposed model with the actual angle values derived from the test dataset. Figure 6.5 provides a visual representation of these comparisons, depicting the predicted and actual values of AoD (the top curve) and AoA (the bottom curve). The remarkable thing about these graphs is how close the predicted and actual values are. They are closely aligned, indicating our proposed model's high accuracy. This analysis proves that our model can predict the optimal pair of beam angles (AoD/AoA) for different vehicle positions while maintaining a low error probability. Furthermore, the effectiveness of our approach is confirmed by a comprehensive evaluation

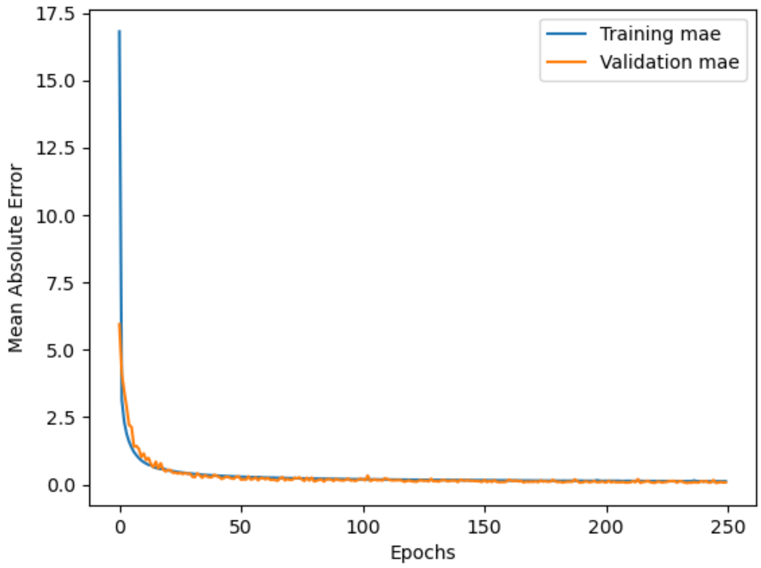

Figure 6.4: Training and validation MAE plot

of the regression measures, as shown below.

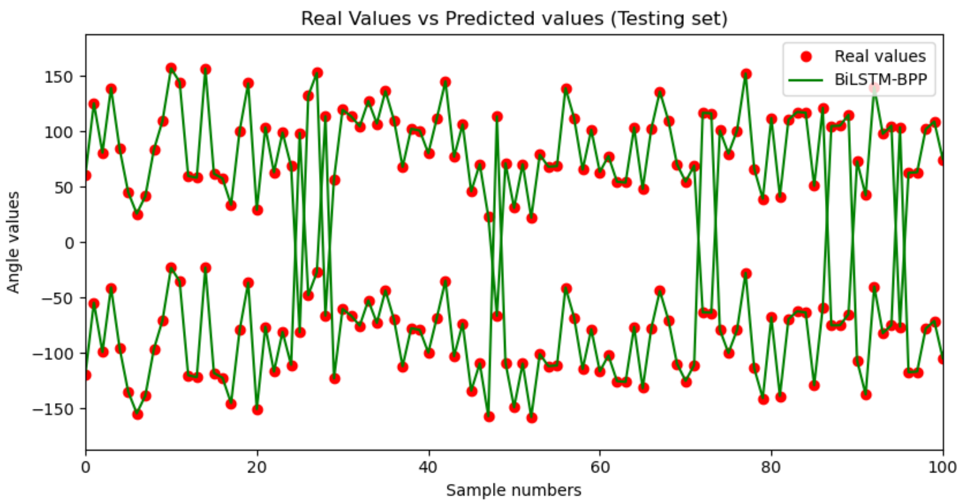

Figure 6.5: Comparison between the predicted and actual values for beam pair angle prediction.

The comparison results of evaluation metrics between the proposed BiLSTM-BPP model and other regression models are presented in Table 6.3. We conducted a detailed evaluation using five machine learning algorithms: Linear Regression, Support Vector Regression (SVR), K-nearest neighbors (KNN) regressor, Decision tree, and Random forest. Each model was trained with identical parameters to ensure equitable performance evaluation in predicting beam pairs.

The above results conclude that the proposed BiLSTM-BPP model performs better than the traditional machine learning algorithms, demonstrating superior prediction capabilities. This superiority is apparent in the significantly lower values achieved by the BiLSTM-BPP model in various evaluation measures, including RMSE, R-squared (R^2), MAE, MSE and median absolute error (MedAE). More specifically, the BiLSTM-BPP model achieves values of 0.11, 0.99, 0.0816, 0.0121, and 0.06 for RMSE, R^2, MAE, MSE, and MedAE, respectively.

In summary, the results of our analysis highlight the superior performance of the proposed BiLSTM-BPP model compared to conventional machine learning techniques. This innovative solution excels in autonomously identifying the optimal angles of the pair of beams connecting the mmBS and the vehicle for each vehicle position. This accuracy is crucial in maximizing the received signal strength in B5G vehicular networks, ensuring highly efficient communication between the mmBS and the mobile vehicle. In addition, this efficiency is achieved quickly, significantly reducing beam search time. This is in contrast to traditional beam search methods, which often involve scanning 360° of beams to identify the most appropriate beam angle, which is not well suited to the fast dynamics of modern environments.

Table 6.3: Comparison of Evaluation Metrics RMSE, R-squared, MAE, MSE, MedAE for regression models.

Models	**RMSE**	**R-Squared**	**MAE**	**MSE**	**MeAE**
Linear regression	14.92	0.93	12.11	222.7	10.92
SVR	1.26	0.95	0.28	1.61	0.17
KNN regressor	0.44	0.97	0.19	0.59	0.14
Decision Tree	0.36	0.99	0.17	0.06	0.12
Random Forest	0.24	0.99	0.08	0.05	0.11
BiLSTM-BPP	**0.11**	**0.99**	**0.0816**	**0.0121**	**0.06**

6.5 Conclusion

In this chapter, we have presented a deep learning-based beam pair prediction model called BiLSTM-BPP, which aims to reduce beam search times in B5G vehicular networks significantly. The principle of our proposal lies in its architectural composition, which comprises a robust set of four BiLSTM layers. This design allows us to exploit past and future channel information, amplifying our model's predictive capabilities. The BiLSTM-BPP model predicts the optimal beam pair angle that aligns the beams between the mmBS and the vehicle, ensuring uninterrupted and reliable communication between different vehicle positions.

A set of simulations was used to evaluate our approach empirically and obtain convincing results. Indeed, our proposed model outperforms traditional machine learning algorithms, including linear regression, SVR, KNN, decision tree, and random forest, in a range of performance measures such as MSE, MAE, MeAE, and RMSE. These results highlight that we have made significant progress in improving the efficiency of beam alignment within B5G vehicular networks, positioning our BiLSTM-BPP model as a formidable solution for optimizing beam search processes.

Chapter 7

Conclusion

Millimeter-wave communications are emerging as a promising solution to the increasing demands for high data rates in future vehicular networks. The fundamental attributes of millimeter-wave systems include compact wavelengths, wide bandwidth, low spatial response, high penetration loss, susceptibility to obstacles, and the need for directional communication. These characteristics distinguish millimeter-wave networks from traditional networks operating below 6 GHz. With the increasing amount of data sensors generated, geographic dissemination in vehicular networks requires higher data rate links, which can be achieved over mmWave frequencies. However, beamforming is necessary to acquire sufficient range due to the high propagation loss imposed by these frequencies. The characteristics of such a system compared with an omnidirectional antenna system require different approaches. Vehicular networks are a crucial element in improving road safety and traffic efficiency and supporting various infotainment services for the future development of intelligent transport. Some fundamental characteristics of vehicular networks are the high mobility of road vehicles and the heterogeneity of communication and service types. With the evolution of vehicular networks, a new requirement for cost-effective and durable network development has also emerged.

In this thesis, we focused on the crucial issue of beam alignment in vehicular networks and its importance in enabling cooperative navigation through V2X communication in 5G/B5G networks. Our research has proposed and explored various innovative solutions, including integrating deep learning techniques, to improve the performance of beam alignment in these networks.

Firstly, we exploited classical optimization techniques, notably the simulated annealing algorithm, to advance beam alignment in 5G vehicular networks. The implementation of this algorithm significantly reduced latency and improved data transmission between millimeter-wave base stations and vehicles, resulting in uninterrupted communication.

In our second contribution, we introduced a hybrid deep learning model, combining a 1D convolutional neural network (CNN) with a bidirectional long-term memory network (BiLSTM) to predict optimal beam angles. This integration of technologies has considerably improved the accuracy of predictions while reducing errors. This innovative approach eliminates the computational overhead associated with traditional methods, ensuring efficient communication in B5G vehicle networks.

The third and final contribution explored advanced beam pair prediction using a BiLSTM-based model. This model predicts the appropriate angles of the beam pairs, in particular, the departure angle (AoD) in azimuth at the mmWave base station and the arrival angle (AoA) in azimuth on the vehicle side. This has improved the reliability of data transmission while significantly reducing the probability of error and the overheads associated with beam searching.

In conclusion, this thesis is not the final destination but an essential step toward realizing the full potential of V2X communication in autonomous navigation. The future is full of opportunities, and our engagement in advancing this field will continue through several promising directions that open up for research and development in this area. Here are some essential perspectives:

- **Mitigation of NLOS blockages:** The development of advanced techniques for mitigating non-linear blockages (NLOS) in millimeter-wave networks on board vehicles is a significant prospect for the future. Innovative strategies, potentially involving machine learning algorithms and intelligent beamforming, should be explored to predict, avoid or minimize NLOS blockages. This approach will ensure uninterrupted V2X communication and cooperative navigation in autonomous vehicles.

- **Integration of Edge and Fog Computing:** Edge and fog computing technologies offer the ability to process data closer to the source, reducing latency and improving real-time decision-making in autonomous vehicles. Future research should focus on developing efficient computing solutions tailored to the specific requirements of V2X communication. This integration will ensure fast response times and optimal network performance for autonomous navigation.

- **Security and confidentiality in V2X networks:** As V2X communication becomes an increasingly integral part of autonomous navigation, it is essential to guarantee the security and confidentiality of transmission data. Future research should focus on developing robust security mechanisms and privacy-preserving protocols in V2X networks. Addressing issues such as authentication, data encryption, and secure information exchange will be essential. In addition, exploring blockchain and other emerging technologies to improve security and privacy in V2X networks is a promising avenue for future work.

- **Energy-efficient V2X communication:** Future studies should explore methods of optimizing the energy consumption of the devices that make up the vehicular environment. This includes developing energy-efficient algorithms, improving hardware components, and integrating renewable energy sources for V2X communication. Energy-efficient V2X can help to reduce the carbon footprint and promote environmentally friendly autonomous navigation systems.

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