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ERBIL POLYTECHNIC UNIVERSITY

Software Defined Networking Using Federated Learning and 5G for Data Dissemination in IoV Networks

A Dissertation

submitted to the council of the college of Erbil Technical Engineering at Erbil Polytechnic University in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Information System Engineering

By

Diana Hayder Hussein

B.Sc. Electrical Engineering/ Electronics and Communications, 2009

M.Sc. Electrical Engineering/Electronics and Communications, 2015

Supervised By

Prof. Dr. Shavan Kamal Askar

Erbil-Kurdistan

June 2024

DECLARATION

I declare that the Ph.D. Dissertation entitled:

“Software Defined Networking using Federated Learning and 5G for Data Dissemination in IoV Networks”

is my own work, and that it has not been submitted for any other degree or professional qualification. The research presented in this dissertation is original, and all sources of information and ideas have been acknowledged appropriately. I have adhered to the standards and guidelines in conducting this research, ensuring the integrity of the data and the validity of the findings.

Signature:

Student Name: Diana Hayder Hussein

Date: / /

LINGUISTIC REVIEW

I confirm that I have reviewed the dissertation titled "**Software Defined Networking using Federated Learning and 5G for Data Dissemination in IoV Networks**" from the English linguistic perspective, and I can verify that it is free of grammatical and spelling errors.

Signature:

Name of Reviewer: Dr. Nabaz Ismael Hamad

E-mail: Nabazismael@yahoo.com

Phone No.: 07502191314

Date: 4/3/2024

SUPERVISOR CERTIFICATE

This dissertation has been written under my supervision and has been submitted for the award of the degree of Doctor of Philosophy in Information Systems Engineering with my approval as supervisor.

Signature

Name: Prof. Dr. Shavan Kamal Askar

Date: / /

I confirm that all requirements have been fulfilled.

Signature

Name: Assistant Lecturer Bayad Abdulqader Ahmed

Head of the Department of Information Systems Engineering

Date: / /

I confirm that all requirements have been fulfilled.

Postgraduate Office

Signature:

Name: Assistant Lecturer Bayad Abdulqader Ahmed

Date: / /

EXAMINING COMMITTEE CERTIFICATION

We certify that we have read this Dissertation: “**Software Defined Networking using Federated Learning and 5G for Data Dissemination in IoV Networks**” and as an examining committee, examined the student (**Diana Hayder Hussein**) in its content and what related to it. We approve that it meets the standards of a dissertation for the degree of Doctor of Philosophy in Information Systems Engineering.

Signature:
Name: Prof. Dr. Kayhan Zrar Ghafoor
Member
Date: 28/7/2024

Signature:
Name: Assist. Prof. Dr. Reben Mohamad Salem
Member
Date: 28/7/2024

Signature:
Name: Assist. Prof. Dr. Jalal Jamal Hamadameen Maghdid
Member
Date: 28/7/2024

Signature:
Name: Assist. Prof. Dr. Halgurd Sarhang
Member
Date: 28/7/2024

Signature:
Name: Prof. Dr. Shavan Kamal Askar
Supervisor
Date: 28/7/2024

Signature:
Name: Prof. Dr. Siddeeq Yousif Ameen
Chairman
Date: 28/7/2024

Signature
Name: Professor Dr. Ayad Zaki Saber
Dean of the College of Erbil Technical Engineering
Date: 28/7/2024

DEDICATION

I dedicate this to

- My lovely family (*Saeed*, *Rasan*, and *Ranj*), whose support and love have been my strength through this academic journey.
- My Parents
- My brothers and sisters, especially Engineer Bahzad Hayder Hussein
- My friends.

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ABSTRACT

The emerging Fifth-Generation (5G) technology towards Internet of Vehicles (IoV) provides numerous advantages, such as lower levels of latency, stable link connections, and support for high mobility. However, avoiding vehicle collisions in IoV is a challenging task due to disseminating Emergency Safety Messages (ESMs) without strict delay and reliability requirements. To address this issue, this study proposes a novel intelligent Software-Defined Networking-based Collision Avoidance (SDNCA) framework assisted 5G. The proposed SDNCA framework employs two system models, each comprising three proposed algorithms. In the first system model, primarily, SDNCA performs the Vehicular Federated Learning (VFL) algorithm that accurately estimates the risk severity for each vehicle via training the proposed Risk Severity-Artificial Neural Network (RS-ANN) model through the implementation of federated learning among vehicles. The SDNCA framework applies the SDN algorithm to achieve three main objectives. First, it calculates the Quality of Service (QoS) of the ESM. Second, it dynamically allocates both 5G network and computing resources for three Virtual Networks (VNs). Third, it selects the optimal 5G base station (gNB) for routing the ESM to the destination vehicle. To ensure effective forwarding for each ESM, SDNCA deploys the gNB algorithm at the selected gNB to schedule the ESMs considering their priorities and configures the 5G network resources and computing resources based on the OpenFlow control message received from the SDN.

The implementation of the second system model integrates the VFL, SDN, and gNB algorithms, focusing on the risk distance between the source and destination vehicles. The objective of the second system model is to ensure the successful transmission of ESMs in scenarios when considering the risk distances between vehicles.

The two system models have been implemented using three simulation tools: Network Simulator (NS3), Python programming language, and a Mininet network emulator. The real-time simulation results demonstrate the evaluation of the SDNCA framework into two sections, compared with the existing related research. The first section assesses the performance of the SDNCA framework by varying the density and speed of the vehicles. These results include 17% and 20% Network Overhead (NO), 17% and 20% Computational Complexity (CC), 0% Collision Rate (CR), 18 ms End-to-End (E2E) Delay, 89%–90% Packet (ESM) Transmission Reliability (TR), 99.5% and 99.4% Successful Routing Ratio (SRR), 0.0050 ms Routing Efficiency (RE), 0% Packet Drop Ratio (PDR), 0.25×10^{-4} and 0.5×10^{-4} Channel Utilization (CU), and 4.5 ms and 4 ms E2E Delay with different values of the allocated bandwidth. The second section evaluates the performance of the SDNCA framework at distances ranging up to 30 meters between the source and destination vehicles, taking into account different vehicle densities and speeds. These results include 97%–99.5% and 98.4%–99.8% SRR, 4 ms and 3.5 ms RE, 0% CR, and 4.5 ms E2E Delay.

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LIST OF ABBREVIATIONS

5G	Fifth-Generation Network
3GPP	3rd Generation Partnership Project
6G	Sixth-Generation Network
AFL	Asynchronous Federated Learning
AI	Artificial Intelligence
AMC	Adaptive Modulation and Coding
API	Application Programming Interface
AVs	Autonomous Vehicles
BWPs	Bandwidth Parts
CC	Component Carrier
C-V2X	Cellular Vehicle-to-Everything
D2D	Device-to-Device
DL	Downlink
DLC	Downlink Control
DSRC	Dedicated Short Range Communication
eMBB	enhanced Mobile Broadband
ESMs	Emergency Safety Messages
eV2X	enhanced V2X
FDD	Frequency Divion Duplexing
FedAvg	Federated Averaging
FFR	Fractional Frequency Reuse
FL	Federated Learning

gNB	Next Generation Base station (Next Generation Node B)
GPS	Global Positioning System
HARQ	Hybrid Automatic Repeat Request
IID	Independent and Identically Distributed
IoT	Internet of Things
IoV	Internet of Vehicles
ITS	Intelligent Transportation Systems
KPI	Key Performance Indicator
LoS	Line of Site
MAC	Medium Access Control
MCS	Modulation and Coding Scheme
MEC	Mobile Edge Computing/Multiaccess Edge Computing
MIMO	Multiple Input Multiple Output
mMTC	massive Machine Type Communications
mmWave	millimeter-Wave
MTU	Maximum Transfer Unit
NFV	Network Function Virtualization
NFV MANO	Network Function Virtualization Management and Orchestration
NLoS	Non-Line of Site
NR	New Radio
NrEesmCcT2	NR Exponential Effective SINR Mapping, HARQ-Chase Combining, MCS Table2
NrEesmIrT2	NR Exponential Effective SINR Mapping, HARQ-Incremental Redundancy, MCS Table2

NS3	Network Simulator version 3
NSPs	Network Service Providers
OFDMA	Orthogonal Frequency Division Multiple Access
PF	Proportional Fair
PGW	Packet Data Network Gateway
PR	Positive Risk
QoS	Quality of Service
R2V	Roadside units-to-Vehicle
RB	Resource Block
RBG	Resource Block Group
ReLU	Rectified Linear Unit
RMa	Rural Macro
RR	Round Robin
RS-ANN	Risk Severity-Artificial Neural Network
RSU	Roadside Unit
RSU-to-RSU	Roadside Unit-to-Roadside Unit
SDN	Software-Defined Networking
SDNCA	Software-Defined Networking-based Collision Avoidance
SFL	Synchronous Federated Learning
SGD	Stochastic Gradient Descent
SINR	Signal-to-Interference-plus-Noise Ratio
SRS	Sounding Reference Signal
TCP	Transmission Control Protocol

TDD	Time Division Duplexing
TDMA	Time Division Multiple Access
UDN	Ultra-Dense Network
UDP	User Datagram Protocol
UE	User Equipment
UL	Uplink
UMa	Urban Macro
UMi	Urban Micro
URLLC	Ultra-Reliable and Low-Latency Communications
V2B	Vehicle-to-Building
V2C	Vehicle-to-Cloud
V2D	Vehicle-to-Device
V2F	Vehicle-to-Fog
V2G	Vehicle-to-Grid
V2I	Vehicle-to-Infrastructure
V2P	Vehicle-to-Pedestrian
V2R	Vehicle-to-Roadside unit
V2S	Vehicle-to-Sensor
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
VANETs	Vehicular Ad-Hoc Networks
VFL	Vehicular Federated Learning
VN	Virtual Network

WAVE	Wireless Access of Vehicular Environment
5G-IoV	IoV based on 5G communication
5G-V2I	5G-Vehicle-to-Infrastructure
5G-V2X	5G-Vehicle-to-Everything

CHAPTER ONE

INTRODUCTION

1.1 Overview

Technological transformations in automated vehicles are leading to vital changes in the transport systems and automotive industries due to their rapid proliferation on roads, contributing to increased safety and effectiveness (Soto *et al.*, 2022, Dhanare *et al.*, 2022, Alhilal *et al.*, 2020). Recently, the concept of the Internet of Vehicles (IoV) (Gao *et al.*, 2021) has drawn significant attention as a promising approach to reduce traffic accidents, alleviate traffic congestion, and provide various convenient applications, such as autonomous driving, interactive entertainment, and real-time traffic information (Zeng *et al.*, 2022, Chang *et al.*, 2021).

The IoV connects hardware devices, network communication channels, and cloud platforms that allow connected vehicles, pedestrians, and intelligent units near the road to exchange information in real-time (Ayaz *et al.*, 2022, Ji *et al.*, 2022, Yin *et al.*, 2022, Song *et al.*, 2021). Autonomous Vehicles (AVs) are nearing commercialization and are expected to become dominant among various emerging vehicles in the future (Mushtaq *et al.*, 2021, Na *et al.*, 2022). Wireless communication technologies, specifically vehicular communications such as Vehicle-to-Everything (V2X) (Xiong *et al.*, 2021), along with existing vehicle-sensing capabilities (Agbaje *et al.*, 2022), provide support for enhanced safety applications, thereby enabling AVs for safer autonomous driving (Hussein *et al.*, 2021). The important supporting technologies of Artificial Intelligence (AI) (Kim *et al.*, 2022) and Fifth-Generation (5G) networks (Hakak *et al.*, 2023, Montero *et al.*, 2022) in IoV technology are considered potential solutions for boosting vehicular critical safety applications (Mekrache *et al.*, 2022).

IoV based on 5G communication (5G-IoV) enables Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Roadside (V2R), Vehicle-to-Pedestrian (V2P), Vehicle-to-Grid (V2G), Vehicle-to-Building (V2B), Vehicle-to-Device (V2D), and Vehicle-to-Cloud (V2C) communication modes with high data rates and very low latency, making AVs a reality (Hichri *et al.*, 2021). Beamforming and virtualization technologies are considered the best solutions to optimize 5G utilization in IoV. Beamforming design aims to reduce the hardware and signal processing complexity while achieving near-optimal performance by directing a narrow beam toward each vehicle destination. Thus, adaptive beamforming can minimize interference, improve network coverage, and increase throughput (Shaik and Malik, 2021). Conversely, Network Function Virtualization (NFV) is an underlying method that enables network operators to create network slices per end-user application or service requirement with guaranteed performance and quality corresponding to service-level agreements. Both cloud and edge computing components are required in these network slices to address the varying performance and latency requirements (Bolla *et al.*, 2022). Thus, emerging 5G-IoV supports high-speed mobility, broad coverage, substantial capacity, and a stable connection (Chen *et al.*, 2019). These attributes are effective for enabling V2X services, particularly in satisfying the stringent latency requirements of safety-critical missions such as autonomous driving (Coll-Perales *et al.*, 2022). Although 5G-IoV aims to provide new capabilities and strict Quality of Service (QoS) requirements, it runs its network functions over a unified operating system, particularly at its edge (Dai *et al.*, 2021).

Mobile Edge Computing/Multiaccess Edge Computing (MEC) has been envisioned for future 5G-IoV, in which some core network functionalities are moved to the network edge, that is, nearer to the vehicles for lower latency and local processing of sensitive data for critical public safety services (Wang and Xu, 2020). However, MEC requires the virtualization of network infrastructure for the utilization of cloud resources at the network edge. As Software-Defined Networking (SDN) (Liu *et al.*, 2020) provides flexibility in network management and large-scale optimization with unified abstraction (Duo *et al.*, 2020, Ravi and Thangaraj, 2021), SDN is combined with MEC to control Virtual Network (VN) customization (Walia *et al.*, 2021). In addition, MEC can be utilized to bolster the control of SDN in the 5G-IoV, improving network and resource management (Zhuang *et al.*, 2020). Thus, the supportive 5G-IoV introduces resilience, elasticity, QoS provisioning, and programmability by efficiently allocating the available 5G resources and minimizing network management latency (Wan *et al.*, 2021, Boukerche and Aljeri, 2021). Moreover, the central SDN controller can manage edge servers deployed at 5G base stations (Gyawali *et al.*, 2021). Therefore, SDN can achieve reliable transmission of Emergency Safety Messages (ESMs) to the destination vehicles in the 5G-IoV environment (Benalia *et al.*, 2020).

ESMs are emergency warnings and delay-sensitive messages transmitted to the targeted vehicles when detecting hazardous events on the road to avoid crucial danger and road congestion (Rastogi *et al.*, 2021). The major challenge of ESM dissemination in traditional vehicular networks is high broadcast storms, which consume large amounts of bandwidth, increase network congestion, and further increase dissemination delay (Ameur *et al.*, 2022). Moreover, the QoS provisioning regarding the reliability of the surrounding vehicles that can receive safety messages from a transmitting vehicle within the message lifetime still has several limitations in high-density IoV scenarios and uneven traffic distributions (Garg *et al.*, 2021b, Noor-A-Rahim *et al.*, 2022). The reason can be attributed to the numerous challenges that vehicular networks face, such as channel interference, limited bandwidth, Line-of-Site (LoS) and Non-Line-of-Site (NLoS) connections, highly dynamic mobility scenarios, and environmental changes (Ghimire and Rawat, 2022).

At the same time, the large amount of data collected by sensors requires high processing and communication capabilities (Yuan *et al.*, 2021). To alleviate the broadcast storm problem and handle the challenges in vehicular networks, SDN-assisted 5G-IoV technology requires the integration of AI techniques (Ayyub *et al.*, 2022).

A significant risk is the dissemination of ESMs to vehicles without strict reliability and delay requirements (Ma and Trivedi, 2021). Therefore, robust collision avoidance mechanisms for vehicles are key challenges that require more advanced approaches than conventional approaches. Federated Learning (FL), a promising framework (Shaheen *et al.*, 2022), is considered a feasible solution for safety-and time-critical applications involving AVs (Kong *et al.*, 2022, Huang *et al.*, 2022). FL enhances IoV owing to its properties, such as alleviation of network bandwidth, privacy protection, and low latency. This is achieved because the training vehicles transmit only the learning models, not the entire dataset, to the edge servers (Jamil *et al.*, 2022). In addition, FL handles scalability issues because a large number of vehicles participate in the training process and can be efficiently used with Non-Independent and Identically Distributed (Non-IID) data partitions. This is in contrast to the most decentralized learning algorithms, which produce a major model quality loss (Billah *et al.*, 2022). Considering FL in IoV (Taik *et al.*, 2022), the vehicles will train and improve the initial downloaded model using their local data and send the resulting model parameters to the edge servers and then to the central server for global aggregation (Posner *et al.*, 2021). In FL, the essential communication between the edge server and federated vehicles can be either Synchronous FL (SFL) or Asynchronous FL (AFL) (Li *et al.*, 2020a). Recent studies have investigated the application of FL in SDN controller, and the central SDN server in this case is used to coordinate the edge servers associated with 5G base stations and aggregate the learning model updates received from these edge servers (Ma *et al.*, 2022).

To overcome the aforementioned bottlenecks, and specifically provide effective coordination and boost safety-critical services in 5G-V2I communication, this research study proposes a novel Software-Defined Networking-based Collision Avoidance (SDNCA) framework for disseminating the ESMs via 5G technology to avoid vehicles' collisions.

1.2 Motivation of the Study

The primary motivation is to address the challenges in the dissemination of ESMs with high performance, particularly in terms of mobility and interoperability. Additionally, taking into account the advantages mentioned for 5G, FL, MEC, and SDN, this dissertation aims to investigate the precise interaction between them in the IoV environment to combine the techniques and technological solutions. Therefore, this dissertation examined FL to enable the SDN controller to implement three objectives for the purpose of disseminating ESMs in 5G-IoV.

1.3 Problem Statement

This section signifies the problems present in the existing ESM dissemination approaches associated with the IEEE 802.11p, 5G, and SDN technologies that hinder resolving the vehicle collision problem. The issues identified in existing studies include the following:

1. **IEEE 802.11P:** Short-range V2V and V2R communications (Li *et al.*, 2023) are basic vehicular communications that are enabled through the IEEE 802.11p protocol/Wireless Access of Vehicular Environment (WAVE) (Karim *et al.*, 2022, Wang *et al.*, 2023). The dedicated spectrum for this protocol

is 75 MHz in the range of 5.850– 5.925 GHz (Moradi-Pari *et al.*, 2023). One of the main problems using IEEE 802.11p technology in emergency traffic situations is broadcast storms, which have been addressed in the literature using various mechanisms. However, ESM dissemination is highly bandwidth-intensive due to broadcast storms. Therefore, the existing solutions in related studies cannot satisfy the requirements of transmitting ESMs to vehicles with high reliability and low latency, which require high-speed network access.

2. **5G:** Data dissemination in vehicular networks, especially ESM dissemination, is one of the main challenges that needs to be identified (Tabassum and Reddyy, 2023). The low-latency feature of 5G technology (Liu *et al.*, 2022b, Chatzoulis *et al.*, 2023) is helpful in this context, particularly in V2I communication, which enables the reliable transmission of ESMs to vehicles on time (Karim *et al.*, 2023). However, the integration of IEEE 802.11p and 5G technologies in some studies elevates the complexity and network congestion due to beacon messages and network signal transmission. One of the main targets of 5G-IoV is to avoid accidents involving vehicles that require intelligent dynamic control for 5G base stations (5G gNBs). The recent research studies that used 5G technology did not consider this point when transmitting ESMs.
3. **SDN:** Recently, SDN has been deployed in vehicular networks to boost many services, including safety (Islam *et al.*, 2021). The major problem that occurs during emergencies is the need to reduce the time taken to analyze the on-location situation to reduce traffic congestion and facilitate critical-time safety information dissemination (Mekki *et al.*, 2021). Using SDN for ESM dissemination in vehicular networks is operationally expensive.

Therefore, efficient mechanisms are required to reduce the overall network overhead and operational costs, an aspect not addressed in the studies.

Additionally, some of the studies related to points 1–3 used the clustering technique, where the formation and modification of clusters for each ESM transmission increase the network overhead.

1.4 Research Objective and Questions

The basic aim of this study is to tackle the issues outlined in the problem statement and propose a novel cellular 5G-V2I framework based on SDN (SDNCA) for ESM dissemination in highway scenarios. More specifically, the proposed SDNCA framework focuses on a specific problem, that is, avoiding vehicle collisions by disseminating ESMs. This study targets to develop practical decision-making and adaptation techniques to solve this problem. The proposed first and second system models include realistic assumptions in order to handle the dynamic characteristics of IoV. In this context, the following research questions need to be addressed in the SDNCA framework:

1. What is the impact of the federated learning approach on addressing the key challenges in estimating risk severity for vehicles in a dynamic and decentralized environment?
2. What specific considerations and solutions does federated learning introduce to improve the training accuracy and test accuracy of the proposed Risk Severity-Artificial Neural Network (RS-ANN) model?
3. During the training and test phases, what concepts and metrics are considered to investigate the level of stability of federated learning?
4. How does federated learning between vehicles contribute to lower training latency and test latency? What is the importance of evaluating these metrics, particularly for ESM dissemination?

5. How can federated learning enhance the efficiency of the SDN controller for routing ESMs when the vehicle density and speed change over time and area?
6. What is the role of federated learning in providing adaptive control of 5G gNBs to ensure optimal performance during the transmission of ESMs?

1.5 Contributions

The key contributions of the proposed framework are as follows:

1. The SDNCA framework employs three proposed algorithms in the first system model for routing ESMs to avoid vehicle collisions by controlling network congestion.
2. A Vehicular Federated Learning (VFL) algorithm has been proposed for improved estimation of the risk severity of vehicles. This algorithm estimates risk severity for each vehicle by training the proposed RS-ANN model through federated learning between vehicles. This method of learning enhances the training and test accuracies, and provides lower training and test latencies.
3. On the basis of the VFL algorithm, a novel SDN algorithm has been formulated to handle three main successive objectives in an OpenFlow control message. First, it identifies the QoS for each ESM by considering succeeding metrics that are risk severity, vehicle speed, and risk distance. Second, it dynamically allocates 5G network resources and computing resources based on the QoS value, risk distance, and vehicle speed. Third, it traces the optimal route (gNB) for routing ESM to the destination vehicle. The SDN algorithm handles each ESM independently in an efficient manner, which controls the network congestion.

4. The gNB algorithm is then proposed at the selected gNB to schedule ESMs based on their priorities. It also configures the 5G network resources and computing resources. In this way, the selected gNB forwards ESM to the destination vehicle with low latency and extremely high reliability, thereby avoiding vehicle collisions.
5. Based on the first system model, the second system model has been applied to consider the risk distance between the source and destination vehicles. The process in this system model is as follows: First, the VFL algorithm has been performed. Second, the algorithm of SDN has been developed by calculating the QoS for each ESM based on the metrics of risk severity, vehicle speed, and risk distance between the source and destination vehicles. Then, SDN selects the nearest gNB to the destination vehicle. Moreover, SDN dynamically allocates the network resources and computing resources of 5G based on the QoS value, the risk distance between vehicles, and the distance between the selected gNB and the destination vehicle. Third, the selected gNB configures its network and computing resources based on the OpenFlow control message received from the SDN and sends the ESM to the destination vehicle. The second system model effectively manages the SDNCA framework when there are significant distances between the source and destination vehicles that pose a risk.
6. The real-time simulation results indicate that the SDN controller in the SDNCA framework can optimize the network communication of ESMs to vehicles in 5G-IoV through the FL scheme. These results include network overhead, computational complexity, collision rate, end-to-end delay, transmission reliability, packet drop ratio, successful routing ratio, routing efficiency, and channel utilization.

1.6 Dissertation Outline

The structure of this dissertation is organized as follows:

Chapter one summarizes the employed technologies that are integrated to establish the scope of this study. It addresses the key issues that promoted the proposal of the SDNCA framework, objectives, and research questions, and also explains the contributions behind it.

Chapter two contains two main sections, which are: The first section covers the theoretical background of VANETs, IoV, and enabling technologies in IoV. The second section provides an extensive literature review on the dissemination of ESMs based on IEEE 802.11p, 5G, and SDN technologies. Existing works are explained along with their limitations.

Chapter three starts with introducing the proposed IoV architecture, concentrates intently on the design and methodology, which covers the FL, MEC, 5G, and SDN in the IoV environment.

Chapter four and chapter five present the simulation scenarios regarding the proposed system models and discuss the results obtained in each specific scenario.

Chapter six concludes the study and provides future research directions.

CHAPTER TWO

LITERATURE REVIEW AND THEORITICAL BACKGROUND

2.1 Introduction

Chapter two of the study provides a comprehensive overview of the theoretical background upon which the research is built, together with an extensive literature review. The theoretical background explores the conceptual framework that provides guidance for the study, explaining the fundamental concepts, principles, and models that form the basis of the research. Additionally, the literature review critically examines existing scholarly works relevant to the research topic, synthesizing and analyzing various perspectives, methodologies, and findings. The literature review examines the previous research to identify any gaps and provides context and justification for the current investigation.

2.2 Vehicular Ad-Hoc Networks (VANETs)

Vehicular communication networks have emerged to enable numerous vehicular data services and applications. Conventional Vehicular Ad-Hoc Networks (VANETs) are often operated in an ad hoc mode and mainly focus on road safety applications based on the connections between vehicles and Roadside Units (RSUs) (Ahangar *et al.*, 2021). Given the expected market growth in the connected vehicles landscape, two different Device-to-Device (D2D) communication technologies, namely, Dedicated Short Range Communication (DSRC), which is based on the IEEE 802.11p standard, and Cellular Vehicle-to-Everything (C-V2X) (Zhou *et al.*, 2020, Mir *et al.*, 2020), have been standardized by international organizations. Further developments and evaluations are progressing worldwide for both technologies (Zeadally *et al.*, 2020).

In VANETs, there are several communication mechanisms available, including V2V mode, which is pure ad-hoc communication without fixed infrastructure (Zeadally *et al.*, 2019), and V2R, or Roadside units-to-Vehicle (R2V) communications, which allow a vehicle to communicate with roadside units primarily for collecting information and analyzing traffic data (Hossain *et al.*, 2020). A hybrid communication mode is a combination between V2V and V2R communications, whereby a vehicle can directly communicate with the road infrastructure; in addition, a vehicle can communicate via multi-hopping with other vehicles when direct transmission to an RSU is not possible with a single hop (Jeong *et al.*, 2021). In addition, an RSU can directly transmit data to another RSU in Roadside Unit-to-Roadside Unit (RSU-to-RSU) communication to facilitate computation, network load-balancing, and information sharing. Figure 2.1 shows a VANET architecture with different transmission modes (Karunathilake and Förster, 2022).

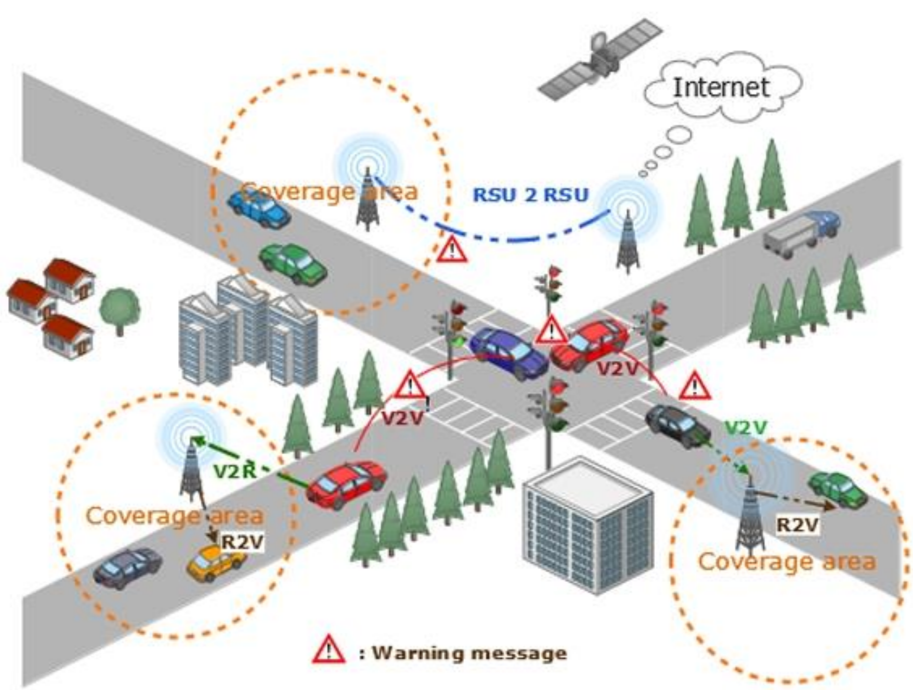


Figure 2.1: Communication modes in traditional vehicular networks (Guerna et al., 2022)

2.3 Internet of Vehicles (IoV)

The concept of the Internet of Things (IoT) (Manogaran *et al.*, 2021) and its intelligent interfaces provide a wide range of services through ubiquitous sensing capabilities that evolved conventional VANETs to the next emerging and evolutionary stage of the IoV (Kumar and Singh, 2020). The main objective behind IoV is to support the recent and forthcoming demands from the mobility world, such as Intelligent Transportation Systems (ITS), advanced driving, and autonomous vehicles (Heo *et al.*, 2021).

IoV maximizes the utilization of information and communication technologies that provide new interactions at the road level among vehicles, humans, and environments. These interactions facilitate the use of many applications, such as data dissemination and aggregation, alleviation of traffic congestion, road safety, traffic management, and mainly routing schemes, and support the significant number of connected vehicles (Magaia *et al.*, 2022, Senouci *et al.*, 2019). In diverse and heterogeneous IoV networks, the vehicles communicate in a partially structured form, influenced by large and dynamic topologies, high mobility and speed of vehicles, and frequent changes in density over time and location (Qureshi *et al.*, 2021). Reliable and scalable wireless transmissions for IoV are technically difficult; some of the challenges of the existing IoV networks are as follows:

- Each vehicle, from driver-assisted to automated, will generate a flood of information, up to thousands of times more than that by a person that requires big data analytics and intelligent decision-making based on this analysis (Arooj *et al.*, 2021).
- During peak traffic hours or when an accident occurs, a large number of vehicles require urgent information exchange. In these situations, the

services are limited or unreliable due to variable-capacity wireless links, bandwidth constraints, and communication channel impacts (Ni *et al.*, 2020).

- Lack of standards and scalability (Qureshi *et al.*, 2021).
- Storage and computation constraints and the unavailability of cloud services (Danquah and Altilar, 2020).
- It is challenging for existing centralized resource allocation approaches in cellular networks to guarantee such diverse QoS requirements, especially the ultra-reliable and low latency requirements (Liang *et al.*, 2020, Zhang *et al.*, 2020b).
- Security issues (Xu *et al.*, 2022).
- Lack of Global Positioning System (GPS) due to reception issues, weak signals, and vehicle position imprecision (Heo *et al.*, 2019).

On the basis of the aforementioned challenges, the motivation for IoV is realistic and huge for greater convenience and comfort, providing service applications and safety applications, as shown in figure 2.2.

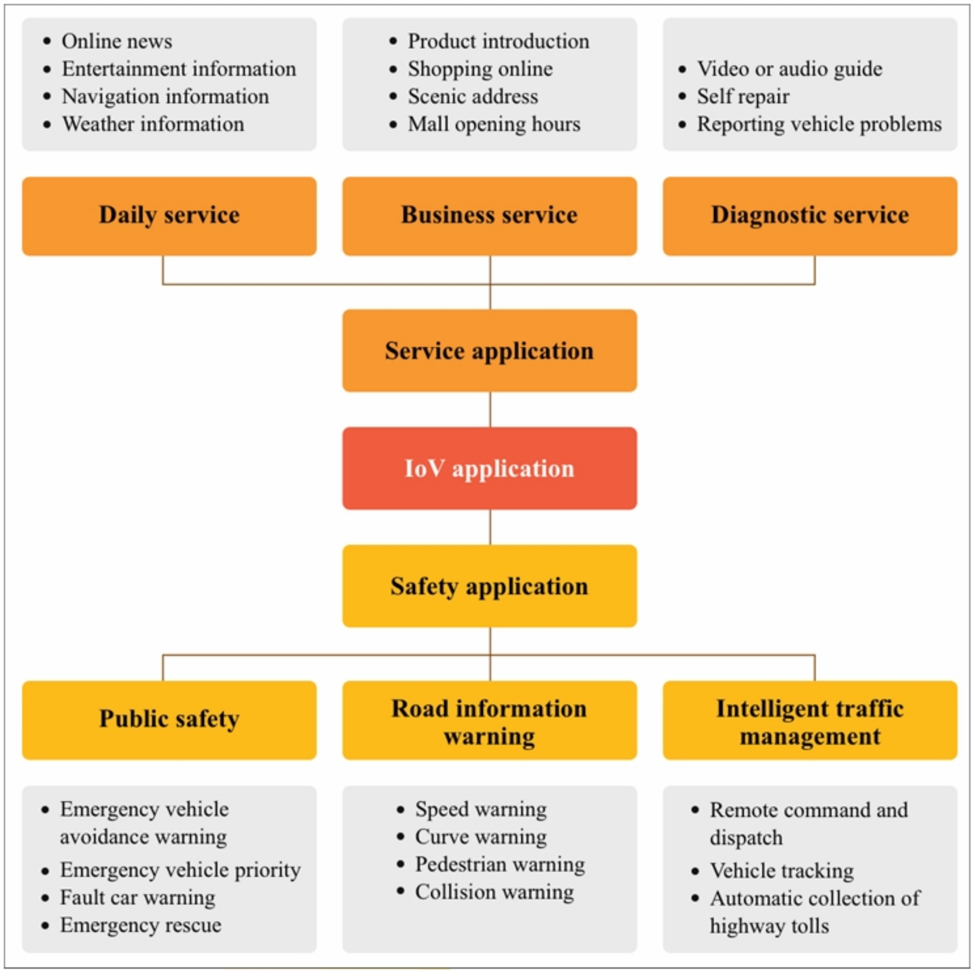


Figure 2.2: Service and safety applications in IoV (Ji et al., 2020)

This motivation can be realized by designing more precise and relevant architectures, as illustrated in figure 2.3, related to V2X communication, computation, and service scenarios.

The V2X in these scenarios contains multiple connections such as V2V, V2I, V2P (Ansari, 2020), V2R, V2C (Shen *et al.*, 2020), V2G, V2B (Ang *et al.*, 2019), V2D (Singh *et al.*, 2019), Vehicle-to-Fog (V2F) (Zhang *et al.*, 2021), and Vehicle-to-Sensor (V2S) (Vasudev *et al.*, 2020).

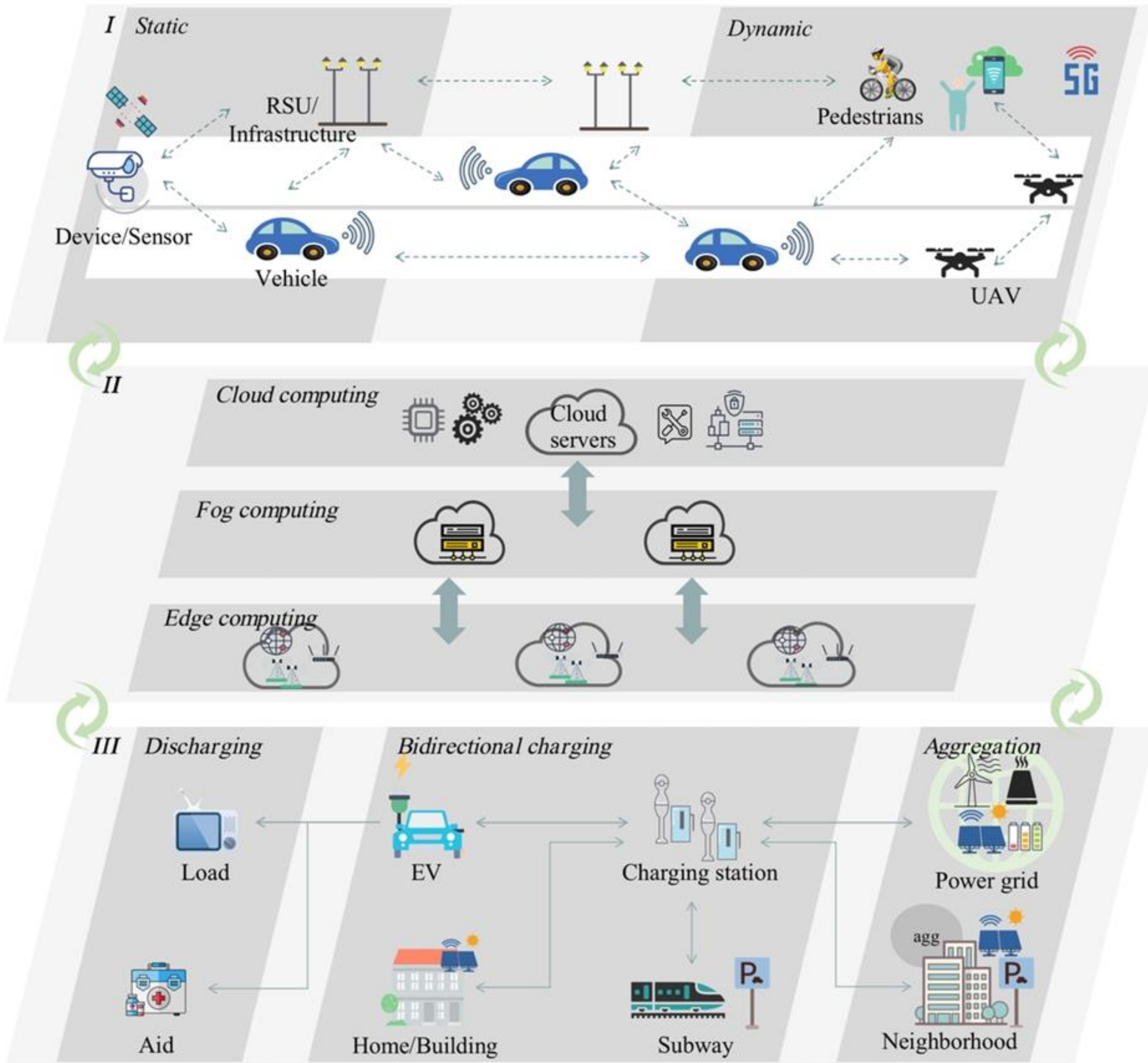


Figure 2.3: V2X in different scenarios. I: communication scenario; II: computation scenario; III: service scenario (Lv et al., 2023).

2.4 Dissemination of ESMs in IoV

Message or data dissemination is a common practice in vehicular networks, where messages and resources are shared among all neighboring vehicles in the network. Routing involves determining the most efficient and optimal path for successfully transmitting information between sender and recipient nodes, ensuring timely delivery and error-free communication, even if any event happens on the road (Ahmed *et al.*, 2023, Kayarga and Kumar, 2021). A vehicle equipped with a DSRC unit based on the IEEE 802.11p standard can communicate with other vehicles to exchange warning messages to avoid accidents and improve traffic situations (Fabi and Thampi, 2022). The capability of receiving the ESMs is important in a dense vehicular communication network with many vehicles attempting to broadcast the ESMs in an uncoordinated way (Li *et al.*, 2022). The most basic ESM dissemination scheme is based on broadcasts. However, broadcast-based ESM dissemination causes the broadcast storm phenomenon. This phenomenon results in excessive transmission delay, packet loss, transmission failure, dissemination interference, and degrades overall network performance. Furthermore, broadcast storms occur more frequently in urban environments with high vehicle density (Ullah *et al.*, 2020a).

The subsequent sections offer a comprehensive and easily understandable overview of four key advancements: 5G, FL, MEC, and SDN. The explanation provided aims to emphasize the inherent benefits of these solutions within the realm of IoV, particularly in the context of transmitting ESMs between vehicles to avoid vehicle collisions. In this study, the exploration of 5G's high-speed, low-latency communication, FL's collaborative and privacy-preserving model training, MEC's edge computing capabilities, and SDN's dynamic network management creates an environment where 5G, FL, MEC, and SDN work together to enhance vehicular safety through efficient ESM transmission.

2.5 Fifth-Generation (5G) Networks

In recent years, 5G wireless networks have attracted extensive research interest. According to the 3rd Generation Partnership Project (3GPP) (Qian *et al.*, 2021), 5G networks should support three major families of applications, including enhanced Mobile Broadband (eMBB), massive Machine Type Communications (mMTC), and Ultra-Reliable and Low-Latency Communications (URLLC) (Weerasinghe *et al.*, 2020, Chen *et al.*, 2021). In addition, the inclusion of enhanced V2X (eV2X) communications is regarded as a crucial service that necessitates support from 5G networks. These scenarios require extensive connectivity with a fast rate of data transfer, and enhanced utilization of the available frequency spectrum. This presents considerable difficulties in designing 5G networks (Cai *et al.*, 2018). Besides, there are various Key Performance Indicator (KPI) requirements for 5G cellular networks, as listed in Table 2.1. Each KPI is related to one or more use cases. The KPIs on mMTC and URLLC are specifically related to IoT (Fuentes *et al.*, 2020).

Table 2.1: KPIs of 5G (Vaezi *et al.*, 2022)

KPI	Requirements	Category
Peak data rate	20 Gbps (downlink), 10 Gbps (uplink)	eMBB
User experienced data rate	100 Mbps (downlink), 50 Mbps (uplink)	eMBB
Spectral efficiency	30-bit/s/Hz (downlink), 15-bit/s/Hz (uplink)	eMBB
Latency (user plane)	4 ms for eMBB, 1 ms for URLLC	eMBB, URLLC
Reliability	$1 - 10^{-5}$	URLLC
Energy efficiency	Qualitative	eMBB
Connection density	10^6 devices/Km^2	mMTC
Mobility	Up to 500 km/hr.	eMBB

Allocating new frequencies is a straightforward solution for increasing the number of connections in the network. A good example is the introduction of millimeter-Wave (mmWave) bands (30–300 GHz) in 5G networks. However, due to the wide bandwidth and high penetration loss, mmWave frequency bands are generally not considered for massive connectivity, but they can be used for broadband IoT and critical IoT (Hu *et al.*, 2020). The Ultra-Dense Network (UDN) is a crucial technology in 5G networks that tackles the pressing issue of system capacity by implementing unique deployment strategies. Small cells, due to their smaller coverage areas and higher spatial reuse, allow for a more detailed and efficient exploitation of the available spectrum (De Ree *et al.*, 2019). This strategy not only enhances data throughput but also mitigates issues related to network congestion and data latency. The implementation of UDN in 5G networks serves as a proactive solution to address the increasing need for faster data speeds, enhanced network stability, and the growing number of connected devices (Alablani and Arafah, 2021).

5G Advanced will build a foundation for more demanding applications, such as extended reality. A key component of 5G Advanced is the use of AI-based techniques to introduce intelligent network management and further optimize the performance of the networks. Based on the 3GPP's 5G evolution tentative time plan shown in figure 2.4, the standardization of 5G Advanced began with Release 18 in 2022 and will continue until 2028 (Release 21) (Rahman *et al.*, 2021).

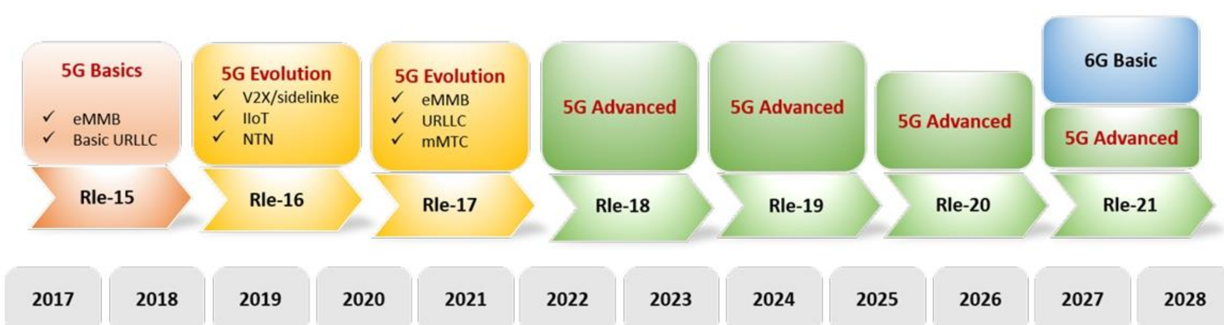


Figure 2.4: Scheduled time plan for the development of 5G by 3GPP (Rahman et al., 2021)

A few KPIs are related to the data rate in one way or another. These are peak data rate, user experience peak data rate, and spectral efficiency. As shown in figure 2.5, 5G networks are expected to offer peak data rates of up to 20 Gbps, whereas peak data rates for Sixth-Generation (6G) networks will be about 1,000 Gbps. Also, compared to 5G, the user experience data rate is expected to increase by about an order of magnitude in 2030. Further, spectral efficiency must improve two to three times. The technologies facilitating these escalations are mmWave, Tera Hertz (THz), and massive Multiple-Input Multiple-Output (MIMO) (Navarro-Ortiz *et al.*, 2020).

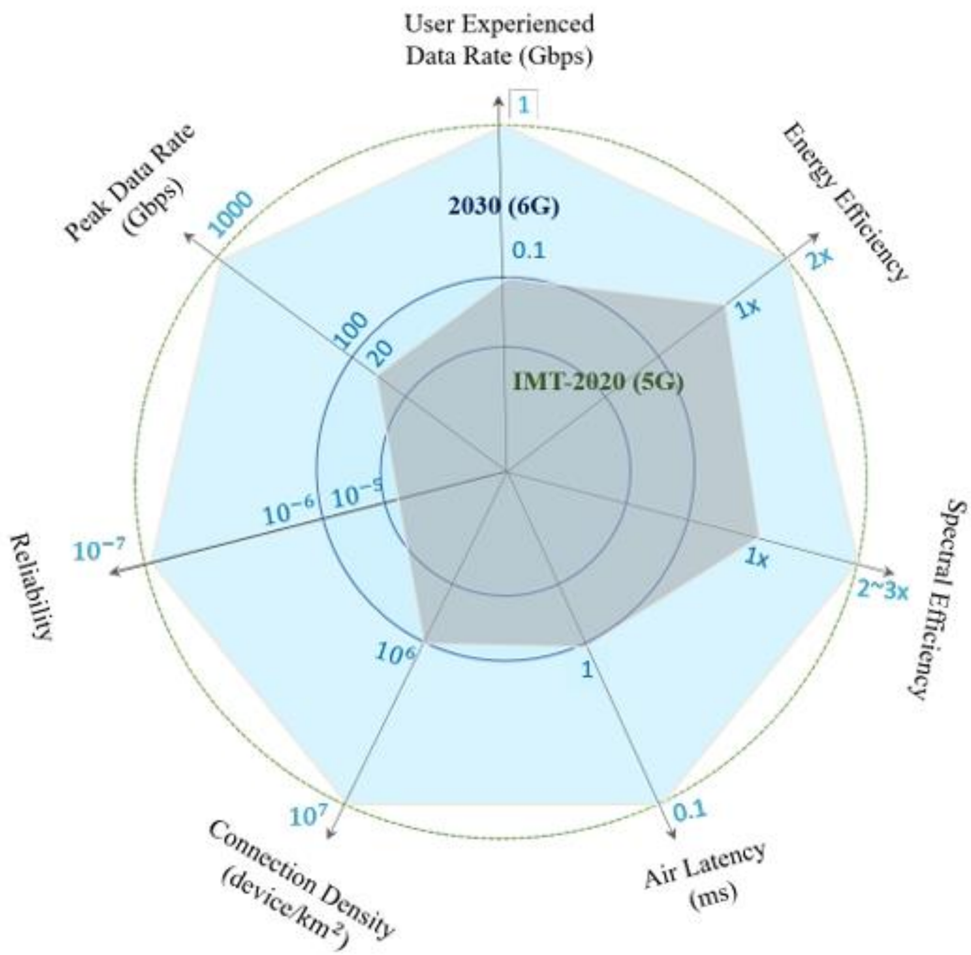


Figure 2.5: Traffic estimates from 2020 to 2030 (Navarro-Ortiz *et al.*, 2020)

2.5.1 Network Function Virtualization (NFV)

NFV is crucial to the advancement of 5G networks as it converts conventional network infrastructures into highly adaptable and efficient environments. In the context of 5G, NFV involves the decoupling of network functions from dedicated hardware and virtualizing them as software applications. Operators can utilize this capability to flexibly implement, expand, and manage network services, including routing, load balancing, and security, on standard servers and in a more cost-effective manner. NFV in 5G enables rapid service innovation, scalability, and efficient use of resources. This allows network operators to promptly respond to changing demands and launch new services with enhanced flexibility (Ghai *et al.*, 2020). Network Service Providers (NSPs) can greatly enhance the performance of Network Function Virtualization Management and Orchestration (NFV MANO) by incorporating advanced intelligence techniques such as federated learning and reinforcement learning. This will provide a solid foundation for tackling the new challenges and opportunities presented by 5G networks and future technological environments. Federated learning enables NSPs to collectively train machine learning models across distributed network elements, promoting collective intelligence while upholding data privacy and security. Reinforcement learning, on the other hand, empowers the NFV MANO system to independently adjust and enhance decision-making by utilizing real-time feedback and dynamic network conditions (Manias and Shami, 2021b).

2.5.2 Network Slicing

Network slicing in 5G networks is a revolutionary architectural concept that allows service providers to partition a single physical network infrastructure into multiple virtual networks, known as slices, each customized to fulfill the specific needs of different applications. The operators can optimally distribute resources using this dynamic and adaptable technique, thereby providing optimal performance for a wide range of use cases. This includes delivering ultra-low latency for critical applications such as autonomous vehicles, as well as providing high-speed, low-delay connections for augmented reality experiences (Ssengonzi *et al.*, 2022). Each network slice functions as a separate, end-to-end logical network with its own allocated resources, network functionalities, and management policies. The isolation and customization provided by this system allow different services to exist on the same physical infrastructure without any interference, resulting in exceptional scalability, efficiency, and service differentiation (Wijethilaka and Liyanage, 2021).

2.5.3 Software-Defined Networking (SDN)

SDN represents a transformative approach to designing network architecture. It involves separating the control plane from the physical hardware infrastructure and allowing centralized control through software (Bi *et al.*, 2019). In SDN, the network's intelligence and decision-making processes are moved to a software layer, enabling the flexible, programmable, and centralized administration of network resources. The segregation of control and data planes enables enhanced agility and flexibility in network setups, simplifying the process of adapting to evolving demands, optimizing traffic flow, and swiftly deploying new services (Rafique *et al.*, 2020).

Integrating SDN into 5G networks plays a crucial role in meeting the complex and ever-changing demands of future communication technologies. SDN introduces a centralized and programmable mechanism for managing networks. This enables operators to effectively distribute resources, optimize traffic, and adapt network configurations in real-time to cater to the various requirements of 5G services. Within the realm of 5G, where network slicing is a fundamental concept, SDN plays a pivotal role in managing and coordinating these slices. SDN facilitates the dynamic establishment, administration, and enhancement of network slices by offering a single and customizable control plane. This ensures that each slice fulfills the distinct performance, latency, and bandwidth prerequisites of various 5G applications (Ahmadi, 2019). Furthermore, SDN improves the overall flexibility and responsiveness of 5G networks by facilitating quick service implementation and automation. SDN facilitates centralized management and control of network functions, enabling the adoption of intelligent and adaptable policies. This allows for optimal usage of resources and an immediate response to changing network conditions (Kakkavas *et al.*, 2021).

2.5.4 Mobile Edge Computing/Multiaccess Edge Computing (MEC)

MEC is a paradigm that aims to optimize the performance of mobile applications and services by bringing computing resources closer to the network edge. This approach reduces latency, or the delay in data transmission, resulting in improved performance. MEC strategically positions processing power, storage, and networking capabilities at the edge of the cellular network. This allows for local data processing instead of depending only on remote cloud data centers (Tropea *et al.*, 2021). The close proximity to end-users enables faster response times, which is especially beneficial for latency-sensitive applications such as augmented reality, virtual reality, and real-time analytics. The implementation of MEC not only reduces latency, improving the user experience, but also creates possibilities for creative and context-aware services. This establishes the groundwork for a more responsive and efficient mobile communication infrastructure (Darwish and Abu Bakar, 2018).

MEC plays a pivotal role in facilitating the implementation of 5G networks, making a significant contribution to the realization of the technology's transformational capabilities. MEC, as a crucial facilitator of 5G, utilizes its capacity to deploy computational resources to the network's edge, perfectly aligning with the anticipated high data rates, low latency, and extensive device connections offered by 5G (Hassan *et al.*, 2019, Pereira *et al.*, 2020). By bringing computational capabilities closer to end-users and their devices, MEC reduces latency and improves data processing. This directly meets the demanding performance needs of forthcoming 5G applications. The strategic deployment of computing capacity in the edge infrastructure improves the overall efficiency and responsiveness of 5G networks, enabling the full realization of revolutionary applications like autonomous vehicles, smart cities, and immersive multimedia experiences (Pham *et al.*, 2020).

2.6 IoV Based on 5G communications (5G-IoV)

The incorporation of 5G technology into the IoV signifies a significant advancement in the domain of interconnected mobility. 5G facilitates a smooth and effective communication network for the IoV, offering exceptional speed, minimal delay, and high capacity. This opens up a wide range of potential applications and opportunities (Sodhro *et al.*, 2021a). By 2030, the profound impact of 5G technology on the IoV is expected to be even more pronounced, with the automotive industry poised to dominate the 5G IoT environment. Approximately 53% of the total 5G IoT endpoints are projected to be allocated to connected cars, underscoring the pivotal role of 5G in shaping the future of transportation (Taslimasa *et al.*, 2023). Vehicles equipped with 5G connectivity can exchange real-time data with each other and the surrounding infrastructure, strengthening traffic management, reducing congestion, and improving overall road safety. The ultrafast data transfer capabilities of 5G enable faster decision-making for autonomous vehicles, which aids in the advancement and implementation of self-driving cars (Garg *et al.*, 2021a, Yuan *et al.*, 2020, Balasubramanian *et al.*, 2022). Furthermore, the minimal delay of 5G guarantees prompt responses to critical situations, such as collision avoidance or emergency braking, hence enhancing the overall reliability and quickness of the IoV (Ali *et al.*, 2021).

V2V communication is a fundamental application in the field of 5G and advanced networks. In the specific context of time-sensitive V2V safety applications, the demand for URLLC is of utmost importance (Yang *et al.*, 2020). The requirement for timely updates on the status of vehicles emphasizes the need for immediate and reliable information transmission. With the ongoing progress of 5G and future technologies, it is crucial to optimize V2V communication by carefully managing the freshness of information. This is not only a technical requirement but also a critical factor for the effectiveness of intelligent and responsive transportation systems (Abdel-Aziz *et al.*, 2019).

Releases 16 and 17 primarily represent subsequent phases of 5G standardization by 3GPP. They aim to enhance and broaden the capabilities of 5G-New Radio (5G-NR) technology, including its implementation in areas such as V2X communications (Chen *et al.*, 2020). Release 16, which was completed in 2020, brought about notable advances for V2X. These changes focused on reducing latency, enhancing reliability, and providing greater support for various vehicular applications. Release 17, which was ongoing at the time, was anticipated to enhance and expand the capabilities of 5G-V2X. This might include the introduction of advanced positioning services and support for more deployment scenarios (Abdel Hakeem *et al.*, 2020, Harounabadi *et al.*, 2021). The technical aspects of 5G-V2X are shown in Table 2.2 (Storck and Duarte-Figueiredo, 2020).

Table 2.2: Technical aspects of 5G-V2X (Storck and Duarte-Figueiredo, 2020)

Technical Aspects	**DSRC**	**LTE-V2X**	**4G**	**5G V2X**
Theoretical bit rate	3–27 Mb/s	20 Mb/s (uplink) 80 Mb/s (downlink)	75 Mb/s (uplink) 300 Mb/s (downlink)	10 Gb/s (uplink) 20 Gb/s (downlink)
Practice bit rate	3.5 Mb/s	---	20 Mb/s	1 Gb/s
Theoretical coverage	500 m	More than 1 km	5 km	1732 m (rural) 500 m (urban macro) 200 m (urban micro)
Practice coverage	Less than 500 m	Up to 150 m (urban) Up to 320 m (highway)	Up to 2 km	---
Theoretical mobility support	More than 250 km/hr.	Less than 140 km/hr.	Between 120 and 350 km/hr.	Up to 500 km/hr.
Theoretical latency	Less than 50 ms	Less than 100 ms or less than 20 ms in emergency situations	Less than 10 ms	Less than 4 ms
Frequency band	5.9 GHz	5.9 GHz	0.45–3.8 GHz Unlicensed band (5 GHz)	0.45–6 GHz (frequency range 1) 24–52.6 GHz (frequency range 2)
System bandwidth	10 MHz	10 MHz	20 MHz	50, 100, 200, 400 MHz (above 6 GHz)
Subcarrier spacing	156.25 kHz	15 kHz	15 kHz	15, 30, 60 kHz (frequency range 1) 60, 120 kHz (frequency range 2)
Multi-tier RAT	2-tier	2-tier	3-tier	n-tier
Number of subcarriers	52	600	1200	3300
Power limits [Effective Isotropic Radiated Power (EIRP)]	33 dBm (private RSUs and mobile OBUs) 40 dBm (public safety mobile OBUs) 44.8 dBm (public safety RSUs)	23 dBm (OBU) 33 dBm (RSU)	23 dBm (OBU) 33 dBm (RSU)	33 dBm (OBU and RSU) 46 dBm (BSs)

2.6.1 SDN for 5G-Enabled IoV

The incorporation of SDN within the framework of 5G-IoV signifies a revolutionary method for managing networks and distributing resources. SDN allows for the efficient and flexible use of resources in the 5G-IoV ecosystem by enabling dynamic and centralized control of network functions. This allows for the optimization of communication paths, bandwidth allocation, and low-latency connectivity, crucial for supporting the diverse and demanding requirements of vehicular communication. SDN enables operators to flexibly adjust to fluctuating traffic patterns, allocate resources according to immediate demands, and optimize network performance, guaranteeing a more dependable and agile environment for the networked vehicles in the 5G-IoV (Di Maio *et al.*, 2019).

In the dynamic environment of 5G-IoV, where vehicles and IoT devices constantly move and exchange data, SDN's centralized control separates the network's control and data planes, enabling dynamic and efficient link optimization. SDN's capability to allocate bandwidth, reroute traffic, and prioritize communication according to the individual needs of connected vehicles and devices improves network responsiveness and resource usage (Sodhro *et al.*, 2021b). Furthermore, SDN's impact also reaches mobility management, enabling proactive decision-making to address the dynamic movements and connection requirements of vehicles. By orchestrating mobility management functions, such as handovers and network reconfigurations, SDN ensures seamless communication by adapting to the dynamic nature of 5G-IoV. SDN's programmability allows for the creation of context-aware policies, which optimize handovers, minimize latency, and prioritize key communication links based on contextual information (Aljeri and Boukerche, 2020).

2.6.2 MEC for 5G-Enabled IoV

MEC is essential for improving the performance and efficiency of 5G-IoV systems by reducing latency and improving overall responsiveness through the placement of computing resources closer to the network edge. In the context of 5G-IoV, MEC facilitates instantaneous data processing from connected vehicles, enabling expedited decision-making and response durations. This is especially advantageous for applications such as autonomous driving, traffic management, and safety-critical services. This technology simplifies the offloading of computational tasks from the centralized cloud to edge servers, thereby maximizing network capacity and minimizing congestion. Moreover, MEC enables the implementation of context-aware services, wherein localized data processing takes place according to the specific requirements of the vehicular environment (Musa *et al.*, 2022, El-Sayed and Chaqfeh, 2019).

2.6.3 SDN and MEC for 5G-Enabled IoV

Moreover, MEC servers can administer the vehicular group in a 5G-SDN-based IoV. SDN's control planes and MEC servers can be positioned in the same place so that MEC servers can act as local controllers to localize the control plane of SDN in 5G-IoV. In addition, sustainable development is another advantage of MEC with SDN (Duan *et al.*, 2020). SDN enables efficient offloading and resource allocation by centrally controlling and programmatically managing network architecture. It achieves this by dynamically orchestrating network resources in response to the changing demands of IoV applications. Simultaneously, MEC, by deploying at the network edge, brings computing capabilities closer to IoV devices, resulting in reduced latency and enabling real-time decision-making (Zhang *et al.*, 2020a). The joint integration of SDN and MEC guarantees smooth handovers by automatically overseeing the transitions between various network cells or access points. The interdependence between SDN and MEC in 5G-IoV settings enhances the efficiency, dependability, and minimal delay of communication among vehicles. This collaboration effectively manages resources and facilitates seamless connectivity transitions in the dynamic IoV environment (Monir *et al.*, 2022).

2.6.4 Device-to-Device Communication (D2D) for 5G-Enabled IoV

Figure 2.6 illustrates the utilization of D2D communication in the context of 5G technology for the IoV application. D2D communication in 5G is essential for improving vehicular connectivity and communication efficiency in the IoV. This technology facilitates direct V2V communication, eliminating the need for intermediaries such as base stations. As a result, it reduces latency and enhances the overall performance of the network. D2D communication in 5G-IoV facilitates the real-time exchange of critical information, such as location data, traffic conditions, and safety warnings, among nearby vehicles. This not only improves road safety but also leads to the development of more intelligent and adaptable traffic management systems (Yang and Hua, 2019, Ali *et al.*, 2023).

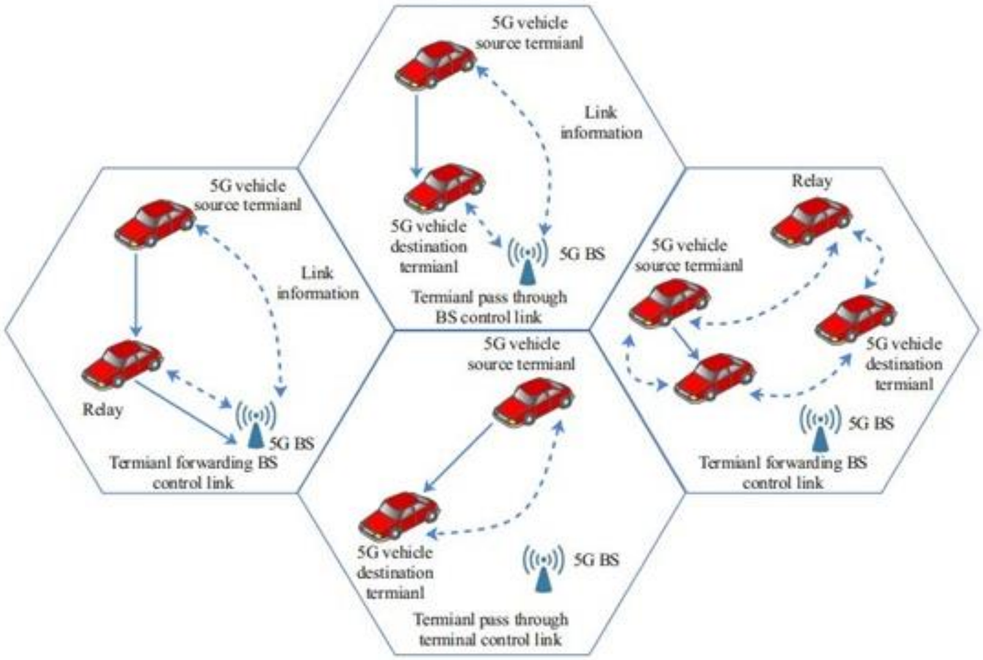


Figure 2.6: D2D communication mode of 5G-IoV (Ali et al., 2023)

2.7 Federated Learning (FL) for IoV

Recently, FL has been emerging for addressing large-scale distributed training across many interconnected devices, or agents, with enhanced privacy-preserving functionalities compared to deep machine learning systems. FL paradigms rely on the exchange of locally trained instances of the machine learning parameters, i.e., the weights and biases of the neural networks, rather than sharing raw data. As opposed to classical big-data fusion approaches, FL makes use of on-device learning functions and an intensive exchange of machine learning parameters over the network (Lim *et al.*, 2020). As shown in figure 2.7, first, a global model is initialized and distributed to all participating devices or nodes. During the training process, each device computes model updates locally using its own data and sends only the model updates (not raw data) to a central server. The central server aggregates these updates to enhance the global model. This iterative process of local computation and global aggregation continues until the model achieves satisfactory performance (Abdulrahman *et al.*, 2021).

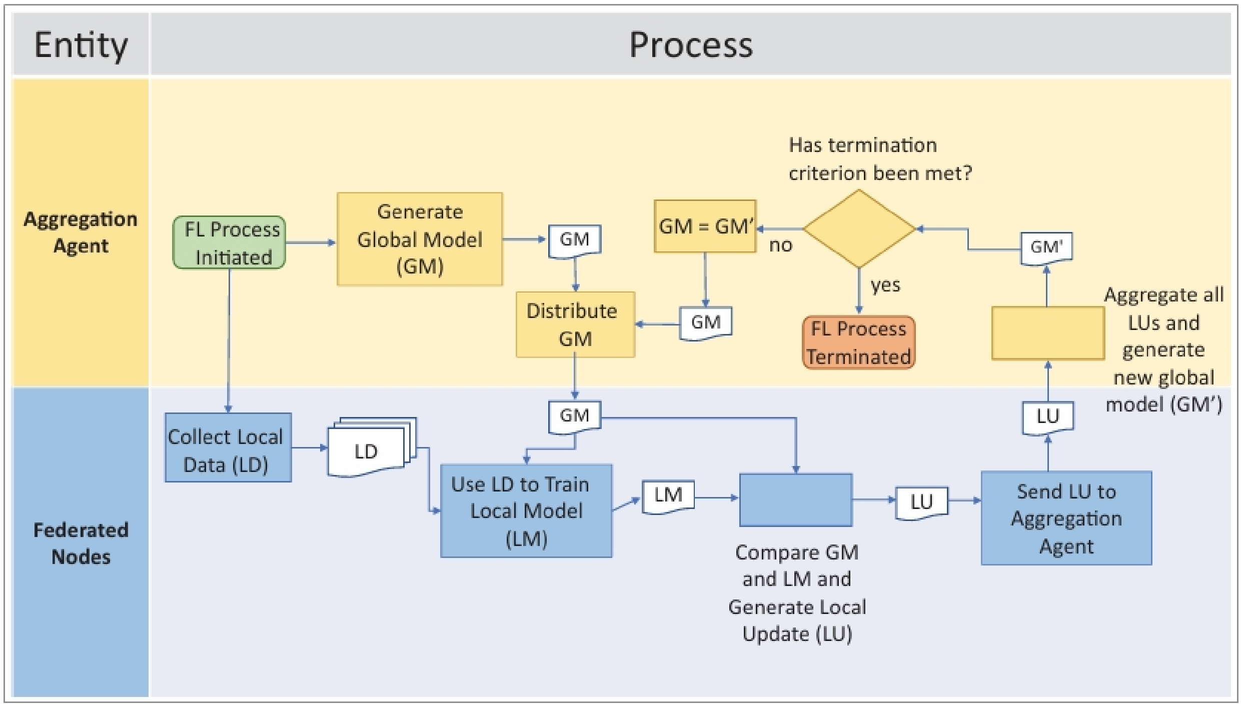


Figure 2.7: A schematic representation of the high-level process of FL (Manias and Shami, 2021a)

A communication type refers to the manner in which the edge server and federated nodes (such as vehicles) communicate with the local training models and global model updates (Nguyen *et al.*, 2021). SFL is the major form of FL owing to its superior performance of Stochastic Gradient Descent (SGD) in edge-server settings compared to AFL. SFL primarily focuses on the evolution of Federated Averaging (FedAvg) (Wahab *et al.*, 2021). However, in SFL (e.g., FedAvg), the edge server has to wait until all the federated nodes upload their local training models to derive the updated global model; therefore, this communication mode is not practical in large-scale scenarios (specifically with the large deployment of 5G networks) and fast hardware growth. This is due to the heterogeneous resources in terms of different computation abilities, various network settings, and unbalanced data distribution, which result in different training times and unknown communication costs. To address the aforementioned issues, AFL has been investigated recently, in which an updated global model can be derived even if not all local models have been received (Xu *et al.*, 2023).

In the context of IoV, where vehicles and infrastructure generate vast amounts of data, FL features several benefits, such as:

- FL enables the collaborative training of models across decentralized nodes without centralized data aggregation. This distributed intelligence strategy enables vehicles to acquire knowledge from their own data within their local environment while also contributing to a global model that enhances the overall IoV ecosystem (Shinde and Tarchi, 2023).
- The ability to make decisions in real-time is greatly improved with FL, as it allows models to quickly adjust to dynamic environments and evolving traffic situations (Barbieri *et al.*, 2022).
- FL reduces the vulnerability associated with centralized data storage by enabling collaborative model updates without exposing sensitive information. This approach mitigates the risk of unauthorized access (Yang *et al.*, 2022).
- FL aligns with the MEC paradigm, where MEC's edge servers serve as aggregators for the FL. This reduces the need for continuous communication with a central server, addresses bandwidth constraints, and ensures low-latency responses (Li *et al.*, 2021b).

2.8 LITERATURE REVIEW

In recent years, increasing safety by transmitting ESMs to vehicles has become a challenge. This section provides related research on safety message dissemination in vehicular networks based on two main categories, which are summarized in Table 2.3.

2.8.1 TRADITIONAL IEEE 802.11P PROTOCOL-ENABLED ESMs DISSEMINATION

Most of the research conducted on vehicular networks utilized IEEE 802.11p technology to disseminate ESMs throughout the network. The issue of broadcast storms has been tackled in several studies, including those referenced as (Ali *et al.*, 2019, Li *et al.*, 2021a, Shah *et al.*, 2019, Ullah *et al.*, 2020b, Wang *et al.*, 2019, Alkhalifa and Almogren, 2020, Rizwan *et al.*, 2023), and (Raja *et al.*, 2020), which employ different mechanisms.

The clustering technique was introduced in (Ali *et al.*, 2019, Shah *et al.*, 2019, Ullah *et al.*, 2020b), and (Alkhalifa and Almogren, 2020) to reduce broadcast storms and disseminate ESMs by choosing a forwarder that has higher compatible interests with other vehicles in (Ali *et al.*, 2019). This forwarder disseminates ESMs to vehicles near the accidental region, thereby attaining ESM dissemination over time. However, the researchers in (Shah *et al.*, 2019) allowed only the furthest vehicles to rebroadcast ESMs after a certain time barrier expiration, which resulted in less network congestion. (Ullah *et al.*, 2020b) outperformed (Shah *et al.*, 2019) by examining the link stable estimation parameter and achieving improved results.

The hybrid methodology of fuzzy and VIKOR was introduced in (Alkhalifa and Almogren, 2020) to examine the best vehicle based on its degree, position, probability of forwarding, and ESM dissemination delay within a segment. Thus, the selected vehicle maximizes the ESM reachability while reducing the dissemination delay.

The protocol in (Li *et al.*, 2021a) strengthened reliability by evaluating each vehicle's transmission probability concerning distance, packet reception ratio, and link availability metrics. The vehicle with the highest value forwards the ESM, with other vehicles as backups in case of failure.

In (Raja *et al.*, 2020), SDN managed network loads, and different machine learning classifiers detected accident events, whereas selected forwarders (RSU and vehicles) transmitted ESMs based on nearby vehicle information with the help of SDN, thereby improving routing efficiency.

The proposed local information-based broadcast protocol in (Wang *et al.*, 2019) also addressed the issue of insufficient topological knowledge. The proposed protocol considers the maximum distance for forwarding, vehicle density, and candidates' number to choose the optimum forwarders that make it more adaptable to the vehicular environment with exceedingly high ESM transmission reliability.

(Rizwan *et al.*, 2023) proposed location-based content prefixing scheme. The proposed scheme uses single or multiple MEC vehicles and RSUs to disseminate the ESMs to the impacted area surrounded by these vehicles. MEC vehicles implement a Deep Learning-based Artificial Neural Network (DL-based ANN) model to accurately anticipate the severity of safety applications. The limited dissemination of ESMs results in high network performance.

ESM delivery at intersections was evaluated in (Yanbin *et al.*, 2020), which obtained vehicles at extreme positions and hidden zones. Subsequently, a Bare Bones Particle Swarm Optimization (BBPSO) algorithm is proposed to adjust multiple transmission factors with improved performance to offer highly reliable vehicular safety services.

In (Li *et al.*, 2019), a Time Division Multiple Access (TDMA)-based MAC protocol was utilized to disseminate ESMs. The protocol controls the collisions by setting the transmission powers dynamically based on the transmission ranges and thus achieves a high QoS for safety applications.

The protocol proposed in (Kim and Kim, 2020) was used to alleviate the burden of DSRC and guarantee reliability. The protocol prioritizes the ESM transmission from a vehicle based on accident risk evaluation, which calculates the distance between the vehicle and the danger zone and hence transmits ESMs with higher reliability.

The Temporary Warning Network (TWN) concept developed in (Liu *et al.*, 2022a) focused on improving the coverage and duration of ESM dissemination. The selection of the forwarder vehicles was based on their correlated space-time information. The forwarder vehicles achieved efficient performance.

An efficient selection of specific vehicles to disseminate ESMs was examined in (Rehman and Ould-Khaoua, 2019), taking into account the distance from the source vehicle. These vehicles are: the farthest vehicles; the surrounding vehicles depending on their links' quality and distances; and the vehicles with the maximum link quality. This study reduces network congestion while improving the overall transmission performance.

Another study in (Ullah *et al.*, 2019) explored the potential of utilizing the fog computing paradigm for disseminating ESMs in VANETs and IoVs. In addition, this study discusses its various open challenges.

(Benrhaiem *et al.*, 2020) tackled the issue of vehicles' distribution in hidden areas and transmitted ESMs with improved reliability and lower latency. This was achieved by accurately estimating the connection quality of the vehicles within a hop. The estimation information determines an optimum number for ESM retransmission, elects the best forwarding vehicles with identifying their locations, and carries out collaborative communication between those vehicles.

An improved mechanism for the existing DSRC has been proposed in (Li *et al.*, 2020b). This mechanism influences the generation rate of ESMs depending on the vehicles' density and attempts to minimize channel congestion. Then, it holds a reliability T-pro evaluation scheme for the provision of extremely reliable vehicle safety applications.

2.8.2 5G-ENABLED ESMs DISSEMINATION

A few 5G-V2X-related schemes are explained in this section. Studies (Alghamdi, 2020) and (Alghamdi, 2021) handled link and packet losses by transmitting ESMs over D2D communication. The routing mechanism selects the best forwarder utilizing the Bayesian Rule-based Fuzzy Logic (BRFL) and Stable Matching (SM) algorithms in (Alghamdi, 2020) and (Alghamdi, 2021), respectively, which improves the QoS.

In (Ghazi *et al.*, 2020), the authors reviewed in detail the latest contributions for ESM dissemination in vehicular networks in a 5G environment. They also highlighted the different implemented mechanisms based on SDN and fog computing.

The new Deep Reinforcement Learning (DRL) model based on the Double Deep Q-learning Networks (DDQN) in (Nguyen *et al.*, 2022) adjusted the ESM transmitting rate by calculating the risk distance between vehicles to mitigate channel congestion. The proposed algorithm satisfies each vehicle's requested resources and maintains safe communication among vehicles.

The authors in (Campolo *et al.*, 2018) introduced a boosted routing framework based on Social Relationships (SRs) for ESM dissemination. SDN and MEC have been utilized in managing these SRs to improve ESM delivery.

The SDN implemented a federated k-means algorithm to cluster vehicles in (Prathiba *et al.*, 2022) to provide efficient ESM transmission. SDN reduces network congestion by transmitting ESMs to the selected Cluster Head (CH). The CH then delivers the ESMs to all its members in single-hop communication.

Table 2.3: Limitations on prior research

Ref.	**Proposed Architecture**	**Implemented Solutions**					**Simulation Parameters**	**Major Limitations**
		IEEE 802.11p /DCF	**IEEE 802.11p + 5G**	**5G**	**FL**	**SDN**		
(Ali *et al.*, 2019)	Clusters	✓	✗	✗	✗	✗	Packet delivery ratio (PDR), Average transmission delay, Information coverage	The current solutions presented in the research papers in section 2.8.1, utilizing IEEE 802.11P/DCF technology, are insufficient to satisfy the requirements of transmitting ESMs to vehicles with both high reliability and low latency. These criteria necessitate a high-speed network connection.
(Li *et al.*, 2021a)	Multi-hop	✓	✗	✗	✗	✗	PDR, Average transmission numbers (ATN), End-to-end average delay (EED), Dissemination Efficiency (DE)	
(Shah *et al.*, 2019)	Clusters	✓	✗	✗	✗	✗	Average transmission delay, PDR, Information coverage	
(Raja *et al.*, 2020)	Multi-hop	✓	✗	✗	✗	✓	Message transmission probability, Message propagation speed	
(Wang *et al.*, 2019)	Multi-hop	✓	✗	✗	✗	✗	PDR, End-to-end delay (E2ED), Broadcast redundancy (BR), Forwarding efficiency (FE)	
(Ullah *et al.*, 2020b)	Clusters	✓	✗	✗	✗	✗	Information coverage, End-to-end delay, PDR, Normalized network overhead, Cluster formation overhead	
(Alkhalifa and Almogren, 2020)	Clusters	✓	✗	✗	✗	✗	Reachability, Average number of collisions, Duplicate data packets, Latency, Packet delivery ratio, Throughput	
(Yanbin *et al.*, 2020)	No specific architecture	✓	✗	✗	✗	✗	Packet reception probability, Execution time of model, Awareness probability,	

							App-Level Delay, Packet generation rate	
(Li *et al.*, 2019)	Multi-hop	✓	×	×	×	×	Number of collisions in transmission, Number of collisions in reception, PDR	
(Kim and Kim, 2020)	No specific architecture	✓	×	×	×	×	Average latency, PDR, Inter-reception time (IRT)	
(Liu *et al.*, 2022a)	Multi-hop	✓	×	×	×	×	Coverage and timeliness of message dissemination, Duration of message dissemination, Overhead	
(Rehman and Ould-Khaoua, 2019)	Multi-hop	✓	×	×	×	×	End-to-end delay, Reachability, Saved rebroadcast	
(Benrhaiem *et al.*, 2020)	Multi-hop	✓	×	×	×	×	Packet reception rate (PRR), Average delay, Network load	
(Li *et al.*, 2020b)	No specific architecture	✓	×	×	×	×	Packet reception ratio (PRR), Awareness probability	
(Rizwan *et al.*, 2023)	Multi-hop	✓	×	×	×	×	Data delivery ratio, Average delay, Average hop count, Network overhead, Content retrieval delay	
(Alghamdi, 2020)	Clusters	×	✓	×	×	×	PDR, Throughput, Transmission delay, Dissemination delay	The integration of IEEE 802.11p and 5G technologies in **(Alghamdi, 2020)** and **(Alghamdi, 2021)** in section 2.8.2 elevates the complexity and network congestion due to beacon messages and network signal transmission.
(Alghamdi, 2021)	Sphere communication	×	✓	×	×	×	Throughput, PDR, End-to-end delay, Emergency information coverage	
(Nguyen *et al.*, 2022)	Multi-agent DRL in multi-hop	×	×	✓	×	×	Packet reception rate, Channel busy ratio, Collision risk, Computing time	The efficiency decreases as the distance between vehicles increases.
(Campolo *et al.*, 2018)	V2X in tree topology	×	×	✓	×	✓	Dissemination delay of Decentralized Environmental Notification Message (DENM)	Lack of intelligent dynamic control for 5G gNBs to transmit ESMs in **(Campolo**

(Prathiba *et al.*, 2022)	Clusters	×	×	✓	×	✓	Computation complexity and Network overhead, Successful delivery ratio, Collision rate, Dissemination efficiency, Average end-to-end delay	***et al.*, 2018)** and **(Prathiba *et al.*, 2022)**.

2.9 Summary

In conclusion, according to the literature analysis and major limitations listed in Table 2.3, this study reaches the following investigations:

1. To reduce the broadcast storm problem, this research introduced and implemented 5G technology. In addition, to optimize the utilization of 5G in IoV, the SDNCA framework focuses on beamforming and virtualization technologies.
2. SDN has been implemented in some studies in the literature in sections 2.8.1 and 2.8.2 to boost safety services, but SDN needs to generate more control traffic to analyze data and manage the network during emergencies, which consumes bandwidth and computational resources and increases network overhead. Therefore, FL has been proposed and executed in this study to reduce network overhead and provide low-latency processing.
3. SDN has been utilized in this study to provide a unified operating system. Further, SDN has been integrated with FL to control virtual networks customization and support strict QoS requirements regarding transmitting ESMs to vehicles with ultra-high reliability and low latency.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

IoV architecture is commonly separated into two essential layers: the edge layer and the backbone layer. These layers operate in conjunction to facilitate effective and seamless communication among vehicles and other connected devices. The integration of these layers creates a unified and adaptable IoV architecture, where the edge layer manages real-time processing and communication, while the backbone layer offers the necessary infrastructure and control for a highly scalable and efficient network. This architecture design enables innovative applications, boosts safety functionalities, and accommodates the evolving connectivity needs of the IoV ecosystem. This study introduces a dynamic IoV architecture that combines 5G and SDN at the edge and backbone layers. The main objective is to enhance the transmission of ESMs, ensuring rapid and reliable communication for critical life-saving alerts. The proposed architecture establishes the basis for an innovative SDNCA framework. The SDNCA framework leverages the solutions of FL, MEC, 5G, and SDN to create a robust system that enhances the responsiveness and effectiveness of disseminating ESMs to avoid vehicle collisions.

In this study, the combination between FL and MEC involves a continuous, iterative learning cycle to maintain a decentralized learning strategy that allowed for personalized adaptation on each vehicle while leveraging the collective intelligence of the entire framework. Further, 5G is used in this research to enhance the reliability and availability of communication in the proposed framework, guaranteeing the consistent delivery of ESMs even in challenging network conditions. Then, the produced ESM is sent to the SDN controller using 5G. The SDN controller has a pivotal role in this particular setting. The SDN controller relies on the collective insights of FL models along with the real-time parameters of vehicle speed, overall distance, and the distances between vehicles to optimize the disseminating of ESMs. Consequently, the SDN contributes to the overall goal of enhancing safety and efficiency in the proposed framework.

3.2 Proposed System Model

The proposed architecture shown in figure 3.1 comprises edge and backbone layers. The edge layer is responsible for collecting information about the environment (including traffic, vehicle speed, risks, obstacles, and weather) and the system state (e.g., latency, channel usage, and packet loss). The edge layer consists of the following:

- Vehicles enabled with 5G technology ($V_1, V_2, V_3, \ldots\ldots\ldots V_N$);
- Multiple 5G base stations; 5G gNBs ($gNB_{E1}, gNB_{E2}, gNB_{E3}, \ldots\ldots gNB_{EL}$), which are

  responsible for intra-communication and routing; and
- Edge Server (ES) for computing and storage processes.

By contrast, the backbone layer interconnects the different 5G edge BSs, providing high-speed routes for transmitting ESMs. The backbone layer includes the following:

- The SDN controller makes the routing and scheduling decisions. The decisions are sent as OpenFlow control messages to the OpenFlow switches. Every networking device can act as an OpenFlow switch (e.g., gNBs and routers).
- Backbone routers are used to communicate with the SDN controller and forward traffic between different 5G edge BSs.

- 5G gNBs cores (gNB_{C1}, gNB_{C2}, gNB_{C3}, …… gNB_{CK}), which are used for inter-communication through the backbone layer and to receive OpenFlow control messages from the SDN controller. The 5G gNBs cores are used to communicate with the edge layer.

We consider that the ES in this architecture is responsible for FL, in which it distributes the initial proposed RS-ANN model to vehicles, receives learning model updates, aggregates them to create a global model, and then sends the updated global model back to the vehicles for further enhancement. This iterative process offers numerous advantages to the SDNCA framework, including:

- Significantly reduces the amount of data transmitted, thereby optimizing network bandwidth and minimizing latency.
- Enhancing real-time reaction, which is crucial in emergency situations, as the aggregated global model reflects the cooperative knowledge of all vehicles.
- Distributing computation tasks between vehicles and the ES, which optimizes the utilization of resources.
- Allows the entire framework to collectively learn and improve over time.

In addition, 5G is proposed in this study to provide the following benefits to the SDNCA framework, which can be described as follows:

- The ultra-low latency of 5G ensures that the ESMs are transmitted to the SDN controller and destination vehicles with minimal delay.
- The high bandwidth capabilities of 5G enable the precise transmission of ESMs.
- 5G's network slicing feature enables the creation of dedicated VNs for each ESM. This allows for prioritization and allocation of resources, ensuring

that these critical messages receive special treatment according to their latency requirements and reliable transmission.

- 5G is designed to support high levels of mobility, making it well-suited for vehicular communication scenarios. This guarantees uninterrupted connectivity for moving vehicles, hence facilitating the smooth transmission of ESMs within the network.

Furthermore, SDN is designed to determine the QoS of ESMs. Then, the SDN intelligently allocates both 5G network and computing resources. As well, it optimizes the routing paths of ESMs. This ensures that the ESMs are transmitted with ultra-high reliability and low latency to the destination vehicles, mitigating the risk of collisions. Table 3.1 provides the main notations used in this study.

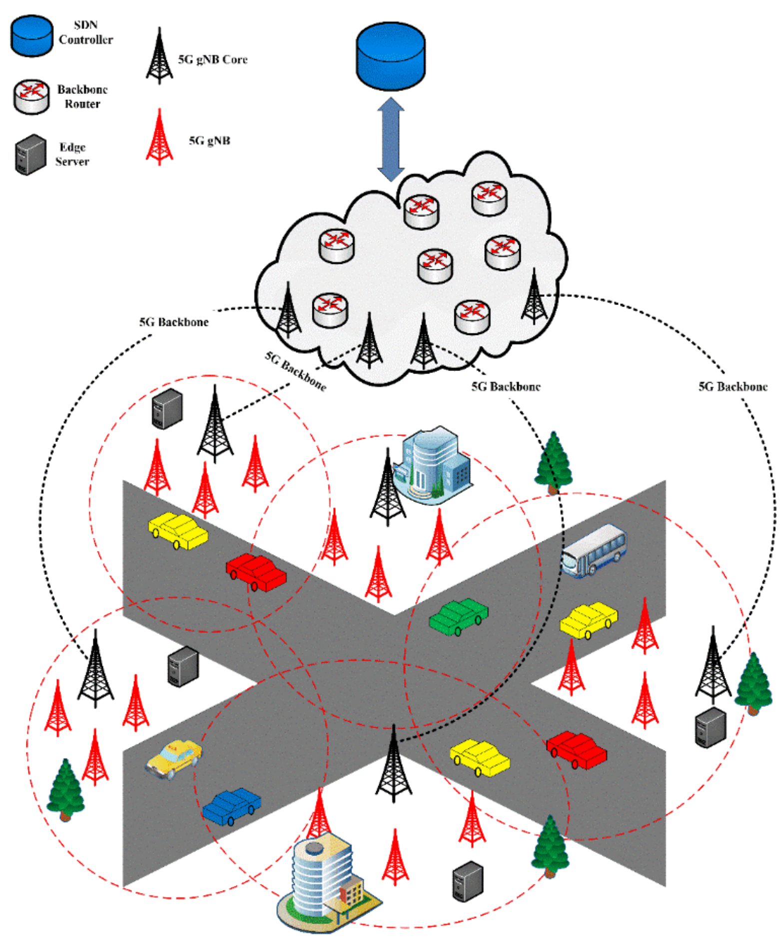


Figure 3.1: SDN-enabled 5G-V2I proposed architecture

Table 3.1: Main notations

NOTATION	DESCRIPTION
N	The number of vehicles
L	The number of edge gNBs
K	The number of core gNBs
V_i	$V_1, V_2, V_3, ...V_N$
gNB_{Ei}	$gNB_{E1}, gNB_{E2}, gNB_{E3}, ...gNB_{EL}$
gNB_{Ci}	$gNB_{C1}, gNB_{C2}, gNB_{C3}, ...gNB_{CK}$
gNB_{nr_i}	Network resources of any gNB at time t_i
gNB_{cr_i}	Computing resources of any gNB at time t_i
B, B_{max}	Bandwidth of the gNB, maximum bandwidth of the gNB
R, R_{max}	Bitrate of the gNB, maximum bitrate of the gNB
A, A_{max}	Number of antennas of the gNB, maximum number of antennas of the gNB
M, M_{max}	Utilized memory of the gNB, maximum memory of the gNB
C, C_{max}	Utilized CPU of the gNB, maximum CPU of the gNB
B_h, B_m, B_l	The highest, medium, and lowest allocated B values used in each VN in the first system model
M_h, M_m, M_l	The highest, medium, and lowest allocated M values used in each VN in the first system model
R_h, R_m, R_l	The highest, medium, and lowest allocated R values used in each VN in the first system model
$A_{VN_h}, A_{VN_m}, A_{VN_l}$	Allocated A values in VN_h, VN_m, and VN_l, respectively, are used in the first system model
$C_{VN_h}, C_{VN_m}, C_{VN_l}$	Allocated C values in VN_h, VN_m, and VN_l, respectively, are used in the first system model
B_{hr}, B_{mr}, B_{lr}	Three defined ranges of B used in the second system model
ES	Edge Server at the edge layer
O_{V_i}	Obstacle of V_i
W_{V_i}	Weather of V_i
S_{V_i}	Speed of V_i
RD_{V_i}	Risk Distance of V_i
RC_{V_i}	Road Condition of V_i
T_{V_i}	Time of V_i
S	Source vehicle: the vehicle sending ESM
LDB_{V_i}	Learning database at V_i

NOTATION	DESCRIPTION
D	Destination vehicle: any vehicle at risk in any direction in the first system model. Destination vehicle: the closest vehicle to the source vehicle in the second system model.
$RD_{S,D}$	Risk Distance between S and D
MS_{V_i}	Maximum S_{V_i}
MRD_{V_i}	Minimum RD_{V_i}
d_σ	Division factor in the first system model
d_λ	Division factor in the second system model
d_r	Decremental factor of the transmission reliability of the gNB
$MRD_{S,D}$	Minimum risk distance between S and D
RS_{V_i}	Risk severity of V_i
M_v	Maximum value of RS_{V_i}
C_v	Critical value of RS_{V_i}
D_i	Dataset of V_i
D_N	Total number of data samples from all vehicles
neural network parameters	Represents the dataset, connected layers, neurons in the hidden layers, activation functions, loss function, optimizer, learning rate, dropout rate, and batch size
Tr_l	Training loss of the RS-ANN model
Te_l	Test loss of the RS-ANN model
α_i	Updated local learning model of V_i
β	Global learning model of ES
β_u	Updated global learning model of ES
Ll_{V_i}	Local learning model of V_i
Tr_{la}	Training latency of the RS-ANN model
Tr_a	Training accuracy of the RS-ANN model
Te_{la}	Test latency of the RS-ANN model
Te_a	Test accuracy of the RS-ANN model
D_p	Represents the destination vehicles
QoS_σ	Quality of service of the ESM in the first system model
QoS_λ	Quality of service of the ESM in the second system model
VN_h	Virtual network for high ranges of QoS_σ and QoS_λ
VN_m	Virtual network for medium ranges of QoS_σ and QoS_λ
VN_l	Virtual network for low ranges of QoS_σ and QoS_λ

NOTATION	DESCRIPTION
$QoS_{\sigma l}$	Lowest value of QoS_{σ}
$QoS_{\sigma m}$	Medium value of QoS_{σ}
$QoS_{\sigma h}$	Highest value of QoS_{σ}
gNB_{TN}	Total network of the gNB
gNB_{TC}	Total complexity of the gNB
gNB_{C}	Connectivity of the gNB
ESM_{P}	Priority of the ESM
ESM_{Pi}	Initial priority of ESM
$QoS_{\lambda l}$	Lowest value of QoS_{λ}
$QoS_{\lambda m}$	Medium value of QoS_{λ}
$QoS_{\lambda h}$	Highest value of QoS_{λ}
$d_{gNB,D}$	Distance between the gNB and *D*
d_{max}, d_{mo}	Two threshold values for the $d_{gNB,D}$
A_{mo}	Moderate number of *A*
A_{mi}	Minimum number of *A*
$Action$	The action taken by the *D*
$s, m, and\ w$	Three main actions that are defined in the second system model

3.3 Proposed SDN-Based Collision Avoidance (SDNCA) Framework-First System Model

Each vehicle in the proposed SDNCA framework is composed of a sensor module that allows the sensor user to interact with the environment and collect system state information of (O_{V_i}, W_{V_i}, S_{V_i}, RD_{V_i}, RC_{V_i}, and T_{V_i}), which has been defined in a tuple format. The value of RS_{V_i} is calculated as follows:

$$RS_{V_i} = O_{V_i} + W_{V_i} + S_{V_i} + RD_{V_i} + RC_{V_i} + T_{V_i} \tag{3.1}$$

$$0 \leq RS_{V_i} \leq M_v$$

We assume each parameter in equation (3.1) contributes to the overall RS_{V_i} by reflecting various factors that can affect driving safety. Higher values in any of these parameters indicate increased risk, resulting in a higher value of RS_{V_i}. The combined effect of these parameters provides a comprehensive assessment of the RS_{V_i} in a given situation. The assumptions of the tuple in this research are illustrated below:

- $\boldsymbol{O_{V_i}}$: considers that the road can be free, slow, or blocked. RS_{V_i} increases when the road is blocked compared with free and slow roads.
- $\boldsymbol{W_{V_i}}$: reflects the impact of weather conditions on driving safety, such as good or bad weather. Adverse weather conditions (e.g., rainy weather) result in higher values of RS_{V_i}.
- $\boldsymbol{S_{V_i}}$: denotes low, medium, and high speeds of the vehicle. Higher speeds generally increase the RS_{V_i} due to reduced reaction time and longer stopping distances.
- $\boldsymbol{RD_{V_i}}$: measures the distance to a potential risk. It is considered close distance, medium distance, or far distance. Shorter distances indicate closer proximity to risks, thereby increasing the RS_{V_i}.
- $\boldsymbol{RC_{V_i}}$: accounts for the quality and state of the road, which are poor, good, or excellent. Poor road conditions (e.g., potholes) lead to higher values of RS_{V_i}.
- $\boldsymbol{T_{V_i}}$: represents the time of the day during which the ESM is generated, distinguishing between daytime and nighttime driving. Nighttime driving often has higher values of RS_{V_i} than daytime driving due to reduced visibility of the vehicle.

Each tuple is transmitted after preprocessing to the AI module implemented in the vehicles to train the RS-ANN model (see figure 3.2) through VFL.

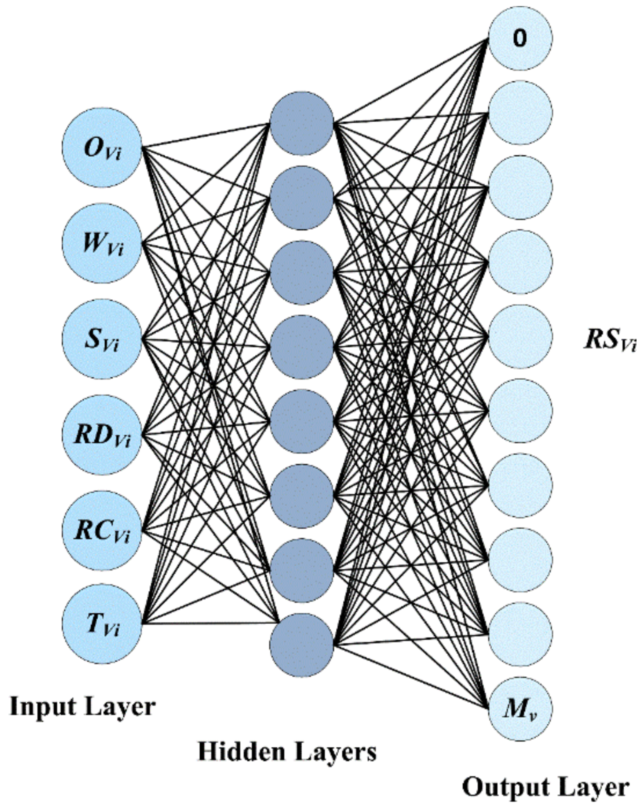


Figure 3.2: RS-ANN Model

On the basis of the received tuple, the AI module predicts whether the tuple is considered a Positive Risk (PR) to the vehicles in terms of the following expression:

$$RS_{V_i} = \begin{cases} \geq C_v, & \text{it is PR} \\ < C_v, & \text{it is not PR} \end{cases} \tag{3.2}$$

In both cases, the data will be stored in LDB_{V_i}, which will be used to train the AI model. In this study, any vehicle can generate an ESM, which contains the information summary of ($S, D, RS_{V_i}, S_{V_i}, RD_{V_i}$, defined tuple). The generated ESM is transmitted to the SDN controller through 5G gNB.

This study assumes that the vehicles move at an initial speed to the destination. At a particular time t_I (i = 1, 2, 3, …..,I) during T, when a vehicle V_i is driving in a real road environment, it faces many circumstances that require it to control its speed and change its direction to avoid accidents and congestion. The proposed framework in figure 3.3 shows how vehicles deal with these circumstances and avoid collisions through VFL algorithm and SDN objectives.

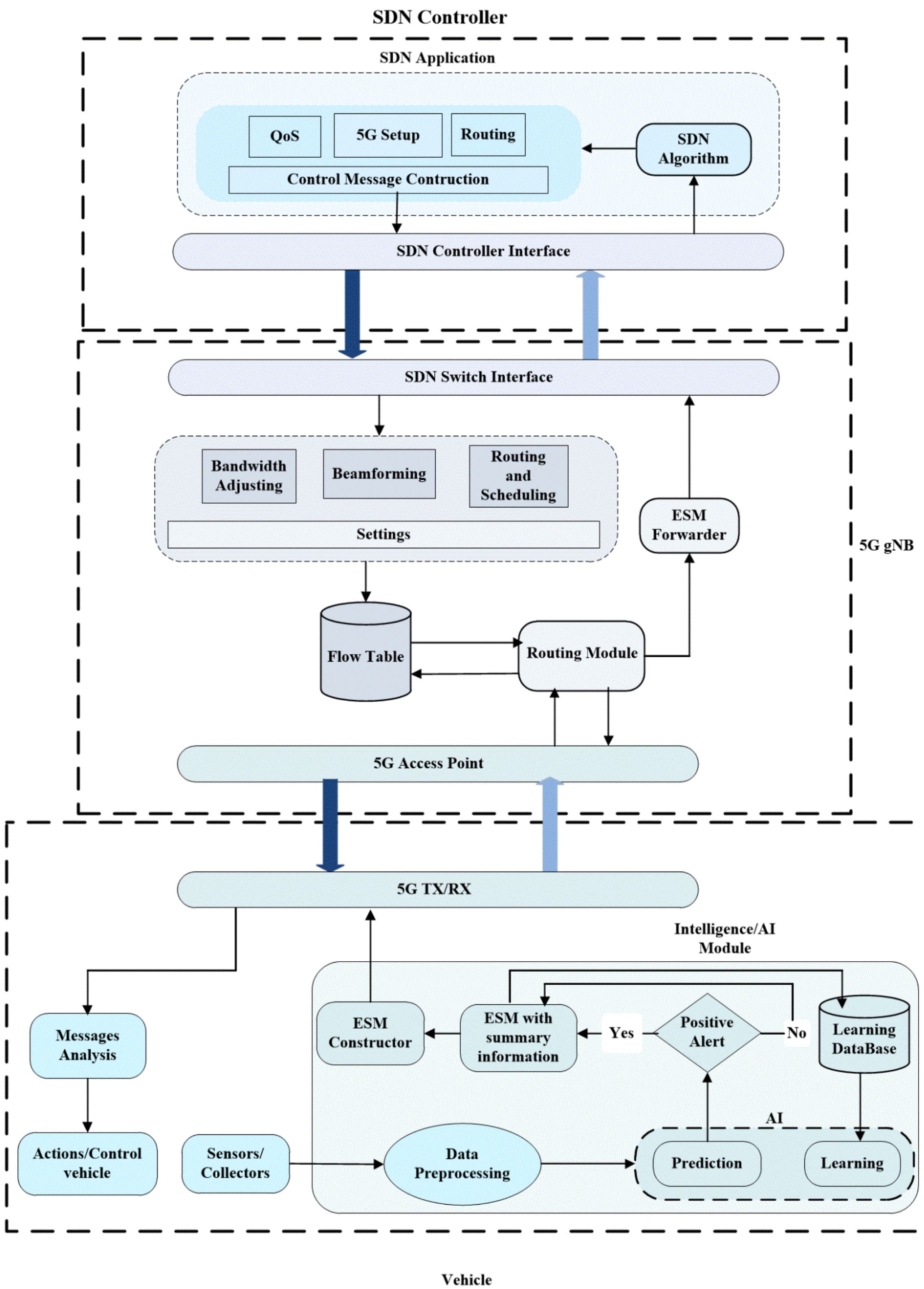


Figure 3.3: Proposed SDN-based Collision Avoidance (SDNCA) Framework in 5G-V2I

3.3.1 Proposed Vehicular Federated Learning (VFL)

In the SDNCA framework, RS-ANN model is proposed to build a VFL algorithm using SFL. The proposed VFL algorithm is processed through the following steps:

- The ES creates a baseline model, which is RS-ANN model and sends it to the vehicles. In this step, the ES sends β to the vehicles.
- The vehicles use their own dataset (O_{V_i}, W_{V_i}, S_{V_i}, RD_{V_i}, RC_{V_i}, and T_{V_i}) to train the model, and generate the updated learning models (α_i). α_i are transmitted to the ES. In this step, equation (3.3) (Manias and Shami, 2021a) has been used to calculate α_i as follows:

$$\alpha_i = Ll_{V_i} - \beta \tag{3.3}$$

- The ES aggregates the model updates received from the vehicles and returns the updated global model (β_u) to the vehicles. In each training round, the ES sends β_u to the vehicles to improve the model for more accurate prediction of the RS_{V_i}. Following equation (3.4), a general formula of FL (Taik *et al.*, 2022), the process is repeated until the model converges. During this step, β_u has been calculated using equation (3.4):

$$\beta_u = \beta + \sum_{i=1}^{N} \frac{|D_i|}{|D_N|} (\alpha_i) \tag{3.4}$$

The proposed VFL algorithm is shown in figure 3.4. Figure 3.4 illustrates the edge layer in the proposed SDNCA framework and figure 3.5 shows the flowchart of this algorithm. Then, the SDN controller performs its objectives (section 3.3.2) based on these model updates.

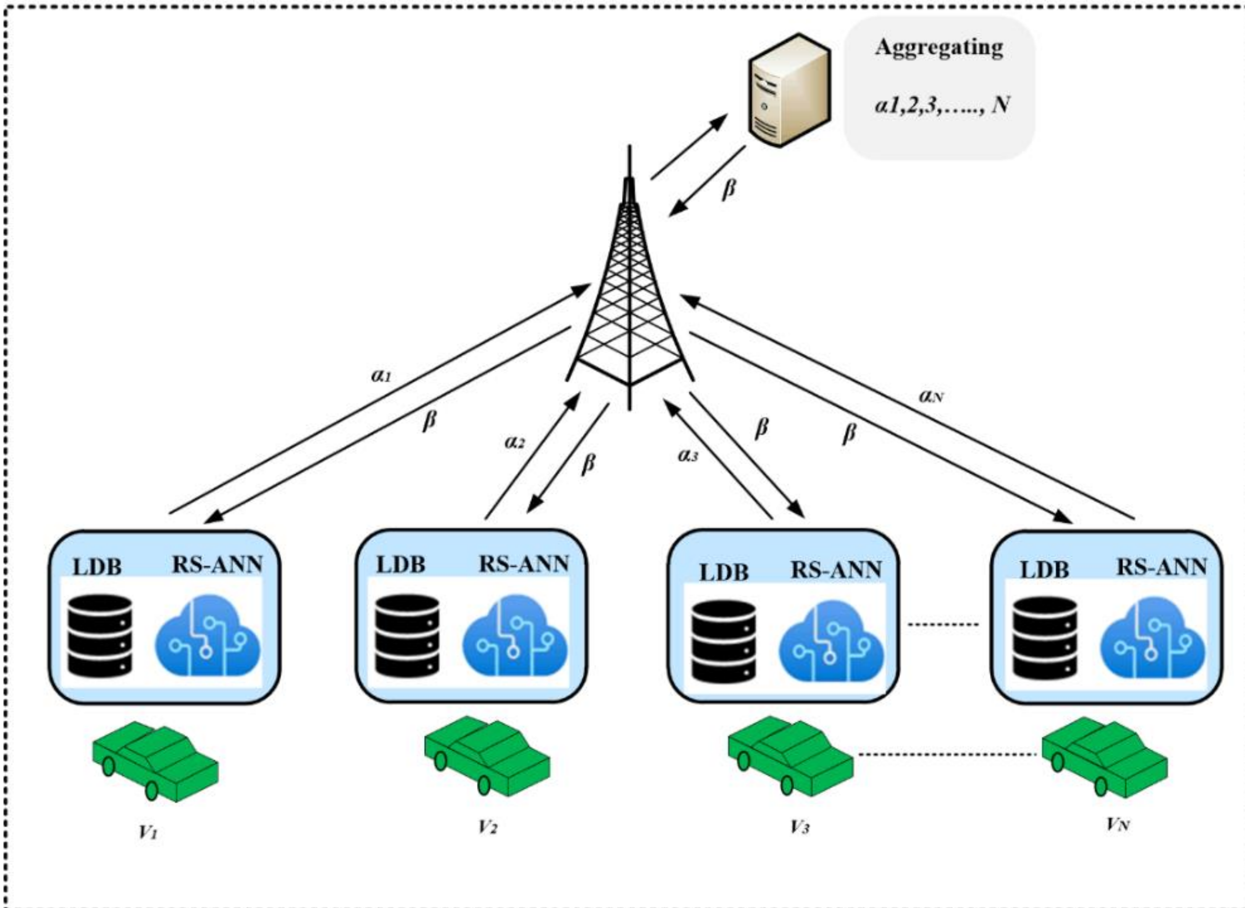


Figure 3.4: Proposed Vehicular Federated Learning

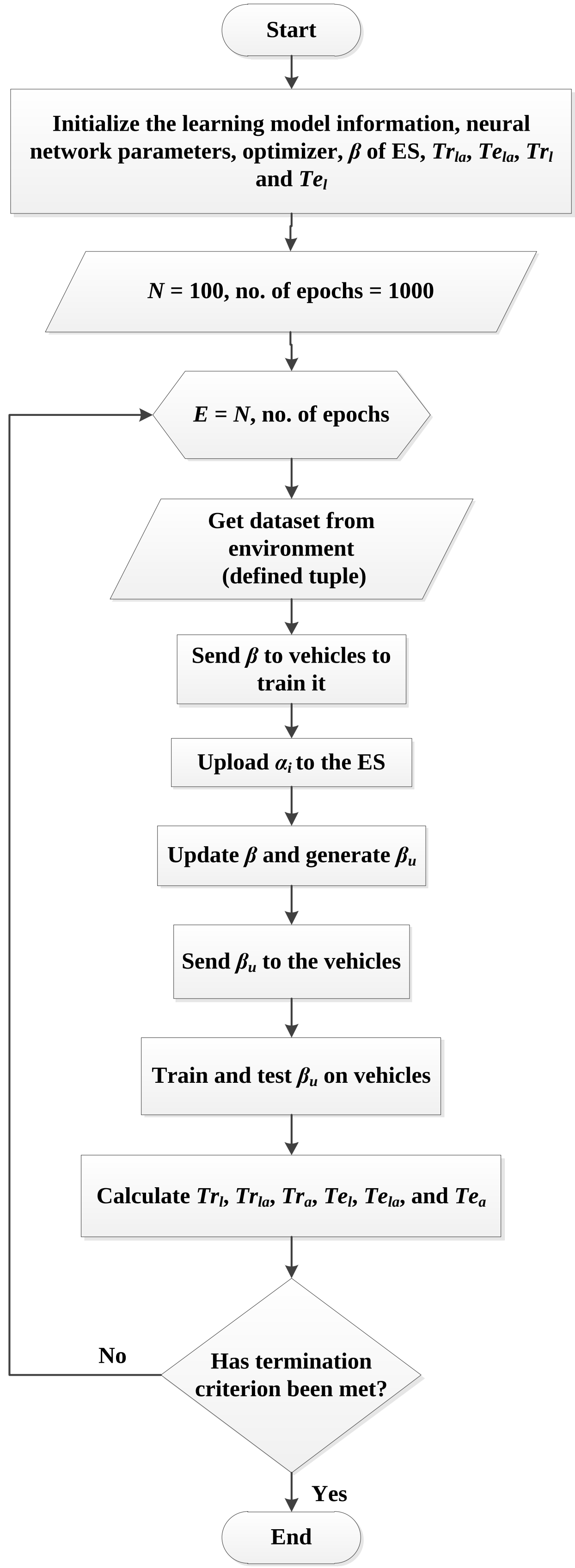


Figure 3.5: Flowchart of the VFL algorithm

3.3.2 Proposed SDN-Based Collision Avoidance Application

In this study, the SDN controller focuses on three objectives to transmit ESM to a destination with low latency and high reliability. The objectives of the SDN controller are summarized in sequential order as follows:

3.3.2.1 SDN-Enabled QoS

The SDN controller enables the 5G gNB to schedule messages based on their priorities. We assume that equation (3.5) aims to combine the effects of RS_{V_i}, S_{V_i}, and RD_{V_i} to provide a single measure of QoS_{σ} of the ESM. The value of QoS_{σ} is calculated using the following proposed equation:

$$QoS_{\sigma} = \frac{RS_{V_i} + S_{V_i}}{RD_{V_i}} \tag{3.5}$$

Equation (3.5) represents a risk assessment, meaning that the S that generates an ESM with a high QoS_{σ} value poses a risk to the D. The following are the assumptions of equation (3.5) in the proposed SDNCA framework:

- A greater value of RS_{V_i} indicates more severe risks, which increases QoS_{σ}. This shows that the equation accounts for the level of danger associated with the vehicle's environment.
- A higher S_{V_i} can also increases the risk of accidents, thereby increasing QoS_{σ}. This implies that the speed of the vehicle is a factor in assessing risk, as higher speeds are often associated with greater danger.
- A smaller RD_{V_i} means the vehicle is closer to the risk, which can increase the value of QoS_{σ}. This demonstrates that proximity to risk is a critical factor in the equation.
- Thus, QoS_{σ} will be the highest if RS_{V_i} is high, S_{V_i} is high, and RD_{V_i} is low.

3.3.2.2 SDN-Enabled 5G Communication

We consider that the 5G network and hardware functions are virtualized based on the calculation of QoS_{σ}. Three gNBs have been used, and three VNs are created in each gNB, as illustrated below:

$$\begin{aligned} &VN_h:\ QoS_{\sigma m} < QoS_{\sigma} \leq QoS_{\sigma h} \\ &VN_m: QoS_{\sigma l} < QoS_{\sigma} \leq QoS_{\sigma m} \\ &VN_l: QoS_{\sigma} \leq QoS_{\sigma l} \end{aligned} \tag{3.6}$$

Equation (3.6) assumes three VNs based on the following configuration:

- When $RS_{V_i} = M_v,\ S_{V_i} = MS_{V_i}$, and $RD_{V_i} = MRD_{V_i}$, then $QoS_{\sigma} = QoS_{\sigma h}$.
- The number of VNs is calculated as $\frac{QoS_{\sigma h}}{d_{\sigma}}$

Each VN operates independently using the allocated gNB_{nr_i} and gNB_{cr_i} according to the need to maximize the spectrum and energy efficiency. gNB_{nr_i} represents *B*, *R*, and *A* of the gNB, and gNB_{cr_i} represents *C* and *M* of the gNB. As per the proposed framework, the virtualization and adaptive beamforming configurations are completely handled by the SDN controller. During this step, SDN provides the dynamic allocation of gNB_{nr_i} and gNB_{cr_i} to handle each ESM independently, thereby improving the spectral efficiency and Signal-to-Interference-plus-Noise Ratio (SINR). The allocation of these resources is illustrated based on the following assumptions:

- Allocating *B* and *M* based on RD_{V_i}: Areas with long distances require higher *B* and *M* values to maintain reliable communications between vehicles and gNBs and to accommodate the larger volume of data and processing requirements, respectively. The values of *B* and *M* have been represented as follows:

$$B, M = \begin{cases} B_h, M_h, & \text{if } RD_{V_i} \text{ is in the range of far distance} \\ B_m, M_m, & \text{if } RD_{V_i} \text{ is in the range of medium distance} \\ B_l, M_l, & \text{otherwise} \end{cases} \quad (3.7)$$

- Allocating R based on S_{V_i}: The data rates of the gNBs directly impact the throughput and latency of communications between vehicles and gNBs. Vehicles moving at higher speeds need higher data rates to reduce the possibility of disruption in communications and preserve seamless connectivity. The value of R has been selected as expressed below:

$$R = \begin{cases} R_h, & \text{if } S_{V_i} \text{ is high} \\ R_m, & \text{if } S_{V_i} \text{ is medium} \\ R_l, & \text{otherwise} \end{cases} \quad (3.8)$$

- Allocating A and C based on the value of QoS_σ: Vehicles that produce ESMs with high QoS_σ values present a greater danger to their destination vehicles. Therefore, the signal quality can be optimized by adjusting the number of antennas. In addition, these ESMs need higher computational demands in order to be transmitted to their destinations more quickly. The values of A and C have been assigned as follows:

$$A, C = \begin{cases} A_{VN_h}, C_{VN_h}, & \text{if } QoS_{\sigma m} < QoS_\sigma \leq QoS_{\sigma h} \\ A_{VN_m}, C_{VN_m}, & \text{if } QoS_{\sigma l} < QoS_\sigma \leq QoS_{\sigma m} \\ A_{VN_l}, C_{VN_l}, & \text{otherwise} \end{cases} \quad (3.9)$$

On the basis of the aforementioned explanation in this step, figure 3.6 shows that the SDN controller applies the right configuration for each task. As well, figure 3.7 explains that the SDN controller enables the optimal beamforming strategy to prioritize ESMs by shifting and amplifying the 5G MIMO antennas toward the *D*. Further, figure 3.8 demonstrates the procedures of figure 3.6 and figure 3.7.

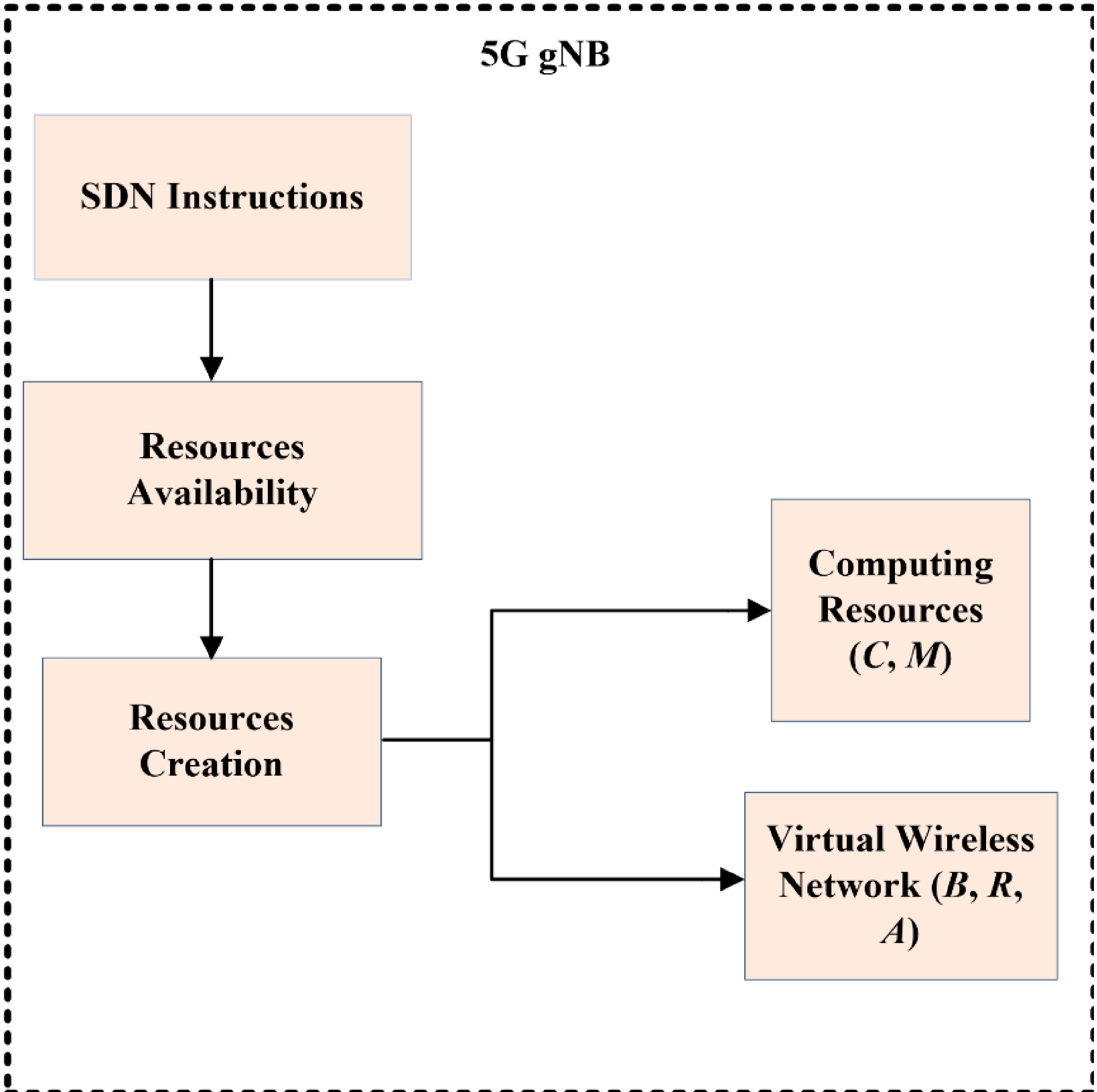


Figure 3.6: Dynamic allocation of 5G resources by SDN

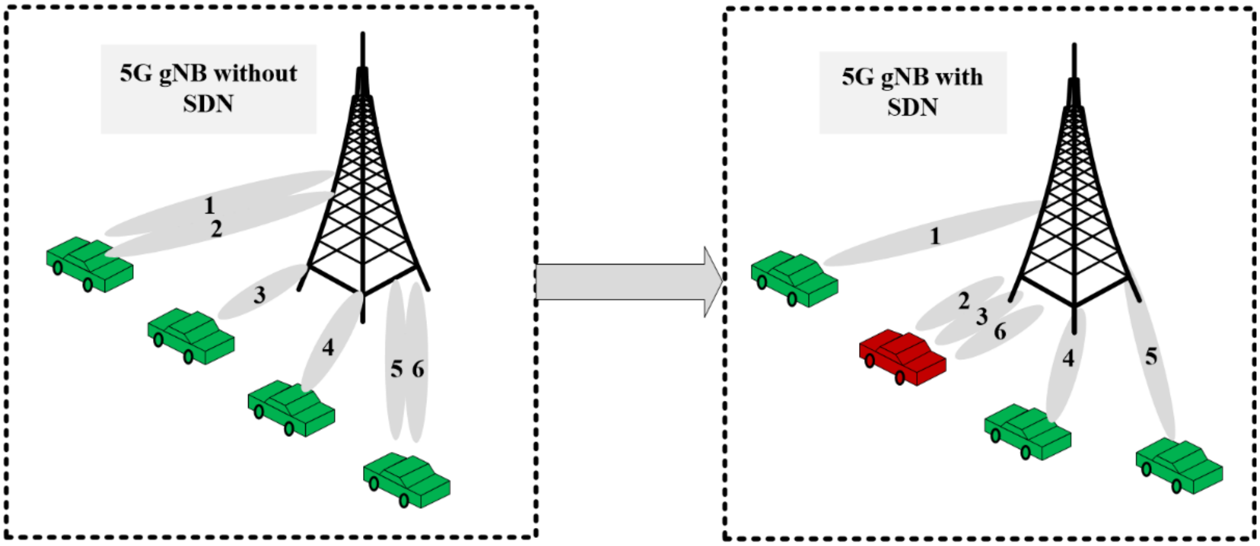


Figure 3.7: Adaptive beamforming by SDN

3.3.2.3 SDN-Enabled Routing

The SDN controller traces the most optimal route to send the ESM to the destination with less packet loss and delay. On the basis of these objectives, the SDN controller sends OpenFlow control messages to the switches (gNBs and routers) to deliver the ESM as reliably as possible, enabling the vehicle to take appropriate action (e.g., stopping and changing direction). OpenFlow control messages contain information of (QoS_{σ}, gNB_{nr_i} and gNB_{cr_i}, S_r), where S_r is the selected route, means the selected gNB. The flowchart in figure 3.8 explains the objectives of the SDN controller. The backbone layer of the proposed SDNCA framework shows SDN objectives.

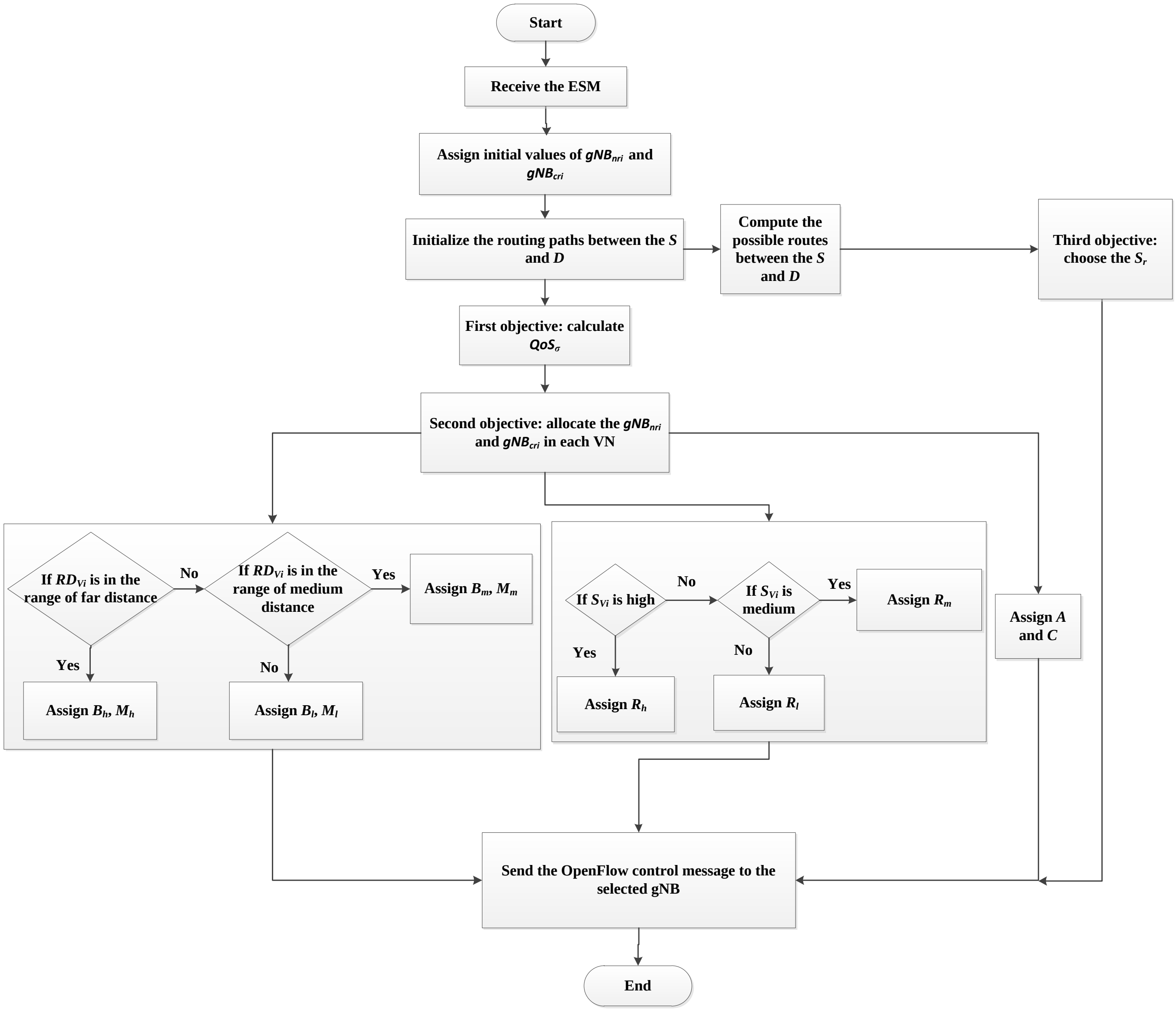


Figure 3.8: Flowchart of the SDN algorithm

In the proposed framework, it is initially assumed that all the gNBs have the same signal that is transmitted to the vehicles over the corresponding transmission range of each gNB. We assign the total network, total complexity, and connectivity of any gNB as follows:

$$gNB_{TN} = B_{max} + R_{max} + M_{max} \tag{3.10}$$
$$gNB_{TC} = A_{max} + C_{max} + M_{max} \tag{3.11}$$
$$gNB_{C} = B_{max} + R_{max} + A_{max} \tag{3.12}$$

Scaling the computing resources of the selected gNB will significantly improve the processing speed of critical tasks, such as ESM transmission. The selected gNB implements the proposed gNB algorithm. In this algorithm, when the gNB receives an OpenFlow control message from the SDN controller, it calculates the priority of ESM based on the following proposed equation:

$$ESM_P = \frac{QoS_\sigma}{QoS_{\sigma h}} \tag{3.13}$$

Equation (3.13) indicates that the gNB provides faster processing of ESMs with higher priority. The purpose of this equation is to schedule the ESMs based on their priorities to identify which VN in the gNB will serve a certain ESM. After determining the VN, the gNB configures its gNB_{nr_i} and gNB_{cr_i} for that VN based on the resources identified in the OpenFlow control message received from the SDN. This step involves the following procedures:

- gNB compares B with B_i: B is the bandwidth value allocated by the SDN controller, which is included in the OpenFlow control message, and B_i is the initial bandwidth value used by the gNB. When $B > B_i$, the gNB will consume more bandwidth from its B_{max}, so that B_i equals the value of B.

This step results in an increase in network overhead. Network overhead can be expressed as follows:

$$NO_a = NO_i + (B - B_i) \tag{3.14}$$

Where NO_i and NO_a represent the initial network overhead and network overhead calculated in this step, respectively. When the consumption of the bandwidth increases, this will negatively impact the transmission reliability of the gNB. Therefore, the transmission reliability of the gNB will reduce during this step, and it is calculated using the proposed equation:

$$TR_a = TR_i - d_r \tag{3.15}$$

Where TR_i and TR_a are the initial transmission reliability and transmission reliability calculated in this step, respectively.

- gNB compares R with R_i: R is the data rate value allocated by the SDN controller, which is included in the OpenFlow control message, and R_i is the initial data rate value used by the gNB. When $R > R_i$, the gNB will consume more data rate from its R_{max}, so that R_i equals the value of R. As well, the network overhead increased, and it is calculated as follows:

$$NO_b = NO_a + (R - R_i) \tag{3.16}$$

- gNB compares A with A_i: A is the number of antennas allocated by the SDN controller, which is included in the OpenFlow control message, and A_i is the initial number of antennas used by the gNB. When $A > A_i$, the gNB will consume more antennas from its A_{max}, so that A_i equals the value of A. During this step, the computational complexity increases, which is measured as follows:

$$CC_a = CC_i + (A - A_i) \tag{3.17}$$

Where CC_i and CC_a represent the initial computational complexity and computational complexity calculated in this step, respectively. Additionally, if the demand for antennas increases, it could lead to congestion and dropped connections, which result in reducing the transmission reliability of the gNB. Thus, it is calculated as follows:

$$TR_b = TR_a - d_r \tag{3.18}$$

We take into consideration that the transmission reliability of the gNB is reduced when the network overhead and computational complexity increase. Therefore, we denote this assumption by equation (3.15) and equation (3.18), respectively.

- gNB compares C with C_i: C is the number of CPU cores allocated by the SDN controller, which is included in the OpenFlow control message, and C_i is the initial CPU cores used by the gNB. When $C > C_i$, the gNB will use more CPU cores from its C_{max}, so that C_i equals the value of C. This consumption increases the computational complexity, which is calculated in this step as follows:

$$CC_b = CC_a + (C - C_i) \tag{3.19}$$

- gNB compares M with M_i: M is the memory value allocated by the SDN controller, which is included in the OpenFlow control message, and M_i is the initial memory value used by the gNB. When $M > M_i$, the gNB will consume more memory from its M_{max}, so that M_i equals the value of M. This step results in increasing the network overhead and computational complexity of the gNB. The calculations of network overhead and computational complexity are expressed as follows:

$$NO_c = NO_b + (M - M_i) \tag{3.20}$$

$$CC_c = CC_b + (M - M_i) \tag{3.21}$$

The flowchart in figure 3.9 explains the proposed gNB algorithm at the backbone and edge layers of the SDNCA framework.

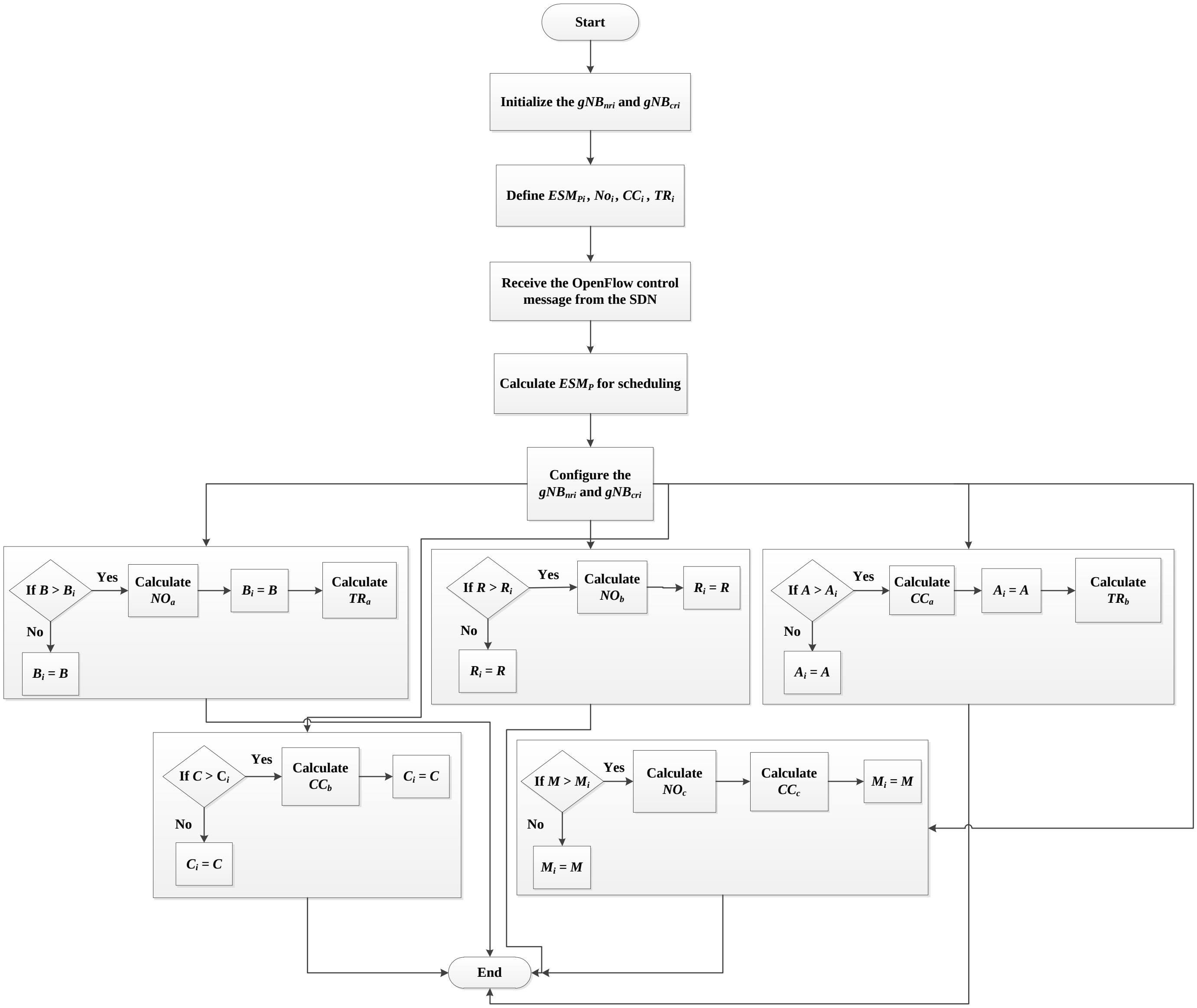


Figure 3.9: Flowchart of the gNB algorithm

3.4 Proposed SDN-Based Collision Avoidance (SDNCA) Framework-Second System Model

According to the prior explanation in section 3.3, this section introduces the second implemented system model based on $RD_{S,D}$. Considering the $RD_{S,D}$ parameter provides a more accurate resource allocation strategy for each ESM, which leads to a further dynamic and adaptive routing mechanism. We propose the second system model based on the following algorithms, along with their assumptions:

1. VFL algorithm: This system model uses the same VFL algorithm as the first system model. When the vehicle predicts the RS_{V_i} through the VFL algorithm, it generates an ESM. The produced ESM contains a summary information of (S, D, RS_{V_i}, S_{V_i}, $RD_{S,D}$). Each vehicle transmits its ESM to the SDN controller through 5G gNB.
2. SDN algorithm: The SDN controller receives the ESM and applies the following:
    - In this context, based on the assumptions in section 3.3.2.1, QoS_λ has been calculated as follows:

$$QoS_\lambda = \frac{RS_{V_i} + S_{V_i}}{RD_{S,D}} \tag{3.22}$$

    - Three VNs are created in each gNB, as expressed below:

$$\begin{aligned} &VN_h\colon\ QoS_{\lambda m} < QoS_\lambda \leq QoS_{\lambda h} \\ &VN_m\colon QoS_{\lambda l} < QoS_\lambda \leq QoS_{\lambda m} \\ &VN_l\colon QoS_\lambda \leq QoS_{\lambda l} \end{aligned} \tag{3.23}$$

    - Equation (3.23) has been configured in terms of the following:

- When $RS_{V_i} = M_v$, $S_{V_i} = MS_{V_i}$, and $RD_{S,D} = MRD_{S,D}$, then $QoS_\lambda = QoS_{\lambda h}$.
- The number of VNs is calculated as $\frac{QoS_{\lambda h}}{d_\lambda}$

- The SDN controller selects the nearest gNB to the *D* as S_r: In this system model, the ESMs are transmitted over the shortest distances to the destinations. This assumption ensures that the ESM will take less time to reach *D*.
- The SDN controller allocates (*B*, *R*, *A*, *C*, and *M*) as follows:
  - Allocating *B* based on the QoS_λ: As explained previously, the QoS of the ESM provides the level of risk in this study. In this system model, we assume that the SDN controller allocates the value of *B* based on QoS_λ. Vehicles that produce ESMs with high values of QoS_λ usually have high RS_{V_i}, high S_{V_i}, and are close to their destinations. In this case, high values of *B* need to be allocated at the gNB to enable faster and more timely ESM transmission. This step is expressed in the following equation:

$$B = \begin{cases} B_{hr}\,, & \text{if } QoS_\lambda > QoS_{\lambda m} \\ B_{mr}\,, & \text{if } QoS_\lambda > QoS_{\lambda l} \\ B_{lr}\,, & \text{otherwise} \end{cases} \qquad (3.24)$$

  - Equation (3.25) indicates that the *R* of the gNB is allocated based on the $RD_{S,D}$. This assumption encourages the gNB to reduce its *R* if the *S* maintains a safe distance from the *D* and increase the value of *R* if the *S* approaches the *D*. The unit of equation (3.25) represent the unit of *R* per distance.

$$R\ (Mbps/m) = \frac{R_{max}}{RD_{S,D}} \tag{3.25}$$

- In this system model, the ESM_P has been identified as $\frac{QoS_\lambda}{QoS_{\lambda h}}$, meaning that the ESM that has a high QoS_λ value needs greater memory and computational capability for storage and accelerated processing. Equation (3.26) and equation (3.27) represent that gNB consumes *C* and *M* from its C_{max} and M_{max}, respectively, for each ESM based on the QoS_λ value.

$$C\ (GHz) = \frac{C_{max} \times QoS_\lambda}{QoS_{\lambda h}} \tag{3.26}$$

$$M\ (MB) = \frac{M_{max} \times QoS_\lambda}{QoS_{\lambda h}} \tag{3.27}$$

- The number of antennas has been allocated based on the distance between the selected gNB and the *D*. Equation (3.28) calculates the number of antennas as follows:

$$A = \begin{cases} A_{max}, & \text{if } d_{gNB,D} > d_{max} \\ A_{mo}, & \text{if } d_{gNB,D} > d_{mo} \\ A_{mi}, & \text{otherwise} \end{cases} \tag{3.28}$$

we consider that the quality of the signal can be strengthened by increasing the number of antennas toward the *D* whenever the $d_{gNB,D}$ increases.

- We added another function to this system model. The SDN controller assigns three main actions based on the QoS_λ value. For example, if the value of QoS_λ is high, it means the *S* has high RS_{V_i} and high S_{V_i}, and is close to the *D*. Therefore, when the *D* receives the action message from the gNB, it performs one of these actions to avoid collision, as illustrated below:

$$Action = \begin{cases} s\,, & \text{if } QoS_\lambda > QoS_{\lambda m} \\ m\,, & \text{if } QoS_\lambda > QoS_{\lambda l} \\ w\,, & \text{otherwise} \end{cases} \tag{3.29}$$

- The SDN controller creates the OpenFlow control message and sends it to the selected gNB. The OpenFlow control message contains ($S, D,\ gNB_{nr_i}, gNB_{cr_i}, Action, S_{V_i}, RD_{S,D}$).

3. gNB algorithm: The gNB receives the OpenFlow control message from SDN and implements the following:
   - It updates its gNB_{nr_i} *and* gNB_{cr_i} based on the resources allocated by the SDN controller.
   - Creates the action message and sends it to the *D*. The action message contains ($S, D, Action, S_{V_i}, B, RD_{S,D}$).

The flowchart in figure 3.10 demonstrates the three integrated algorithms in the second system model.

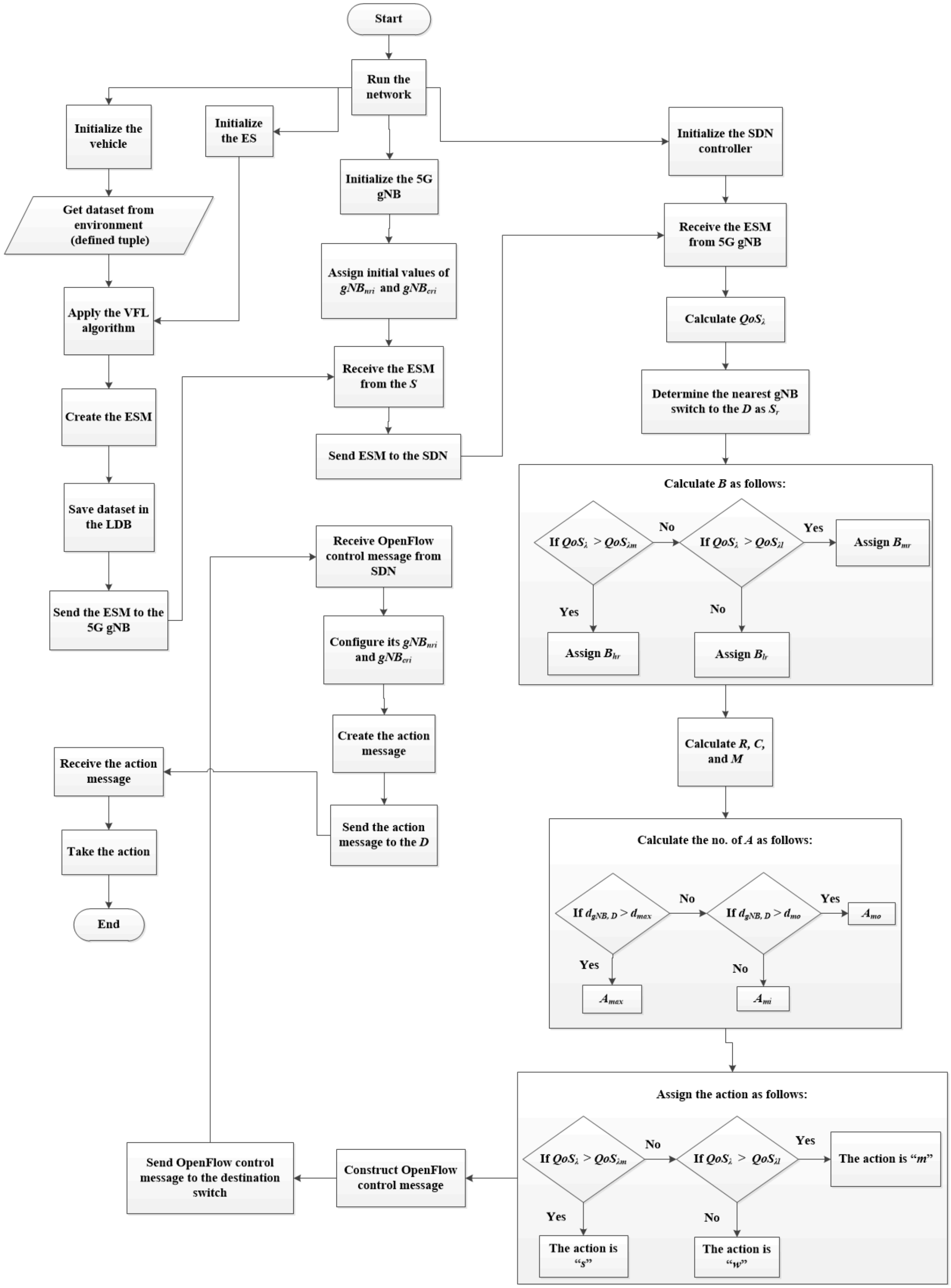


Figure 3.10: Flowchart of the second system model

3.5 Summary

This chapter started with the introduction of the proposed IoV architecture, which is essential to handling the challenges of ESM dissemination within a demanding and dynamic IoV environment. The proposed architecture provided an overview of the suggested advancements for accomplishing the objective of the study.

This chapter focused on the formulation of the SDNCA framework utilizing two system models. The first system model incorporates three proposed algorithms: a novel VFL algorithm that involves the learning of the proposed RS-ANN model on vehicles to estimate the RS_{V_i}value for each vehicle. The estimated RS_{V_i} value, S_{V_i}, and RD_{V_i} parameters are sent to the SDN controller through 5G gNB. On the basis of this information, the SDN controller implements a new application that achieves three successive objectives (SDN-enabled QoS, SDN-enabled 5G communication, and SDN-enabled routing). The instructed OpenFlow control message is transmitted from the SDN controller to the 5G gNB that has been chosen to forward the ESM to the D. During this step, the gNB executes the third algorithm to schedule the ESMs and also configures the gNB_{nr_i} and gNB_{cr_i}. To be more precise, the second system model performs the VFL algorithm; the estimated RS_{V_i} value, S_{V_i}, and $RD_{S,D}$ parameters are transmitted to the SDN controller by 5G gNB. Then, the SDN controller applies its algorithm to create the OpenFlow control message. The last step has been executed by the gNB that received the OpenFlow control message to forward the ESM to the D. The comprehensive discussion of the two system models is further explained. As a result, the SDNCA framework provided an efficient mechanism for enhancing the disseminating of ESMs to the destination vehicles, thus avoiding vehicle collisions.

CHAPTER FOUR

SIMULATION RESULTS AND ANALYSIS OF THE FIRST SYSTEM MODEL

4.1 Introduction

This chapter presents four scenarios that are executed to build the first proposed system model explained in chapter three. The first scenario simulates 5G technology to provide insights into the operational efficiency of the 5G network structure. The second and third scenarios implement the edge layer in the proposed architecture depicted in figure 3.1. The fourth scenario involves the execution of the edge and backbone layers in the architecture provided in figure 3.1, which form the SDNCA framework. Furthermore, this chapter discusses the outcomes achieved in each specific scenario.

4.2 Simulation Setup and Scenarios

To build and implement the proposed SDNCA framework, three software tools are used: Network Simulator (NS3), Python programming language (Pytorch for the machine learning library), and a Mininet network emulator. NS3 is used to simulate 5G technology in the proposed architecture. The Python programming language is utilized to simulate and evaluate the proposed VFL algorithm. The implementation and evaluation of the SDNCA framework are carried out in the Mininet emulator, including the RYU controller for a custom-designed topology that consists of vehicles and OpenFlow switches (5G gNBs).

NS3 is a free and open-source discrete event simulator for communication models targeted for the education and research industry. With its modular architecture and extensive library of protocols, NS3 enables the simulation of vehicular communication scenarios (Aljabry and Al-Suhail, 2021). Very recently, a few implementations of some of the 5G-V2X features have been added to NS3 and presented in (Saad *et al.*, 2021, Lusvarghi and Merani, 2021).

Mininet is an emulator used to create virtual switches, links, hosts, and controllers. Mininet helps to create a virtual environment of switches and links to simulate different networking models. It is very flexible in terms of SDN. The advantage of Mininet is that it is simple and inexpensive. Mininet is highly flexible for SDN models (Khan *et al.*, 2021). Further, Ryu is an open-source SDN framework written in Python. Ryu facilitates the creation of customized network management applications and protocols, empowering network administrators and researchers with a high level of programmability as it provides a Python Application Programming Interface (API). One of its key features is support for the OpenFlow protocol, which enables seamless communication between the SDN controller and network devices like switches and routers (Bhardwaj and Panda, 2021).

4.2.1 First Scenario: 5G Simulation

NS3 is used for the simulation of 5G technology in this particular scenario, the simulation setup is illustrated in Table 4.1. Various NS3 modules have been utilized; these modules provide functionalities related to networking, mobility, spectrum management, application support, configuration handling, output statistics, etc. Within this context, several functions have been defined and established for executing setup tasks related to the NR simulation. The main functions include:

- Reporting the statistics for SINR, power, slot, and Resource Block (RB) of a 5G gNB.

- Setting up the specific characteristics of the physical layer for a 5G gNB. This setup encompasses the implementation of beamforming, shadowing, numerology, transmit power, pattern, and adjustment of the antenna orientation. Simultaneously, the NR physical layer of the User Equipment (UE) is configured.
- Configuring the parameters of the radio networks, such as specifying values for RB overhead, the number of reference symbols per RB, the number of Hybrid Automatic Repeat Request (HARQ) processes, delays, and error models.
- Implementation of the 3GPP channel model.
- Determining the power allocation type for the NR spectrum and applying it for both UEs and 5G gNBs.
- Executing the Adaptive Modulation and Coding (AMC) model for the 5G gNB in both Downlink (DL) and Uplink (UL) directions.
- Formulating the operational bands and Bandwidth Parts (BWPs) and utilizing the following equations to calculate the total bandwidth and central frequency.

$$B_{CC} = N_{BWP} * B_{BWP} \tag{4.1}$$

Where B_{CC} refers to the total bandwidth for a single Component Carrier (CC), N_{BWP} represents the number of BWPs per CC, and B_{BWP} is the bandwidth per BWP.

$$B_b = N_{CC} * B_{CC} \tag{4.2}$$

B_b is the total bandwidth for the entire frequency band, and N_{CC} is the number of CC per frequency band.

$$b_C = b_S + \frac{B_b}{2} \tag{4.3}$$

$$b_C = b_C + B_b \tag{4.4}$$

b_C is the central frequency of the band, and b_S is the minimum frequency value of the band. Equation (4.4) is applied to move to the center frequency of the next BWP in the overlapping and non-overlapping frequency scenarios.

- Configuration of the attributes related to the antennas for UEs and 5G gNBs.
- Identifying the granularity of resource allocation in the MAC layer of NR.
- Establishing a high-speed point-to-point communication link between the Packet Data Network Gateway (PGW) and a remote host.
- Assign IP addresses for the nodes (PGW, remote host, gNB, and UEs) in the simulation to enable communication between them.
- Attaching UEs to their corresponding 5G gNB.
- Establish traffic applications while considering the uniform and non-uniform packet arrival rates (lambda) among 5G gNBs.
- Calculating the average throughput, delay, jitter, and received packets for each flow.

Table 4.1: NS3 Environmental settings

Parameters	**Values/Types**
Transmit power of the gNB	Initial value = 0 dB, configuration values = 30, 43 dB
Antenna type of the gNB	Uniform planar array
Simulation NR scenarios	UMi, UMa, RMa
Operation modes	TDD, FDD
Directions	UL, DL
B_{BWP}	20, 15, 10, 5 MHz
Frequency scenarios	Overlapping, non-overlapping
Number of reference symbols per RB	1
RB overhead	Initial value = 0.1, configuration values = 0.1, 0.04
HARQ processes	Initial value = 20, configuration values = 8, 20
Default update period of the 3GPP channel model	100 ms
Update period of the channel condition model	0 ms
Noise figure for the UE	9.0 dB
AMC model	Shannon model
b_S	2110 MHz
N_{BWP} in FDD	2
N_{BWP} in TDD	1
N_{CC}	1
Beamforming Methods	Quasi omni direct path beamforming, Direct path beamforming
Schedulers types	NR mac scheduler ofdma PF, NR mac scheduler ofdma RR
Number of SRS symbols used by the scheduler	1
Number of DLC symbols used by the scheduler	1
Antenna Model of the UE	Isotropic

Parameters	Values/Types
Gain of the isotropic antenna	0.0 dB
Transmit power of the UE	23.0 dB
Number of RBs per RBG	4, 4, 3, 2
Error model	NrEesmCcT2

4.2.2 Results Analysis and Discussion of the First Scenario

In 5G NR, the concept of BWPs is introduced to enable flexibility in configuring different parts of the available spectrum for various applications. Each BWP can have its own set of frequency and bandwidth parameters, allowing for adaptable allocation of resources.

According to the simulated parameters and models outlined in Table 4.2, the simulation employs TDD, a mode where the same frequency band is used for both uplink and downlink transmissions with a predefined time division. The simulation results indicate that the 5G gNBs have the same BWP configuration (i.e., the same BWP id, frequency range, and bandwidth), demonstrating that the 5G gNBs use the same set of frequency resources. In this scenario, the obtained central frequency of 2150 MHz denotes operating in the sub-6 GHz frequency range, which is common for 5G deployments, especially in the mid-band spectrum. Further, the resulting channel bandwidth of 80 MHz is a typical configuration for 5G networks. It allows higher data rates compared to narrower bandwidths. The objective of acquiring these findings is to understand the resource allocation process of the simulation for each BWP. Then, the configured BWPs determine the frequency resources available for communication and analyze how the network manages and allocates these resources to different users or services.

As a result, this information is vital for evaluating the efficacy of the simulated 5G network.

Table 4.2: Simulated parameters of the first scenario

Parameters	**Values/Types**
Scenario	UMi
Radio network	NR
Error model	NrEesmIrT2
Operation mode	TDD
Direction	DL
Numerology	2
Pattern	F|F|F|F|F|UL|UL|UL|UL|UL|
Power allocation	Uniform power allocation per bandwidth
Scheduler	PF
B_{BWP}	40 MHz
Frequency scenario	Overlapping
Simulation time	1400 ms
L	3
Number of UEs per 5G gNB	2
FFR	3
UDP packet size	600 bytes
Lambda (packet generation rate)	2000 packets/s
Remote host	1
Data rate for the point-to-point link between PGW and the remote host	100 Gb/s
Delay for the point-to-point link between PGW and the remote host	0 s
MTU for the point-to-point link between PGW and the remote host	2500 bytes
Interval (packet generation interval)	1/Lambda

4.2.3 Second Scenario: Simulation of the Edge Layer in the Proposed Architecture (5G gNBs and Vehicles)

Building upon the environmental explanation in the first scenario, the current scenario starts a simulation of the edge layer of the proposed architecture. This scenario investigates the interaction between the 5G gNBs (gNB_{Ei}) and vehicles. The vehicles have included the proposed RS-ANN model to predict the RS_{V_i} value. The simulation parameters for this scenario are described in Table 4.3.

Table 4.3: Simulated parameters of the second scenario

Parameters	**Values/Types**
Scenario	UMa
Radio network	NR
Error model	NrEesmCcT2
Operation mode	TDD
Direction	DL
Numerology	0
Pattern	F|F|F|F|F|F|F|F|F|F|
Power allocation	Uniform power allocation per RB used
Scheduler	PF
B_{BWP}	20 MHz
Frequency scenario	Non-overlapping
L	57
Number of UEs (vehicles) per 5G gNB	2
FFR	3
UDP packet size	1000 bytes
Lambda (packet generation rate)	5000 packets/s
Remote host	100
Interval (packet generation interval)	1/Lambda
Data rate for the point-to-point link between PGW and the remote host	100 Gb/s

Parameters	Values/Types
Delay for the point-to-point link between PGW and the remote host	0 s
MTU for the point-to-point link between PGW and the remote host	2500 bytes
Application generation time	1000 ms
UDP application start time	400 ms

4.2.4 Results Analysis and Discussion of the Second Scenario

The provided simulation results in Table 4.4 describe 5G communication with non-overlapping frequency bands and TDD operational mode at the edge layer in figure 3.1. The simulation involves three BWPs (BWP id = 0, BWP id = 1, and BWP id = 2), each with a central frequency and bandwidth. The central frequencies for each BWP are spaced apart, ensuring that each BWP operates in a distinct frequency range. The central frequencies specified for each BWP, along with their corresponding bandwidths, are critical parameters that influence the communication characteristics. The use of multiple BWPs allows for efficient spatial resource allocation, enabling simultaneous communication in different frequency bands. Depending on the specific requirements of vehicular applications and the mobility patterns of vehicles, this design aligns with best practices in 5G network planning, ensuring that each frequency band operates independently to minimize interference between adjacent 5G gNBs or vehicles operating on different BWPs and enhance overall network performance.

TDD is often preferred in dynamic and mobile environments like vehicular networks, allowing efficient utilization of the available spectrum and flexibility in adapting to varying traffic conditions. TDD, along with designated frequency ranges for each BWP, facilitates temporal resource allocation, optimizing communication slots for uplink and downlink transmissions. The details of this scenario are presented in Appendix (A).

Table 4.4: Results of the second scenario-part 1

BWP id	Lower Frequency	Central Frequency	Higher Frequency	BW
0	2110 MHz	2130 MHz	2150 MHz	40 MHz
1	2150 MHz	2170 MHz	2190 MHz	40 MHz
2	2190 MHz	2210 MHz	2230 MHz	40 MHz

4.2.5 Third Scenario: Simulation of the Edge Layer in the Proposed Architecture (Federated Learning)

In this section, two scenarios have been considered to simulate the proposed VFL algorithm in the SDNCA framework. Scenario 1 has 100 vehicles with one ES, whereas scenario 2 has 400 vehicles with four ESs. The Python programming language (Pytorch) is utilized to simulate both scenarios. We generate the training and testing datasets for each vehicle as integer values of “0”, “1”, and “2” as follows:

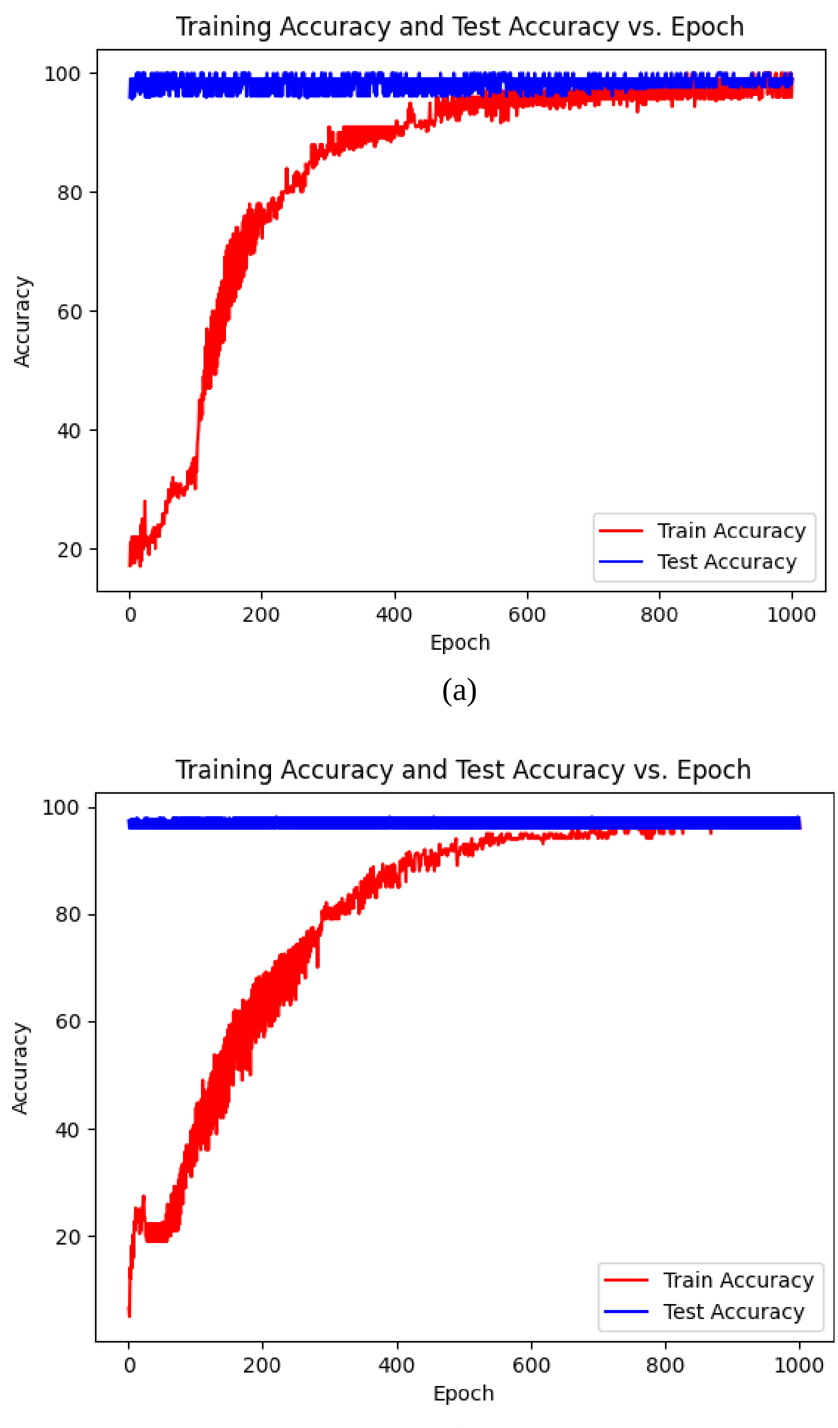
- $\boldsymbol{O}_{\boldsymbol{V}_{i}}$: “0” for free road, “1” for slow road, and “2” for blocked road.
- $\boldsymbol{W}_{\boldsymbol{V}_{i}}$: “0” for clear weather and “1” for rainy weather.
- $\boldsymbol{S}_{\boldsymbol{V}_{i}}$: “0” for low speed, “1” for medium speed, and “2” for high speed.
- $\boldsymbol{RD}_{\boldsymbol{V}_{i}}$: “0” for far distance, “1” for medium distance, and “2” for close distance.
- $\boldsymbol{RC}_{\boldsymbol{V}_{i}}$: “0” for excellent road condition, “1” for slippery road condition, and “2” for potholes road condition.
- $\boldsymbol{T}_{\boldsymbol{V}_{i}}$: “0” for daytime and “1” for nighttime.

By taking a random number for each feature, the estimated RS_{V_i} takes a range of 10 values (0–9). The proposed RS-ANN model is a deep neural network model. The datasets are generated with a batch size of 32 to feed the RS-ANN model implemented in the vehicles. The RS-ANN model consists of four fully connected layers with 32, 64, and 32 neurons in three hidden layers and a dropout of 0.2. Rectified Linear Units (ReLUs) are used as the activation functions of the three fully connected layers. The RS-ANN model is trained for 1000 epochs with cross-entropy loss and an Adam optimizer with a learning rate of 0.0001. The simulation time for the two scenarios is 14820 s.

4.2.6 Results Analysis and Discussion of the Third Scenario

The evaluation results of the real-time simulation of the proposed VFL algorithm are shown in figures 4.1–4.3. Figure 4.1 (a) shows the training and test accuracies in scenario 1. In this scenario, 95.60% training accuracy and 98.00% test accuracy have been achieved at epoch 346. Figure 4.1 (b) shows the training and test accuracies in scenario 2. This scenario results in 95.30% training accuracy and 96.00% test accuracy at the same epoch. Given an increase in the number of training vehicles, these values reach 98.10% training accuracy and 99.00% test accuracy at epoch 1000 in figure 4.1 (a), whereas training accuracy is 97.90% and test accuracy is 96.00% at epoch 1000 in figure 4.1 (b).

Overall, high average accuracy values are obtained in figure 4.1 (a) and figure 4.1 (b) because an accurate RS-ANN training model has been designed, in addition to the participation of all vehicles in the training process, which results in higher accuracy values. Thus, the proposed VFL algorithm yielded identical results, except for a small gap in its convergence speed between the two scenarios. Using the ES that has the capacity of four ESs (each 100 vehicles handled by one ES) that distribute the load in scenario 2 constitutes a key factor for obtaining these identical values.

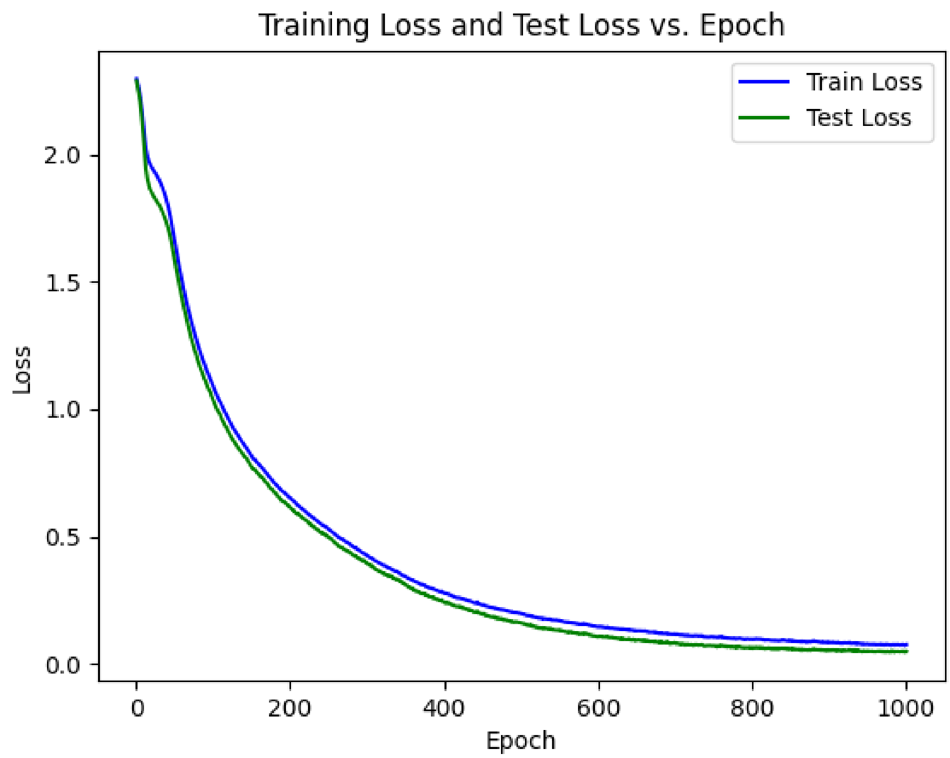


(a)

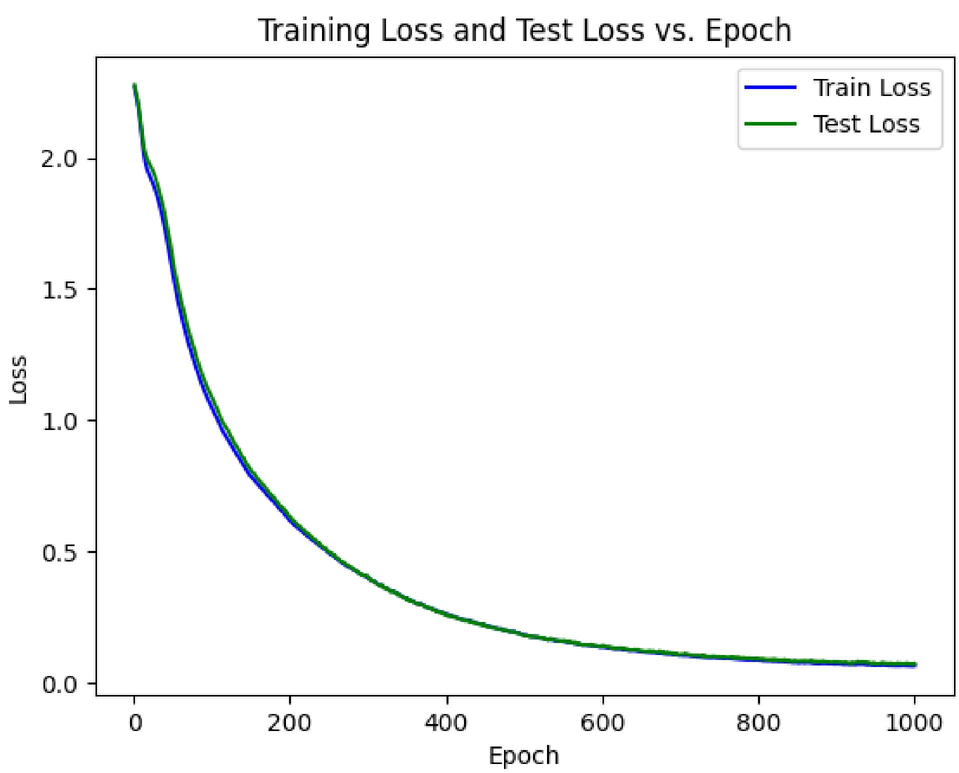
(b)

Figure 4.1: (a) Training and test accuracy for 100 vehicles. (b) Training and test accuracy for 400 vehicles.

Figure 4.2 (a) and figure 4.2 (b) demonstrate the training and test losses for the RS-ANN model in scenario 1 and scenario 2, respectively. The train and test losses significantly drop from more than 2.0 to 0.0760 train loss and 0.0493 test loss in figure 4.2 (a), and to 0.0657 train loss and 0.0727 test loss in figure 4.2 (b). Figure 4.2 (a) and figure 4.2 (b) show smooth curves without any fluctuations and with little differences between them in both scenarios. This indicates that the proposed VFL algorithm is stable due to the load balancing of the data packets and because there are no major losses in the entire system.



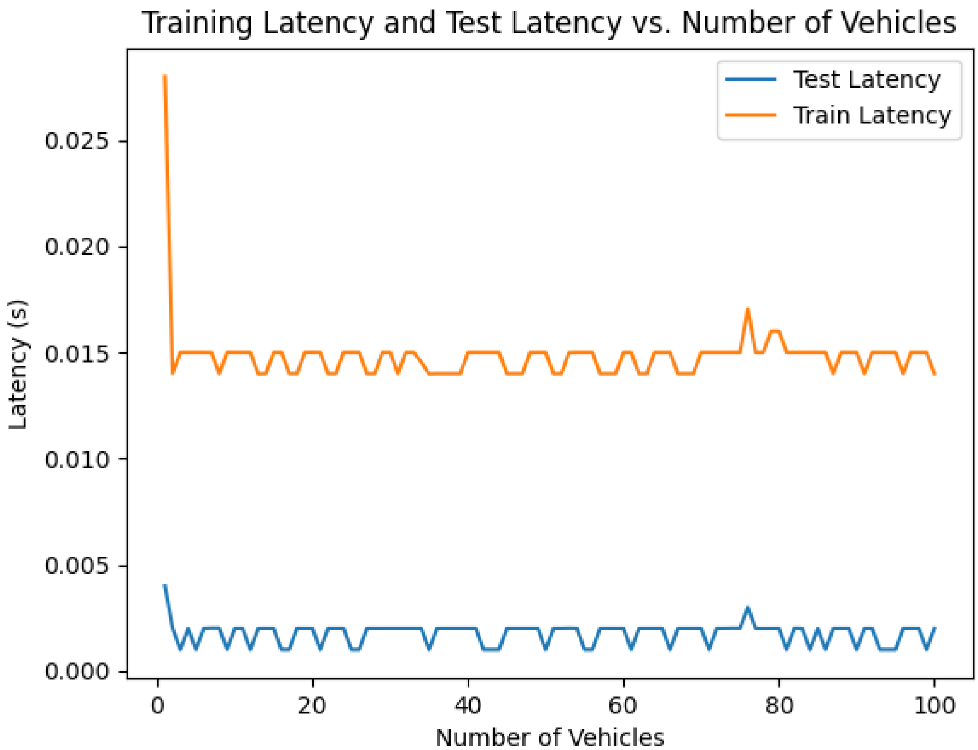
(a)



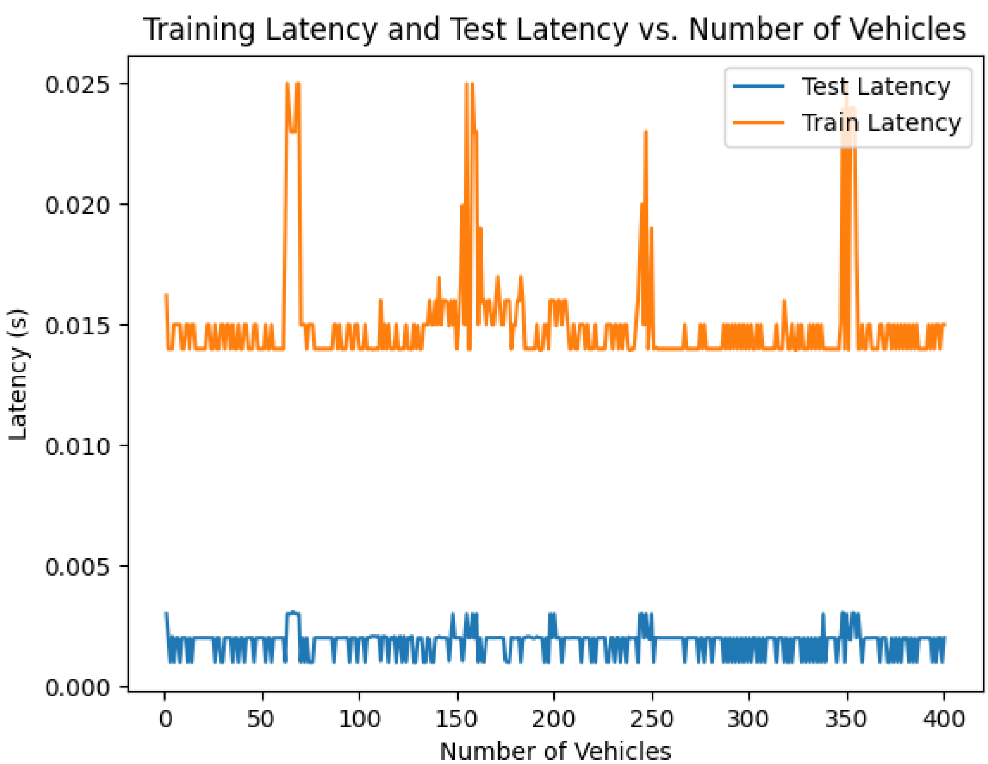
(b)

Figure 4.2: (a) Training and test losses for 100 vehicles. (b) Training and test losses for 400 vehicles.

The training and test latencies are critical parameters that should be investigated in the federated learning process as they affect the transmission latency of ESMs in any system model. These parameters have been measured, as shown in figure 4.3 (a) for scenario 1 and figure 4.3 (b) for scenario 2, with accurate and desirable values. Initially, the training latency is more than 0.025 s and then decreases to approximately 0.0150 s in figure 4.3 (a); however, the value of the test latency remains constant at 0.002 s in figure 4.3 (a). As shown in figure 4.3 (b), the average training latency is 0.02 s; fluctuations are observed at some values (e.g., the training latency is 0.025 s when the training vehicles are more than 50). These fluctuations are due to the training process, and the same test latency value has been achieved, as shown in figure 4.3 (b). Technically, the test latency should be lower than the training latency, which our results scrutinize. Figure 4.3 (a) and figure 4.3 (b) also show that increasing the number of vehicles does not affect the training and test latencies, which makes our system model more adaptable to IoV as the number of vehicles is increased or decreased in a specific area at a certain time.



(a)



(b)

Figure 4.3: (a) Training and test latencies for 100 vehicles. (b) Training and test latencies for 400 vehicles

4.2.7 Fourth Scenario: Simulation of the Edge and Backbone Layers in the Proposed Architecture (SDNCA Framework)

The proposed SDNCA framework has been simulated in a scenario of three 5G gNBs (gNB_{Ci}), 100 vehicles, one ES, and one SDN controller. The 5G gNBs at the backbone layer are connected through an SDN switch. An Open-Flow v1.0 OpenVSwitch virtual switch is used. The switch is managed by a Ryu SDN controller, which is written in Python. Table 4.5 displays the simulated parameters of SDNCA.

Table 4.5: simulated parameters of the fourth scenario

Parameters	**Values/Types**
MAC protocol	OFDMA
Transport protocol	TCP
ESM packet size	1024 bytes
Range of S_{V_i} values (km/hr)	Low speed: 50-80 Medium speed: 80-100 High speed: 100-150
N	100
Environment	Highways
K	3
SDN Controller	1
ES	1
Simulation time	2400 s
C_v	≥ 5
$QoS_{\sigma h}$	1.06
$QoS_{\sigma m}$	0.7
$QoS_{\sigma l}$	0.3
MS_{V_i}	150km/hr
MRD_{V_i}	150m
d_σ	3
d_r	1
NO_i	0
CC_i	0
TR_i	100

Parameters	Values/Types
ESM_{Pi}	100
Initial values of gNB_{nr_i} and gNB_{cr_i} assigned by gNB	$B_i = 50$MHz, $R_i = 500$Mbps, $A_i = 1$, $C_i = 1$ core, $M_i = 256$MB
Initial values of gNB_{nr_i} and gNB_{cr_i} allocated by SDN	$B = 0, R = 0, A = 0, C = 0, M = 0$
Maximum values of gNB_{nr_i} and gNB_{cr_i}	$B_{max} = 10000$MHz, $A_{max} = 10$, $M_{max} = 4096$MB, $C_{max} =$ 32 cores, $R_{max} = 10000$Mbps
gNB_{nr_i} and gNB_{cr_i} in each VN allocated by SDN including highest, medium, and lowest values of (*B*, *R*, *A*, *C*, and *M*)	VN_h (*B*: 80MHz, 60MHz, 50MHz) (*M*: 1GB, 768MB, 512MB) (*R*: 1Gbps, 750Mbps, 500Mbps) (*A*: 3, *C*: 2) VN_m (*B*: 60MHz, 50MHz, 50MHz) (*M*: 768MB, 512MB, 256MB) (*R*: 750Mbps, 650Mbps, 500Mbps (*A*: 2, *C*: 2) VN_l (*B*: 60MHz, 50MHz, 50MHz) (*M*: 512MB, 256MB, 256MB) (*R*: 650Mbps, 550Mbps, 500Mbps) (*A*: 1, *C*: 1)
Range of RD_{V_i} values (m)	Close distance: 150-400 Medium distance: 400-700 Far distance: 700-1000

4.2.8 Validation Metrics of the Fourth Scenario

The effectiveness of SDNCA is evaluated based on the following validation metrics by varying the density and velocity of the vehicles:

1. Network Overhead (NO) and Computational Complexity (CC): This study defined network overhead and computational complexity percentages in terms of consuming gNB_{nr_i} and gNB_{cr_i}. Network overhead represents the percentage of the consumption of $B, R,$ and M of the gNB_{TN}. As well, computational complexity represents the percentage of the consumption of A, C, and M of the gNB_{TC}. These metrics are computed at the selected gNB that forwards the ESM to the D by the following equations:

$$NO_{t_i} = \frac{NO_c}{gNB_{TN}} \tag{4.5}$$

Then, the total network overhead at a given time ($NO_{t_i}^{\sigma}$) is calculated by adding (NO_{t_i}) to its value at the previous time ($NO_{t_{i-1}}$) as follows:

$$NO_{t_i}^{\sigma} = NO_{t_{i-1}} + NO_{t_i} \tag{4.6}$$

$$CC_{t_i} = \frac{CC_c}{gNB_{TC}} \tag{4.7}$$

Then, the total computational complexity at a given time ($CC_{t_i}^{\sigma}$) is calculated by adding (CC_{t_i}) to its value at the previous time ($CC_{t_{i-1}}$) as follows:

$$CC_{t_i}^{\sigma} = CC_{t_{i-1}} + CC_{t_i} \tag{4.8}$$

2. Collision Rate (CR) of ESMs: The packet collision rate has been defined as the number of data packet collisions occurring in a network over a specified period. This metric is computed as the ratio of the number of collisions (N_c) of the packets at the gNB with respect to the number of packets received by gNB (NP_{gNB}) as follows:

$$CR = \frac{N_c}{NP_{gNB}} \tag{4.9}$$

3. End-to-End (E2E) Delay: This metric is defined as the difference between the time at which the source vehicle (S) transmits the ESM packet to the SDN controller (t_{tESM}) and the time at which the destination vehicle (D) receives the ESM packet (t_{rESM}). It can be measured as follows:

$$E2E\ Delay = t_{tESM} - t_{rESM} \tag{4.10}$$

4. Packet (ESM) Transmission Reliability (TR): This metric evaluates network connectivity and its ability to successfully deliver ESMs from the S to the D without errors, losses, or delays. This metric is affected by increasing the network overhead in terms of consuming B, increasing the computational complexity in terms of consuming A, and increasing the collision rate, respectively. The transmission reliability can be expressed mathematically as follows:

$$TR = TR_b - CR \tag{4.11}$$

4.2.9 Results Analysis and Discussion of the Fourth Scenario

The proposed SDNCA framework is simulated by considering vehicle density and vehicle speed and compared with (Prathiba *et al.*, 2022) for one common point, that is, SDNCA and (Prathiba *et al.*, 2022) simulated 5G technology for IoV. The novelty of the SDNCA framework compared with (Prathiba *et al.*, 2022) relies on the following main facts: First, the SDNCA framework takes vehicle speed into account, but its implementations were not considered in (Prathiba *et al.*, 2022), which is a drawback of the study. Second, the SDNCA framework implements federated learning, which is not simulated in (Prathiba *et al.*, 2022). Third, the SDNCA framework performs a real-time simulation of the SDN core routers at the backbone layer, along with ES execution at the edge layer to handle the overall network load. However, the topology in (Prathiba *et al.*, 2022) requires more than one SDN controller and one core router to balance the load of 800 vehicles, and it does not mention the technical aspects of the core layer. Thus, technically, the system model in (Prathiba *et al.*, 2022) has jitters, delays, and damage at a certain stage.

Controlling the network overhead and computational complexity is crucial for any real-time simulation. Figures 4.4, 4.5, 4.6, and 4.7 show the optimized network results of 17% and an average of 20%, respectively in the SDNCA framework, due to the intelligent utilization of gNB_{nr_i} and gNB_{cr_i}. By contrast, the study in (Prathiba *et al.*, 2022) obtained less network overhead and computational complexity than the SDNCA framework when $N = 100$ vehicles/km. In addition, when $N = 800$ vehicles/km in (Prathiba *et al.*, 2022), the network overhead is 21% and the computational complexity is 19.8%. Hence, the study in (Prathiba *et al.*, 2022) did not simulate the federated learning and core layer because the real-time simulation for more network devices, core routers, and ESs will increase the network overhead and computational complexity by more than 21% and 19.8%, respectively. Thus, achieving 17% and an average of 20% in the SDNCA framework for the real-time simulation of 100 vehicles/km with different speeds, which is considered ideal values.

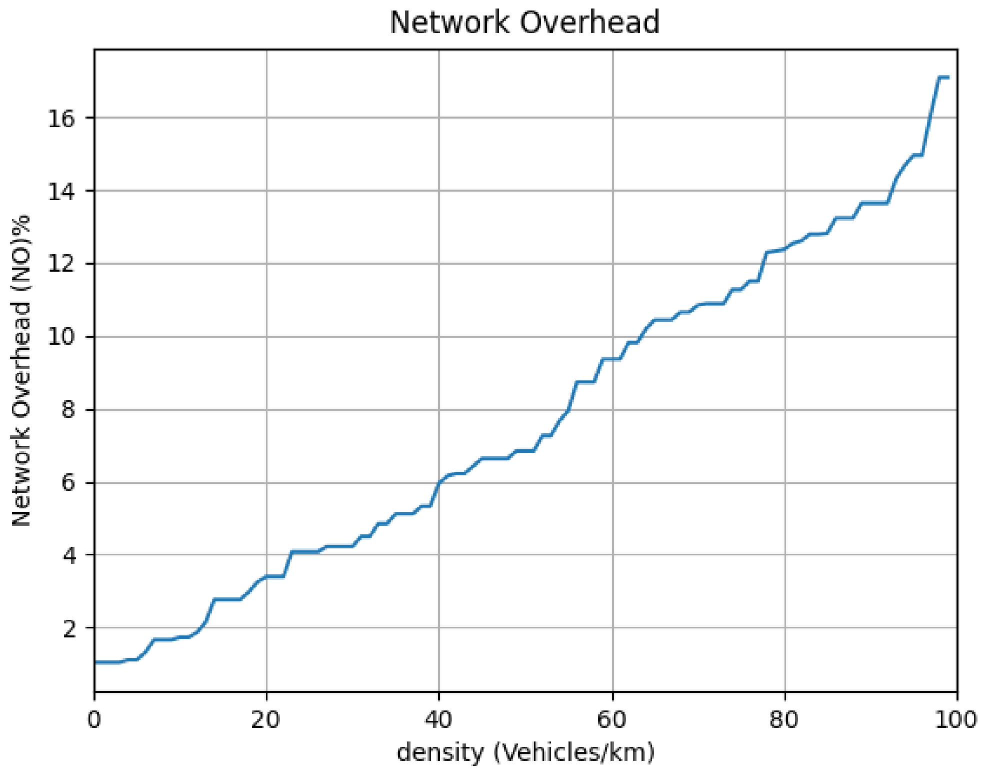


Figure 4.4: Evaluation of Network Overhead vs. vehicle density

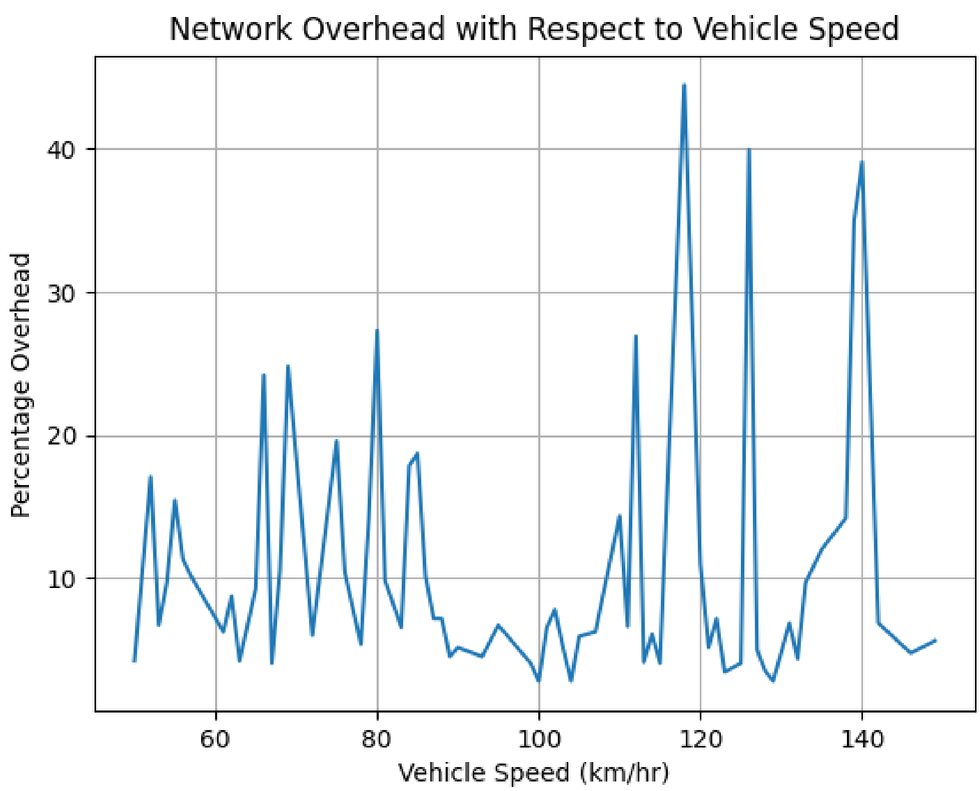


Figure 4.5: Evaluation of Network Overhead vs. vehicle speed

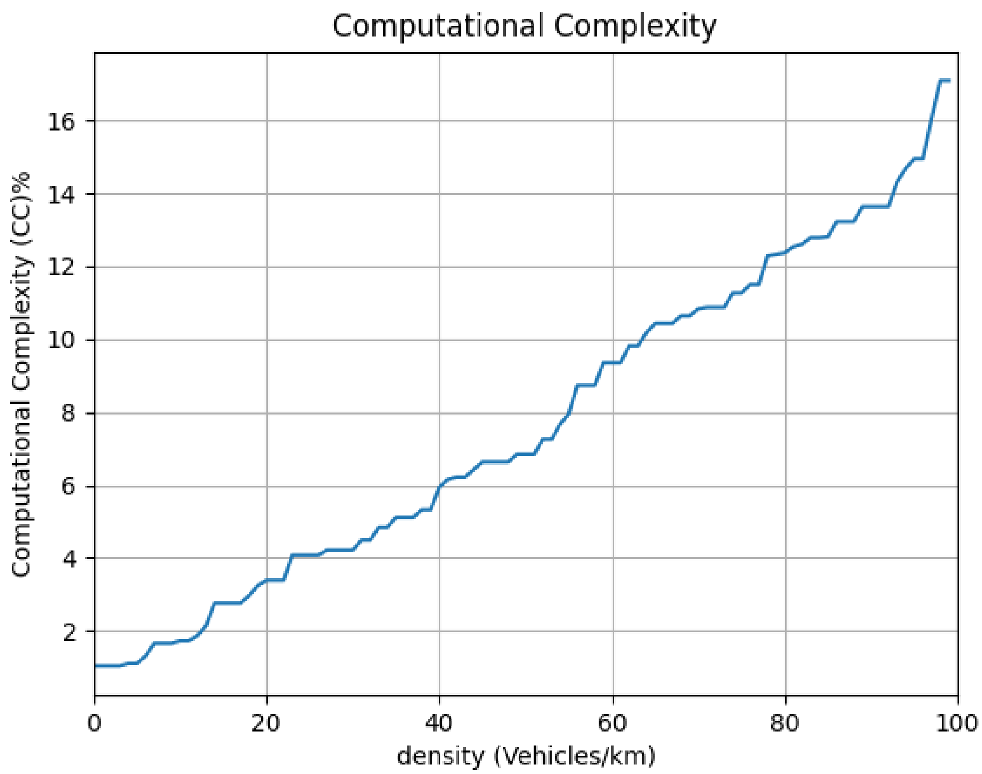


Figure 4.6: Evaluation of Computational Complexity vs. vehicle density

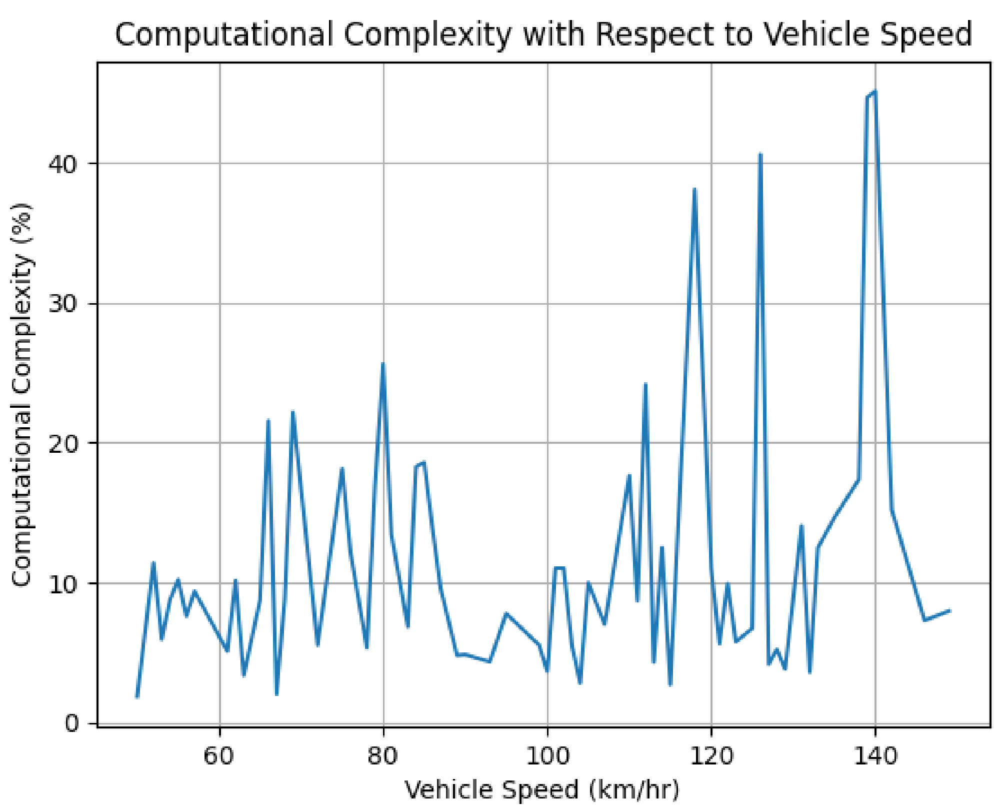


Figure 4.7: Evaluation of Computational Complexity vs. vehicle speed

The SDNCA framework possesses a 0% collision rate for ESMs, as shown in Table 4.6. With increasing vehicle density and vehicle speed, the collision rate remains at 0, which denotes the ideality of SDNCA and its proper configuration to transmit ESMs based on their priorities, thereby realizing the avoidance of vehicle collisions in 5G environment. The SDNCA framework outperforms the method in (Prathiba *et al.*, 2022), with collision rates of approximately 4% and 9% at $N = 100$ vehicles/km implemented in two different scenarios.

Table 4.6: Results of CR vs. vehicle density and vehicle speed

Vehicle density (vehicles/km)	**CR**	**Vehicle speed (km/hr)**	**CR**
10	0	50	0
20	0	60	0
30	0	70	0
40	0	80	0
50	0	90	0
60	0	100	0
70	0	110	0
80	0	120	0
90	0	130	0
100	0	140	0

In contrast with (Prathiba *et al.*, 2022), the analysis of the average end-to-end delay of the SDNCA framework, which is depicted in figure 4.8 and figure 4.9, reveals that the end-to-end delay in the SDNCA framework is 18 ms at $N = 100$ vehicles/km, which is approximately equal to the value obtained in (Prathiba *et al.*, 2022) for more than 300 vehicles/km. The lower end-to-end delay values in the SDNCA framework, when vehicle density and speeds increase, are due to the utilization of high computing resources to transmit ESMs faster based on their priorities. These results considered ideal values for simulating the core and edge layers compared with (Prathiba *et al.*, 2022).

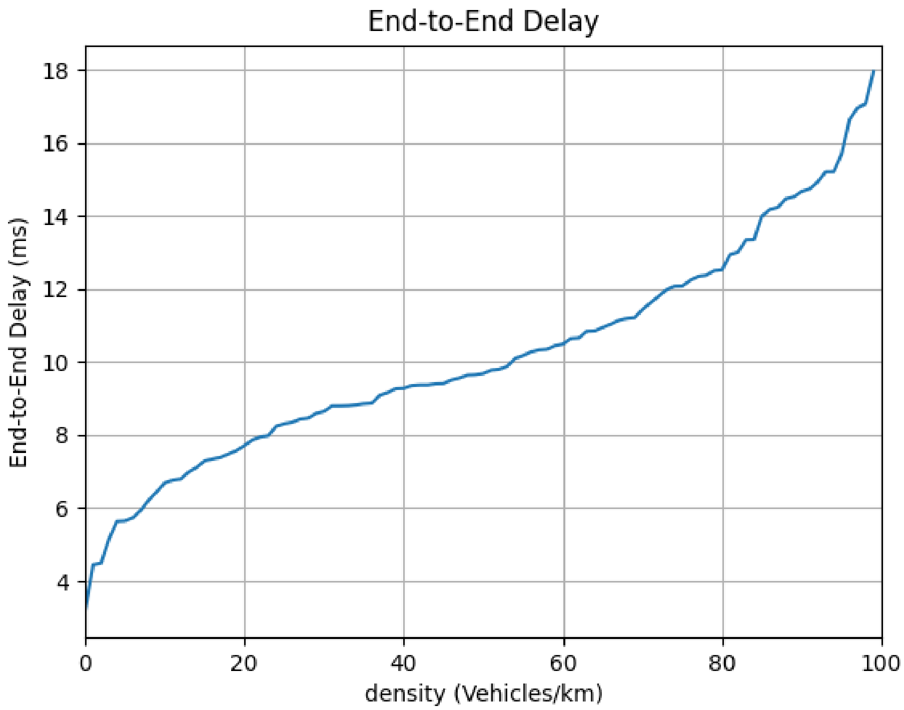


Figure 4.8: Evaluation of End-to-End delay vs. vehicle density

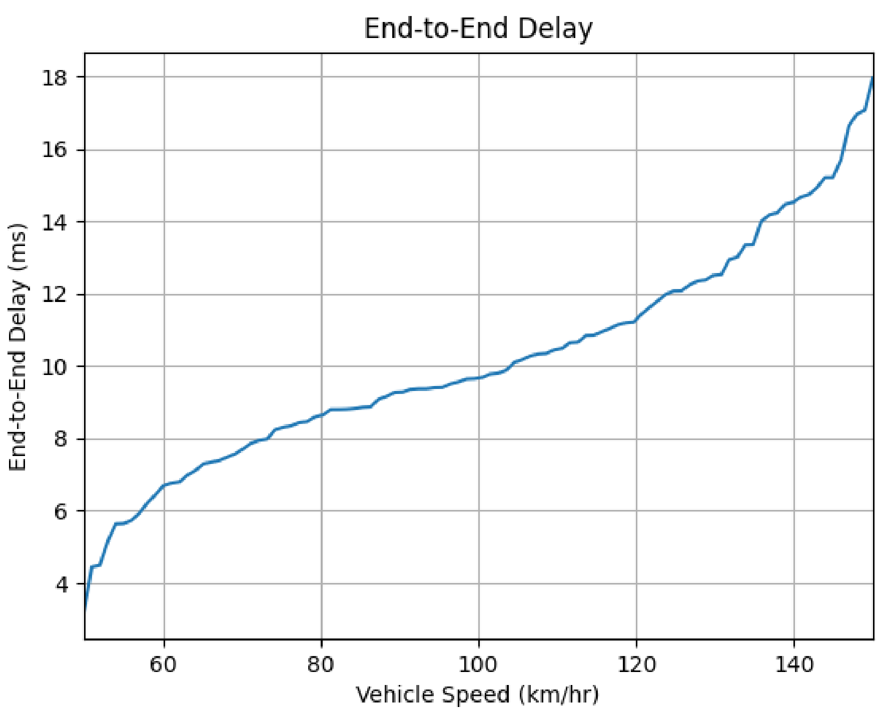


Figure 4.9: Evaluation of End-to-End delay vs. vehicle speed.

The results shown in figure 4.10 and figure 4.11 indicate that the SDNCA framework can provide high reliability of ESM transmission because it has a constant value of 89%–90% as the vehicle density and vehicle speed increase. In comparison, the transmission reliability of ESM was not assessed in (Prathiba *et al.*, 2022). Achieving 0% collision rates in SDNCA leads to a constant value of 89%–90%.

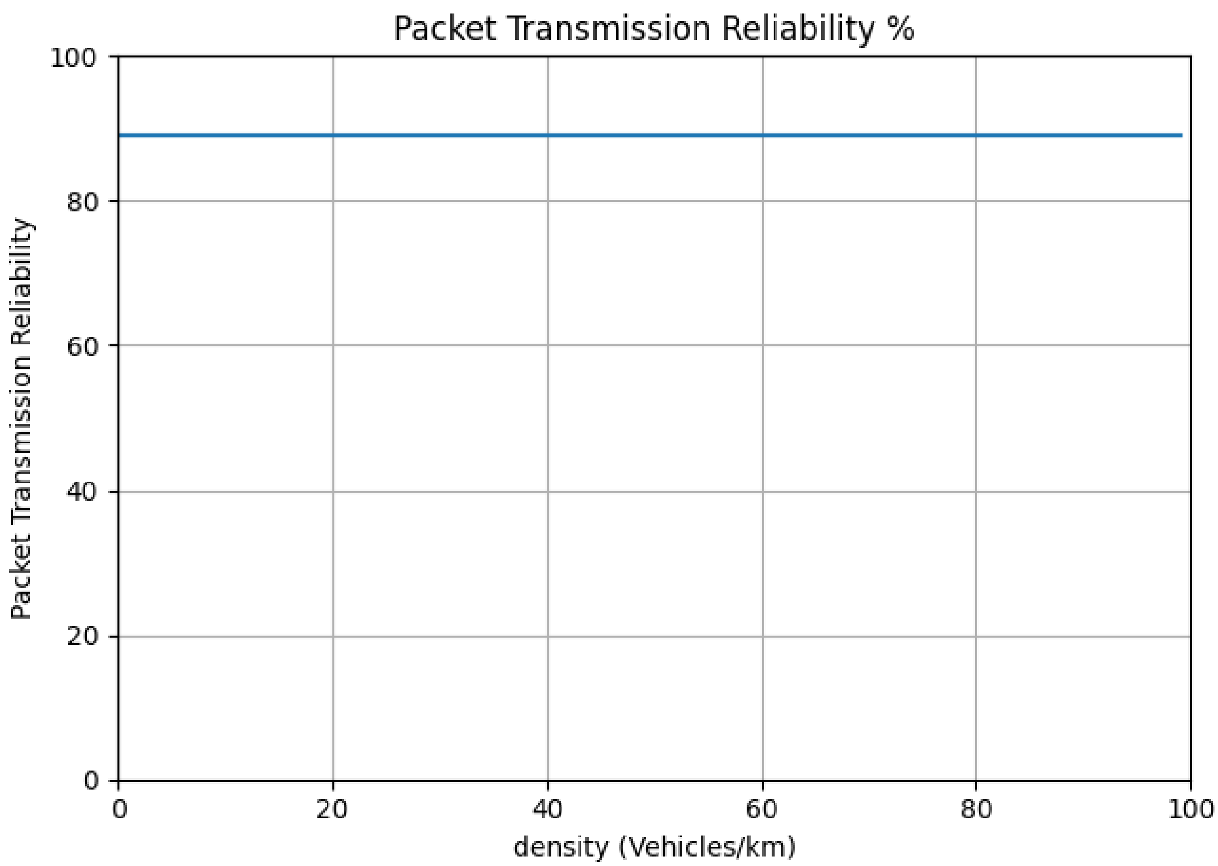


Figure 4.10: Evaluation of Packet (ESM) Transmission Reliability vs. vehicle density

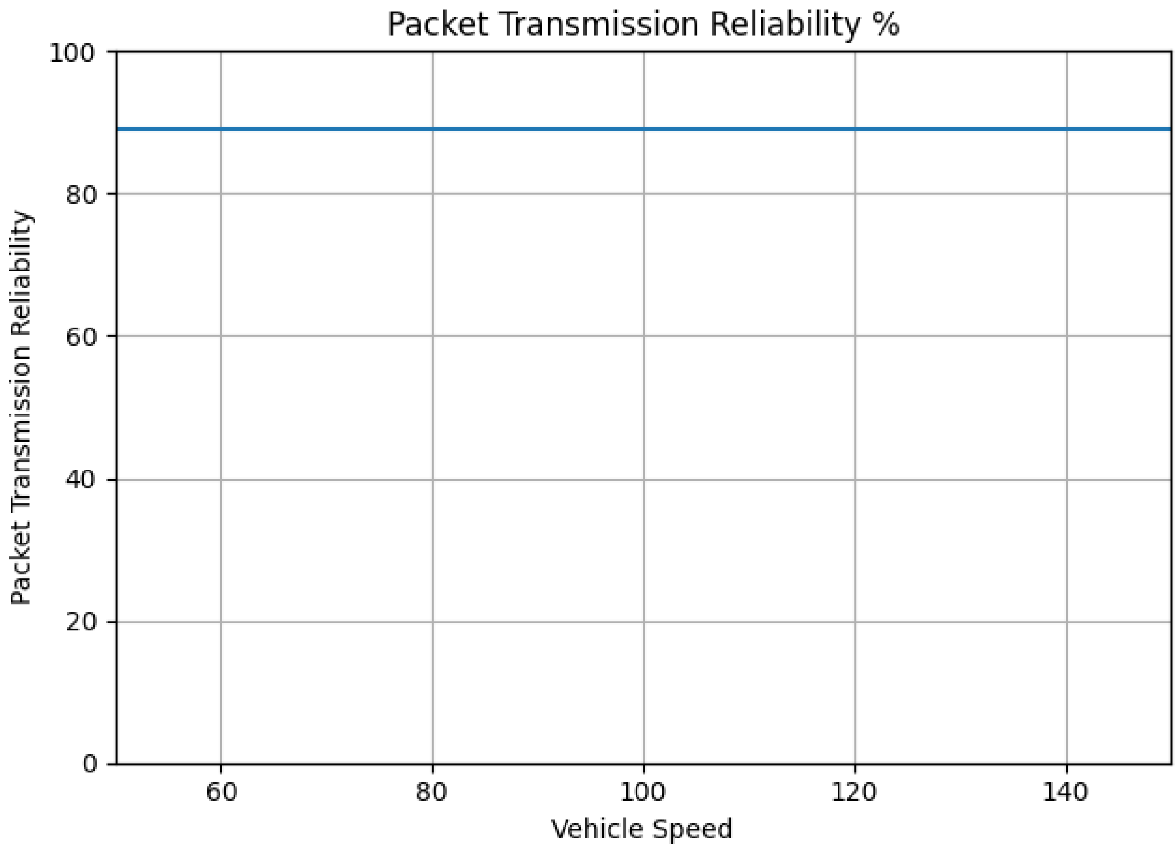


Figure 4.11: Evaluation of Packet (ESM) Transmission Reliability vs. vehicle speed

Table 4.7 details the comparison of the study in (Prathiba *et al.*, 2022) and the proposed SDNCA framework based on the provided discussion.

Table 4.7: Comparison of the SDNCA framework and related study

Research	**Evaluation Metrics for $N = 100$ vehicles/km**									
	NO (%)		CC (%)		CR (%)		E2E Delay (ms)		TR (%)	
	Vehicle density	Vehicle speed	Vehicle density	Vehicle speed	Vehicle density	Vehicle speed	Vehicle density	Vehicle speed	Vehicle density	Vehicle speed
(Prathiba *et al.*, 2022)	9	----	8	----	4 and 9	----	0	----	----	----
Proposed (SDNCA)	17	20	17	20	0	0	18	18	89–90	89–90

4.3 Summary

Two main points can be concluded from figures 4.4–4.11 and Table 4.6 in the SDNCA framework that should be scrutinized in real-time simulation. First, the same values of network overhead and computational complexity have been achieved because these metrics are complementary and directly proportional to each other. Second, Table 4.6 and figures 4.8–4.11 have the same values of collision rates, end-to-end delay, ESM transmission reliability when increasing the vehicle density, and vehicle speed. These results show the effectiveness of the SDNCA framework, which handles the ESMs simultaneously to avoid vehicle collision compared with the system model in (Prathiba *et al.*, 2022), which cannot consider an efficient system to cater to the critical requirements of ESM transmission in the network due to the reasons mentioned previously in section 4.2.9.

CHAPTER FIVE

SIMULATION RESULTS AND ANALYSIS OF THE SECOND SYSTEM MODEL

5.1 Overview

In chapter five, a simulation of chapter four has been conducted in a different scenario (the fifth scenario) to assess the efficacy of the proposed SDNCA framework using the validation criteria described in section 5.2.1. This chapter discusses the significance of taking into account these metrics when disseminating the ESMs in IoV.

5.2 Fifth Scenario: Simulation of the Edge and Backbone Layers in the Proposed Architecture (SDNCA Framework)

The proposed SDNCA framework has been simulated in a scenario of ten 5G gNBs (gNB_{Ci}), 100 vehicles, one ES, and one SDN controller. The complete implementation of the fifth scenario is explained in the flowchart depicted in figure 3.10. Table 5.1 displays the simulated parameters of SDNCA in this scenario.

Table 5.1: Simulated parameters of the fifth scenario

Parameters	**Values/Types**
MAC protocol	OFDMA
Hidden layers	2
Number of neurons	64, 256
Activation function	ReLU
Number of epochs	1000
Batch size	32
Loss function	Cross-entropy
Optimizer	Adam
Learning rate	0.0001

Parameters	Values/Types
Transport protocol	TCP
ESM packet size	1024 bytes
Range of S_{V_i} values (km/hr)	Low speed: ≥ 50 Medium speed: > 80 High speed: > 110
MS_{V_i} (km/hr)	151
$MRD_{S,D}$ (m)	1
N	100
Environment	Highways
K	10
SDN Controller	1
ES	1
Simulation time	7200 s
C_v	≥ 5
$QoS_{\lambda h}$	160
$QoS_{\lambda m}$	107
$QoS_{\lambda l}$	54
d_{λ}	3
d_{max}	50
d_{mo}	25
Initial values of gNB_{nr_i} and gNB_{cr_i} used by gNB	$B_i = 0$MHz, $R_i = 0$Mbps, $A_i = 0$, $C_i = 0$MHz, $M_i = 0$MB
B	B_{lr}: 5–20MHz B_{mr}: 20–100MHz B_{hr}: 100–200MHz
R_{max}	100Mbps
A_{max}	3
A_{mo}	2
A_{mi}	1
C_{max}	2GHz
M_{max}	1024MB
Range of RD_{V_i} values (1–900 m)	Close distance: > 0 Medium distance: > 300 Far distance: > 600
s	"slow down"
m	"maintain a steady speed"
w	"watch out"

5.2.1 Validation Metrics of the Fifth Scenario

The performance of the SDNCA framework is carried out using the following validation metrics while altering the density and velocity of the vehicles:

1. Packet (ESM) Drop Ratio (PDR): This metric measures the ratio of transmitted ESMs that do not successfully reach their intended destination vehicles and are therefore dropped or lost during the communication process.
2. Successful Routing Ratio (SRR): It represents the distance that an ESM has to cover after being routed by the SDN controller. This metric emphasizes the success of routing in terms of covering short distances.
3. Routing Efficiency (RE): It is defined as the time taken to transmit the ESM; less time means better efficiency for routing ESMs. It has been calculated as a percentage of the time taken by the SDN switch (5G gNB) in relation to the total processing time for transmitting the ESM to the D.
4. V2I Channel Utilization (CU): It is defined as the time utilized by the 5G gNB ($t_{gNB_{Ci}}$) to send the ESM from the S to the SDN controller. It is measured mathematically using the following equation:

$$CU = \frac{t_{gNB_{Ci}}}{T_r} \qquad (5.1)$$

where T_r is the total running time of the gNB_{Ci}

In addition, the E2E delay and CR metrics, as stated in chapter four, section 4.2.8, have been evaluated in this particular scenario.

5.2.2 Results Analysis and Discussion of the Fifth Scenario

This section compares the simulation results of the SDNCA framework with the existing method, which is (Prathiba *et al.*, 2022). This method has been chosen for comparison because the contribution is similar to the proposed SDNCA framework. Comparisons are made based on the metrics of PDR, SRR, RE, CU, and E2E delay

Table 5.2 displays the packet (ESM) drop ratio for the SDNCA framework. From the table, it is inferred that, due to the extensive performance of the SDNCA for routing the ESMs, it has a 0% packet drop ratio when vehicle density and vehicle speed change. Table 5.3 compares PDR for SDNCA and the existing method, it shows that the study in (Prathiba *et al.*, 2022) obtains a 5% packet drop ratio considering vehicle density only.

Table 5.2: Results of PDR vs. vehicle density and vehicle speed

Vehicle density (vehicles/km)	**PDR**	**Vehicle speed (km/hr)**	**PDR**
10	0	50	0
20	0	60	0
30	0	70	0
40	0	80	0
50	0	90	0
60	0	100	0
70	0	110	0
80	0	120	0
90	0	130	0
100	0	140	0

The evaluation of the successful routing ratio in the SDNCA framework is conducted by selecting shorter distances to forward the ESMs to the destination vehicles. This criterion results in enhanced ESM transmission efficiency, characterized by decreased latency, reduced bandwidth requirements, and mitigated the possibility of packet loss. The SDN controller chooses the nearest gNB to the D in order to forward the ESM to it. Figure 5.1 and figure 5.2 demonstrate that the ESMs have an average distance of 8.75 m and 10.5 m, respectively. Figure 5.3 and figure 5.4 indicate the successful routing ratio of ESMs in relation to varying the vehicle density and vehicle speed, based on the findings presented in figure 5.1 and figure 5.2.

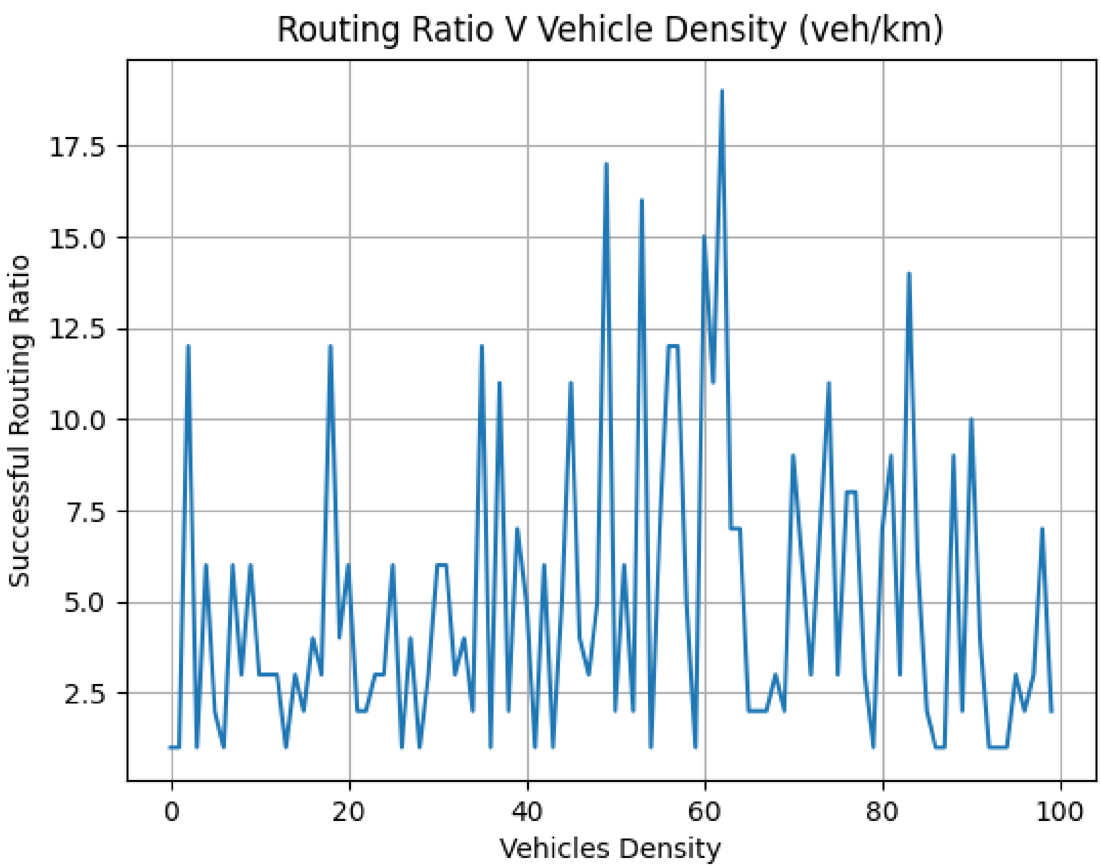


Figure 5.1: Evaluation of short distances vs. vehicle density

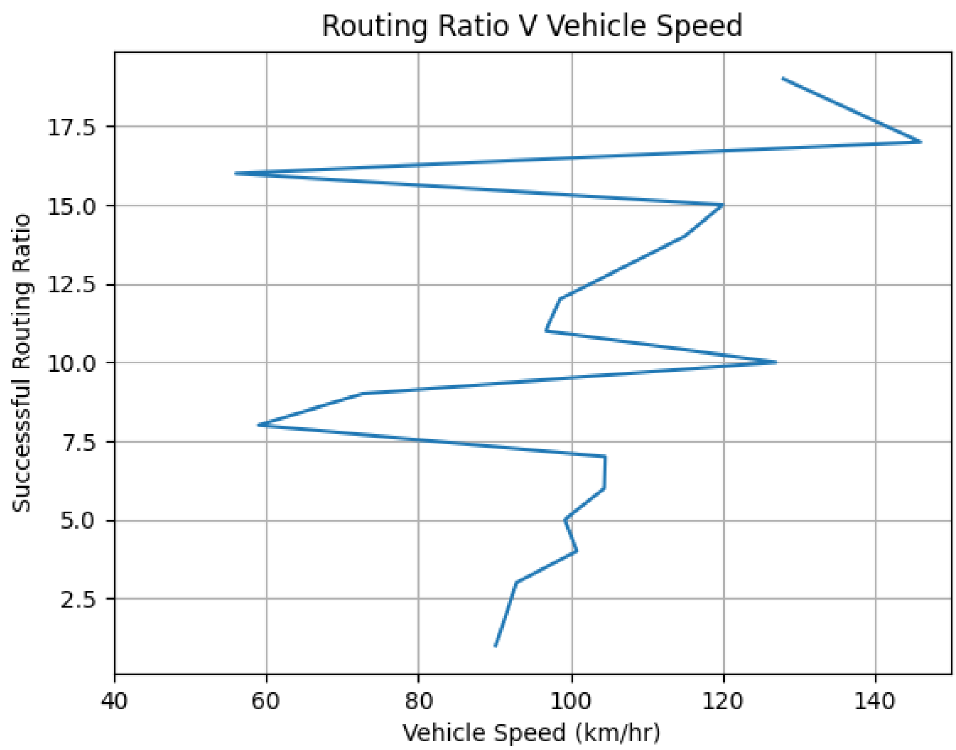


Figure 5.2: Evaluation of short distances vs. vehicle speed

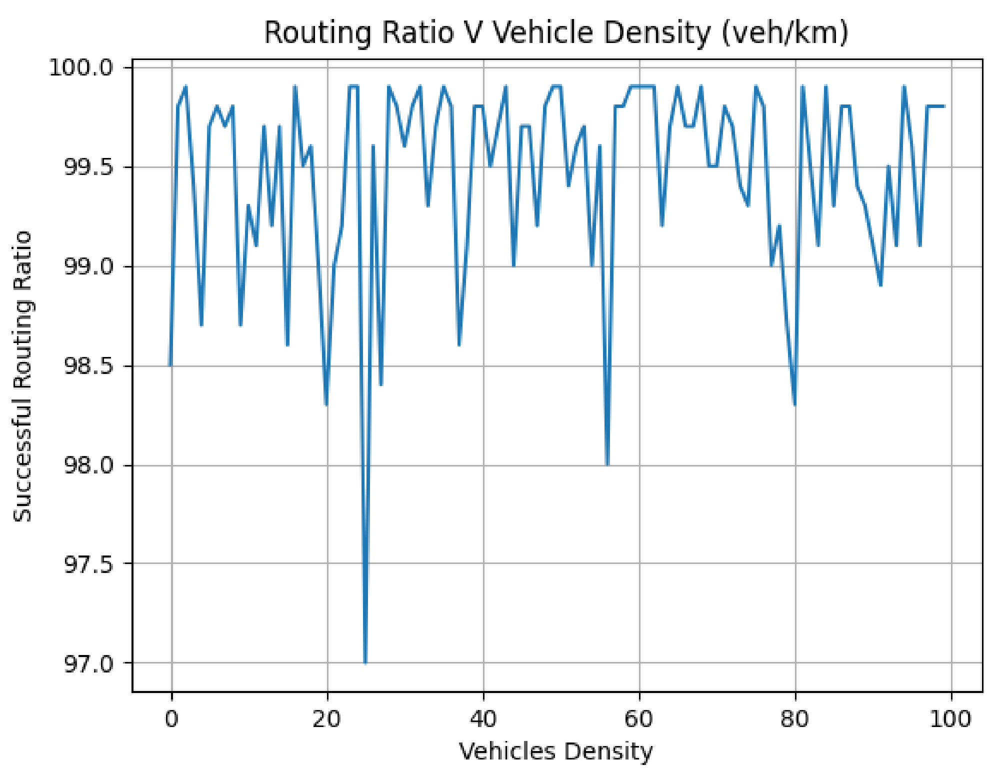


Figure 5.3: Evaluation of Successful Routing Ratio vs. vehicle density

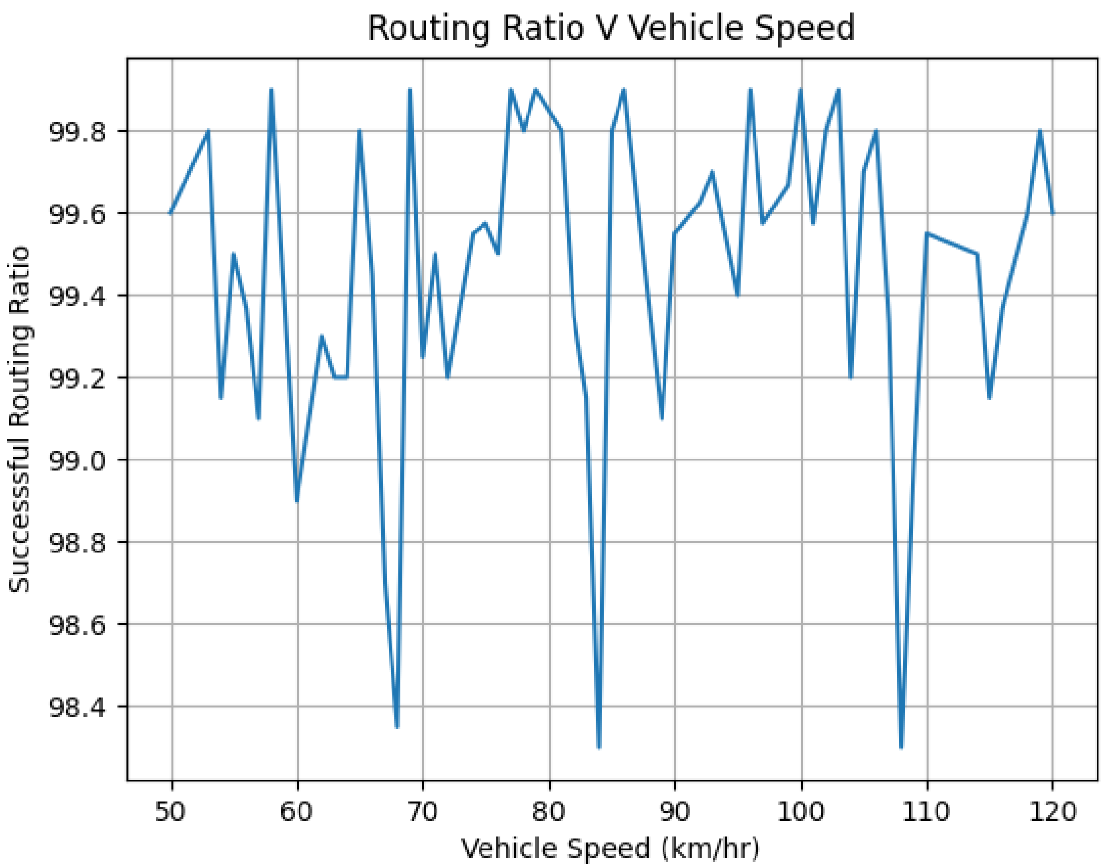


Figure 5.4: Evaluation of Successful Routing Ratio vs. vehicle speed

The results of the SDNCA framework presented in figure 5.5 and figure 5.6 show that the routing of ESM to the *D* takes an average of 0.005 ms even when the number of vehicles and their velocities change. The achievement of these results can be attributed to the prioritization of transmitting the ESM to the *D* by considering the shortest distances. In comparison, the study in (Prathiba *et al.*, 2022) as depicted in Table 5.3 evaluates the successful delivery ratio based on the number of ESMs that are effectively routed. More specifically, the routing of ESMs necessitates the consideration of both short distances and timely delivery, the factors that have not been addressed in (Prathiba *et al.*, 2022).

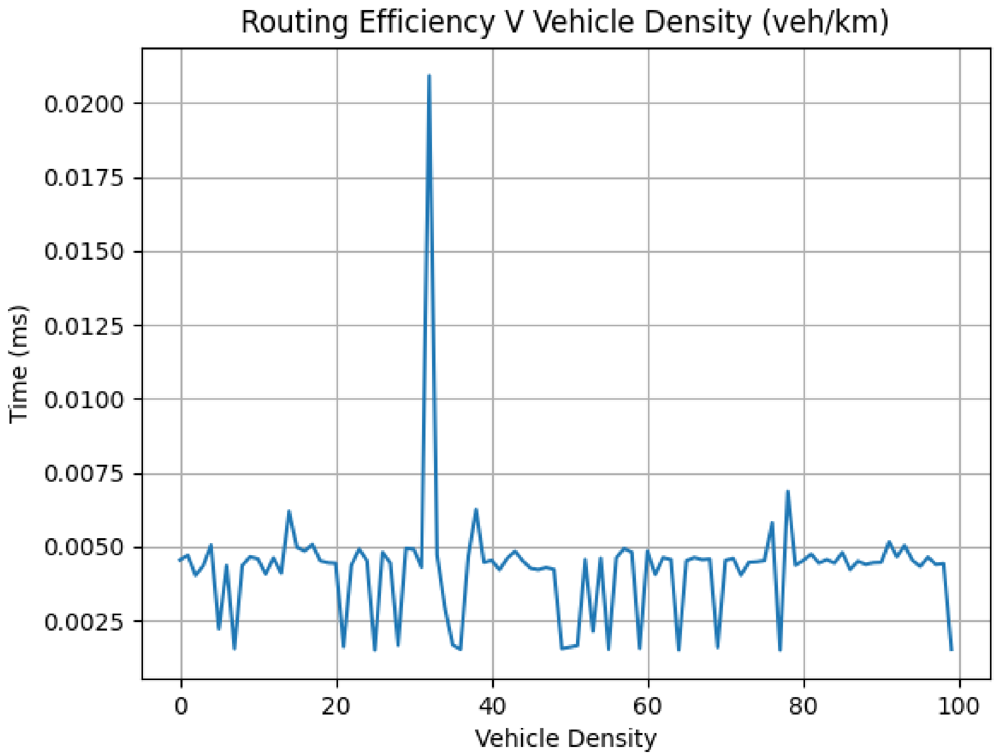


Figure 5.5: Evaluation of Routing Efficiency vs. vehicle density

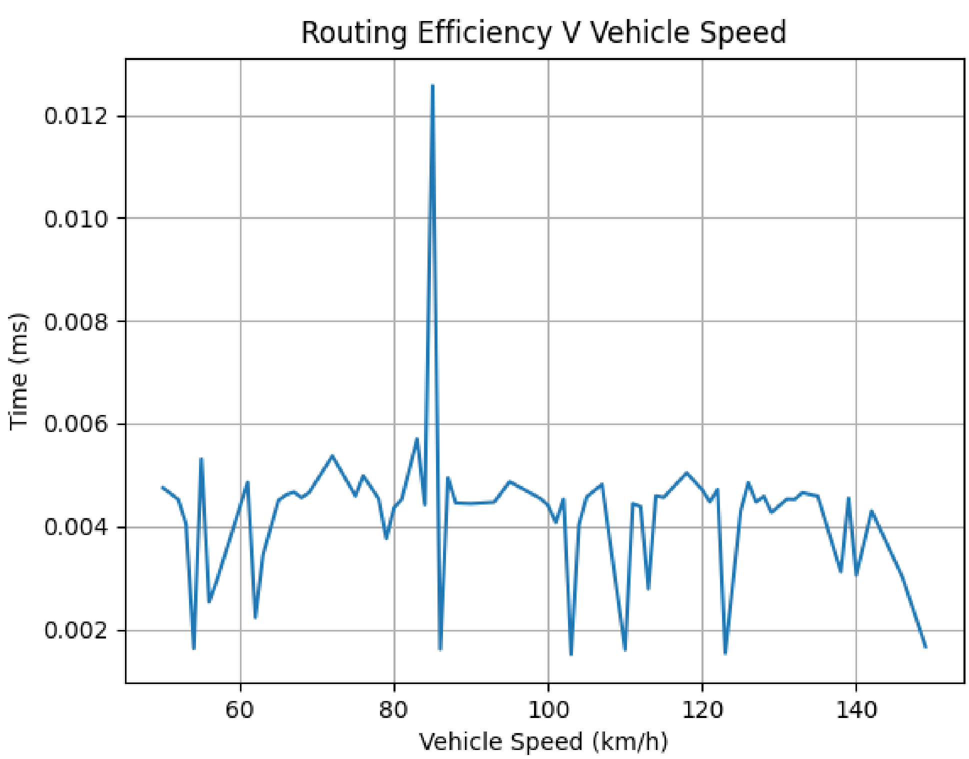


Figure 5.6: Evaluation of Routing Efficiency vs. vehicle speed

The ability of 5G gNB to transmit the ESMs efficiently contributes to effective channel utilization, which is essential with different vehicle densities and speeds. Figure 5.7 and figure 5.8 display the channel utilization percentages in the SDNCA framework, with average values of 0.25×10^{-4} and 0.5×10^{-4}, respectively. The low percentages seen in real-time simulation are indicative of ideal values, which implies that the communication between the S and SDN controller is reliable and timely. These measurements are required in this study for quick decision-making and response times. Table 5.3 shows that the relevant research has not considered this aspect.

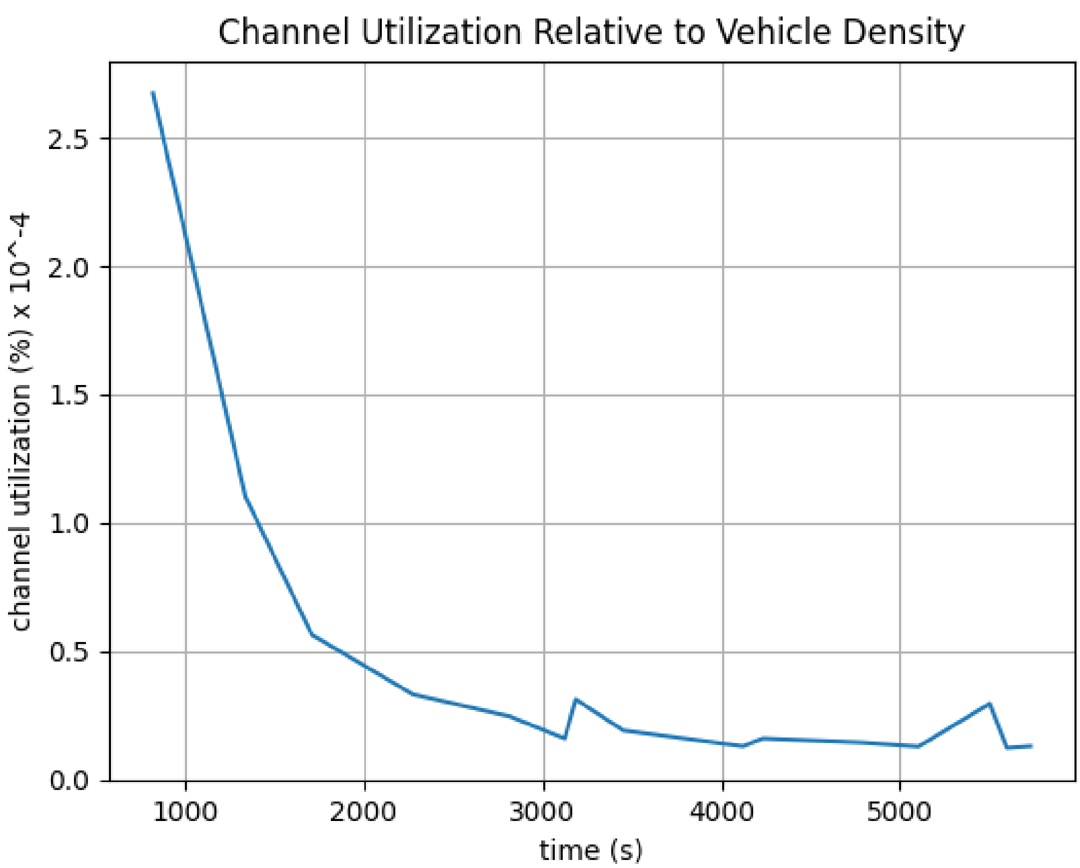


Figure 5.7: Evaluation of V2I Channel Utilization relative to vehicle density

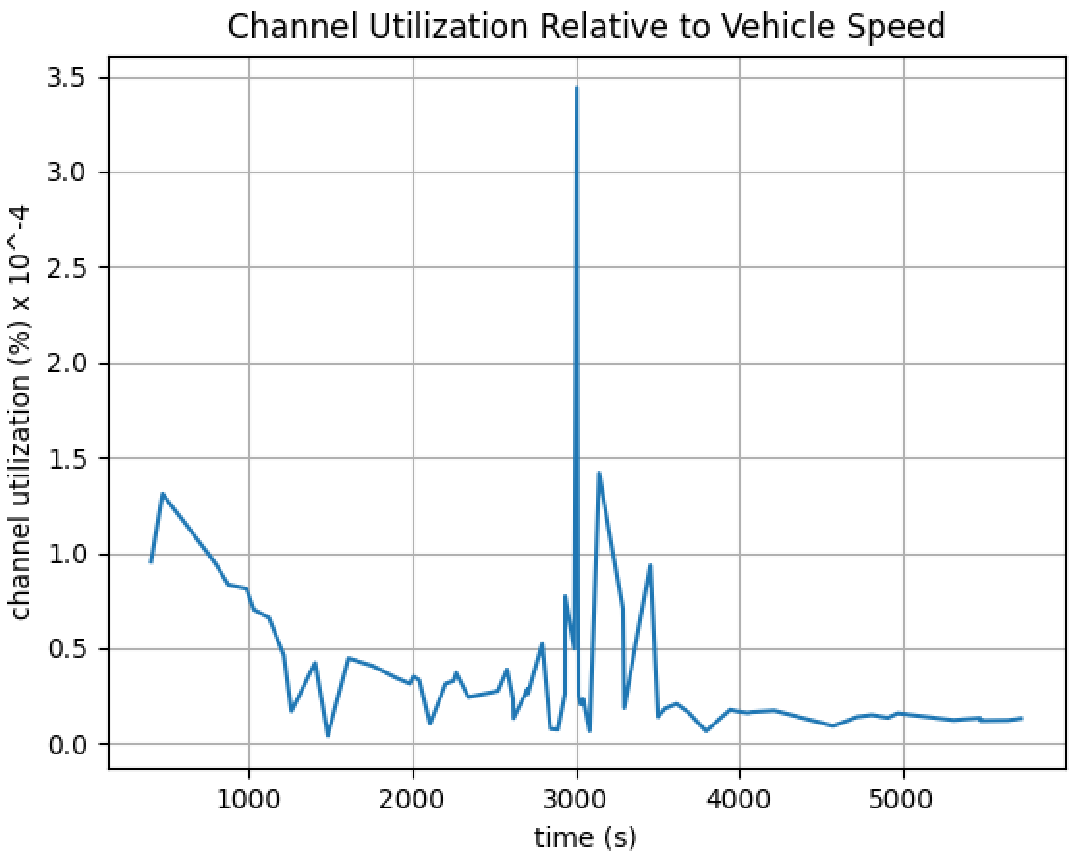


Figure 5.8: Evaluation of V2I Channel Utilization relative to vehicle speed

The specified bandwidth values of 5G gNB in the SDNCA framework determine the effective communication range for transmitting ESMs to the destination vehicles, resulting in an end-to-end communication delay of 4.5 ms in figure 5.9 and 4 ms in figure 5.10, with changing vehicle densities and speeds. The reason behind obtaining these results is due to the optimal utilization of the B in the gNB to transmit the ESM to the D. The study in (Prathiba *et al.*, 2022) mentioned in Table 5.3 has not examined the impact of the allocated bandwidth on the end-to-end delay.

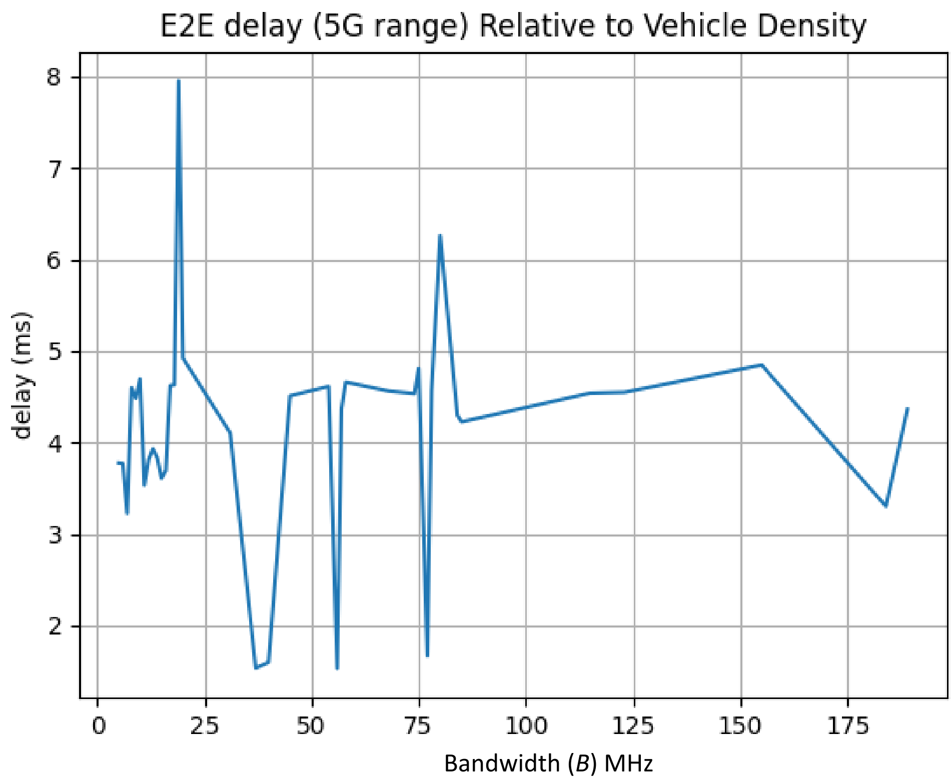


Figure 5.9: Evaluation of E2E Delay vs. transmission range of 5G (relative to vehicle density)

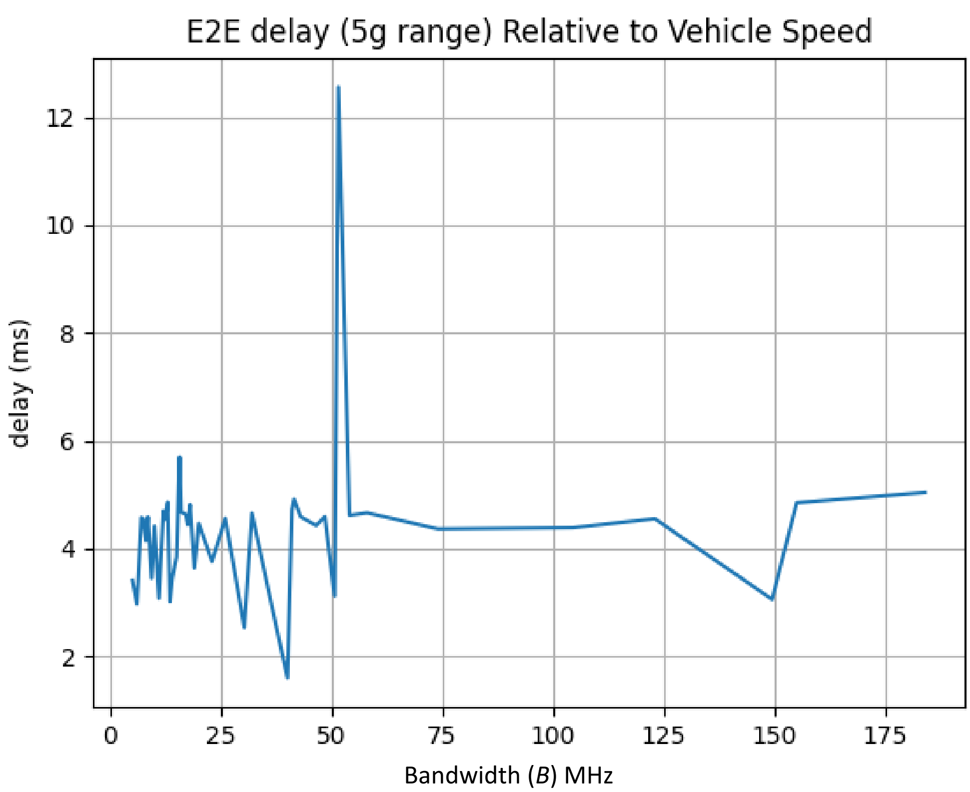


Figure 5.10: Evaluation of E2E Delay vs. transmission range of 5G (relative to vehicle speed)

Based on the given discussion and analysis, Table 5.3 presents a comparison between the study conducted by (Prathiba *et al.*, 2022) and the proposed SDNCA framework.

Table 5.3: Comparison of the SDNCA framework and related study

Research	**Evaluation Metrics for $N = 100$ vehicles/km [Average]**									
	PDR (%)		SRR (%)		RE (%) (ms)		CU ($\times 10^{-4}$) (%)		E2E Delay vs. transmission range of 5G (ms)	
	Vehicle density	Vehicle speed	Vehicle density	Vehicle speed	Vehicle density	Vehicle speed	Vehicle density	Vehicle speed	Vehicle density	Vehicle speed
(Prathiba *et al.*, 2022)	5	----	99 and 98	----	----	----	----	----	----	----
Proposed (SDNCA)	0	0	99.5	99.4	0.0050	0.0050	0.25	0.5	4.5	4

The risky distances between vehicles ($RD_{S,D}$) are directly linked to safety in the context of vehicular communication. The following figures provide an assessment of the SDNCA framework's performance in terms of SRR, RE, CR, and E2E delay. The evaluation is conducted for distances up to 30 meters between the S and D, taking into account different vehicle densities and speeds.

The observed decrease in the successful routing ratio as $RD_{S,D}$ increases is attributed to the prolonged path from the S to the destination gNB assigned by the SDN controller. The ESM traverses through several stages, starting from the S to the gNB, then through the SDN controller for decision-making, and finally reaching the destination gNB. The simulation results in figure 5.11 and figure 5.12 specify a significant impact of the $RD_{S,D}$ on the successful routing ratio. Specifically, the comparison between $RD_{S,D} = 30$m and $RD_{S,D} = 5$m reveals a notable difference in the SDNCA framework's performance. When $RD_{S,D} = 30$m, which means the S and D are poisoned 30 meters apart, the successful routing ratio is measured at 97%. However, as the $RD_{S,D}$ decreases to 5 meters, the successful routing ratio improves to an impressive 99.5%. These results assure that the SDNCA framework evaluates the successful routing ratio based on the short distances traversed by the ESMs.

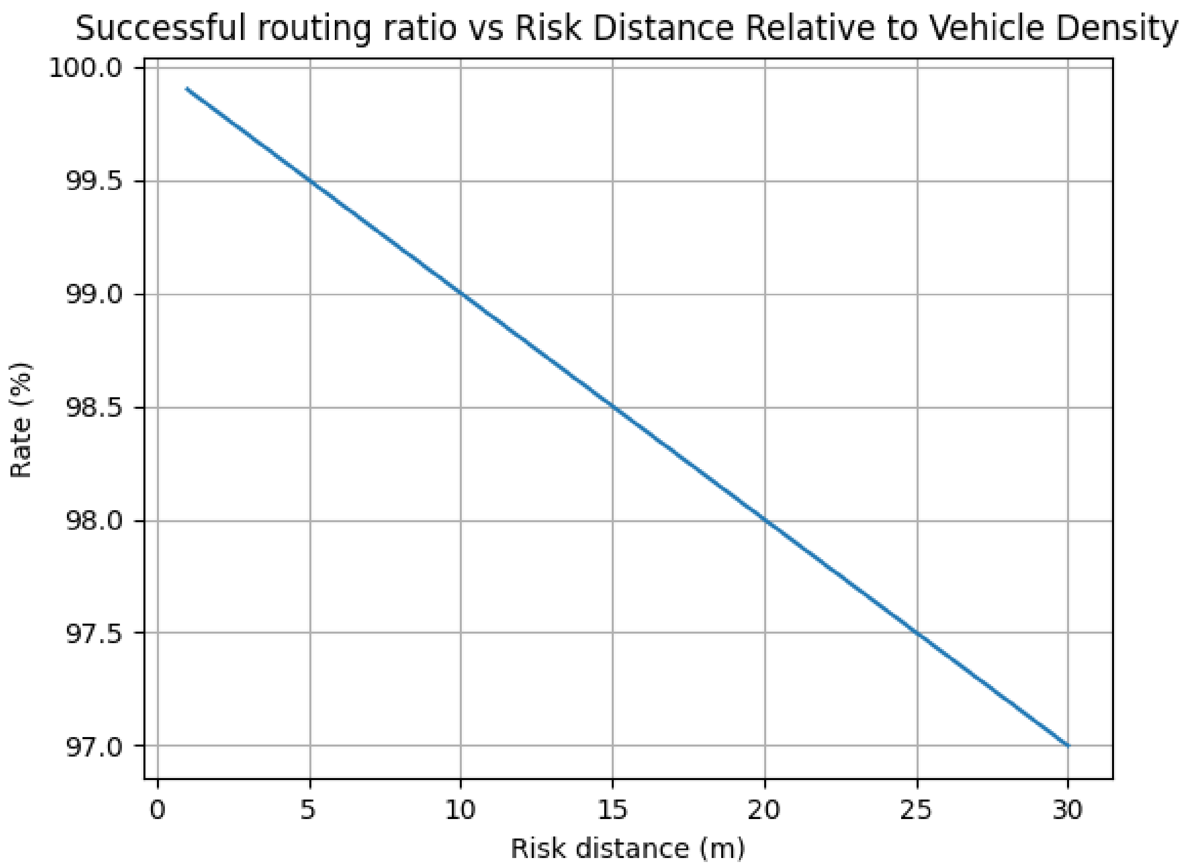


Figure 5.11: Evaluation of Successful Routing Ratio vs. $RD_{S,D}$ *(relative to vehicle density)*

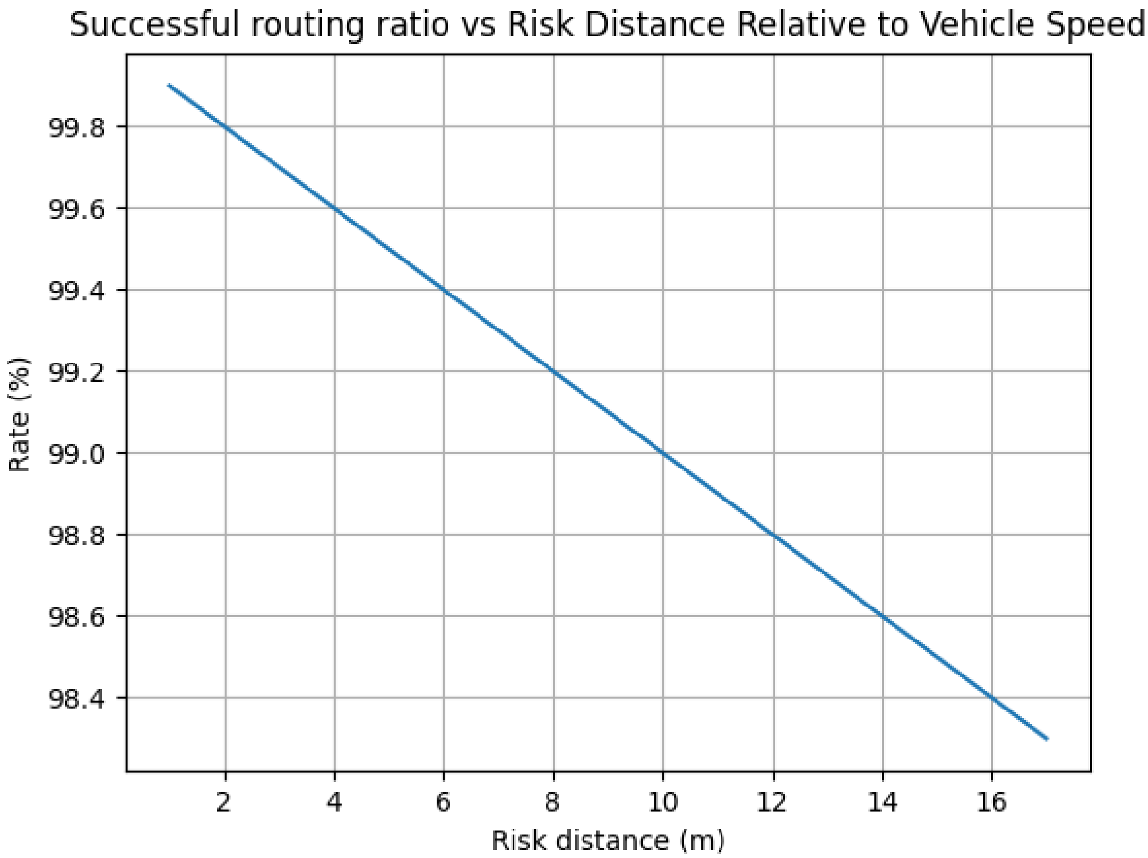


Figure 5.12: Evaluation of Successful Routing Ratio vs. $RD_{S,D}$ *(relative to vehicle speed)*

By leveraging SDN controller to prioritize shorter distances for ESM transmission, the latency induced by transmitting the ESM to the *D* has been reduced, as illustrated in figure 5.13 and figure 5.14. Figure 5.13 and figure 5.14 display the optimal values of the routing efficiency, which are 4 ms and 3.5 ms, respectively.

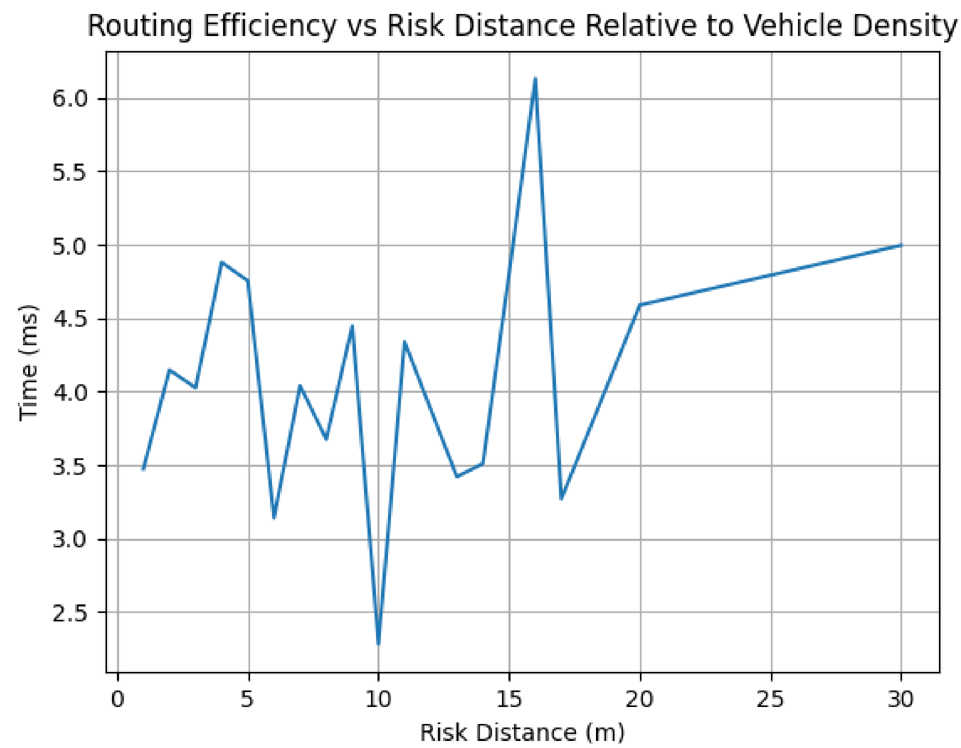


Figure 5.13: Evaluation of Routing Efficiency vs. $RD_{S,D}$ (relative to vehicle density)

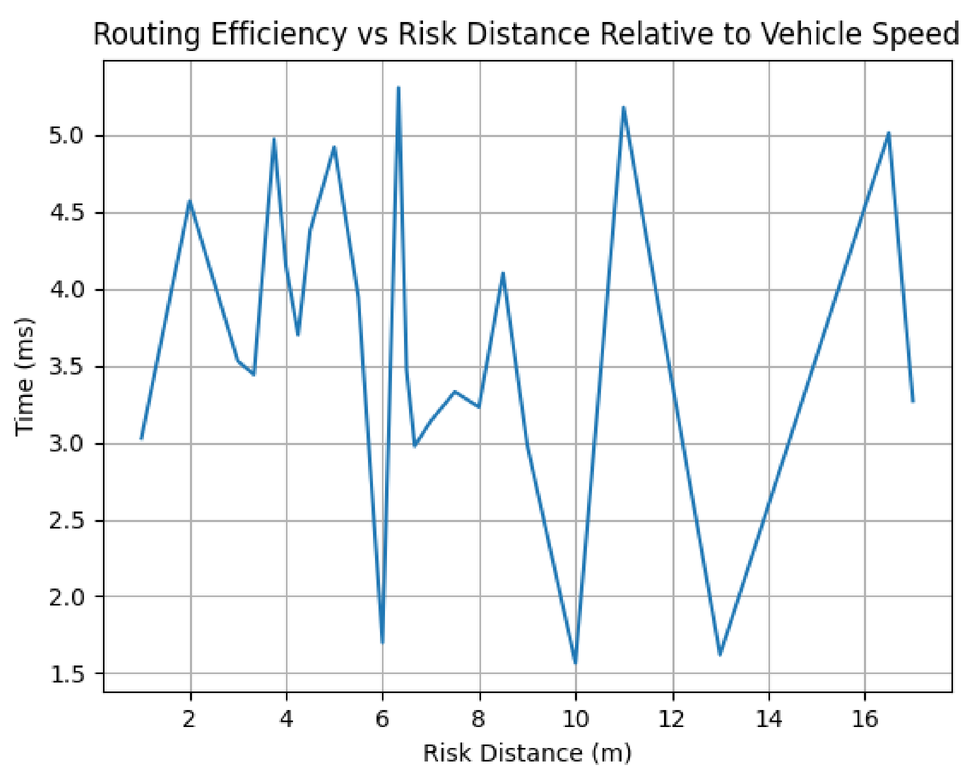


Figure 5.14: Evaluation of Routing Efficiency vs. $RD_{S,D}$ (relative to vehicle speed)

The achieved 0% collision rate of ESMs in Table 5.4 and Table 5.5 underscores the effectiveness of the SDN controller and 5G gNBs in providing reliable communication for collision avoidance. These results suggest that the implemented routing mechanism is robust in dynamically managing the network to prevent interference and collision while transmitting the ESM from the S to the D.

Table 5.4: Evaluation of CR vs. $RD_{S,D}$ (relative to vehicle density)

$\boldsymbol{RD_{S,D}}$ **(m)**	**CR**
2	0
5	0
10	0
15	0
20	0
25	0
30	0

Table 5.5: Evaluation of CR vs. $RD_{S,D}$ (relative to vehicle speed)

$\boldsymbol{RD_{S,D}}$ **(m)**	**CR**
1	0
2	0
4	0
6	0
8	0
10	0
14	0
16	0

The average end-to-end delay of 4.5 ms in figure 5.15 and figure 5.16, respectively, suggests that the SDNCA framework is capable of providing quick responses within 1–7 meters. The average end-to-end delay being consistent at 4.5 ms across different risk distances is due to the utilization of high computing resources to transmit ESMs faster based on their QoS values.

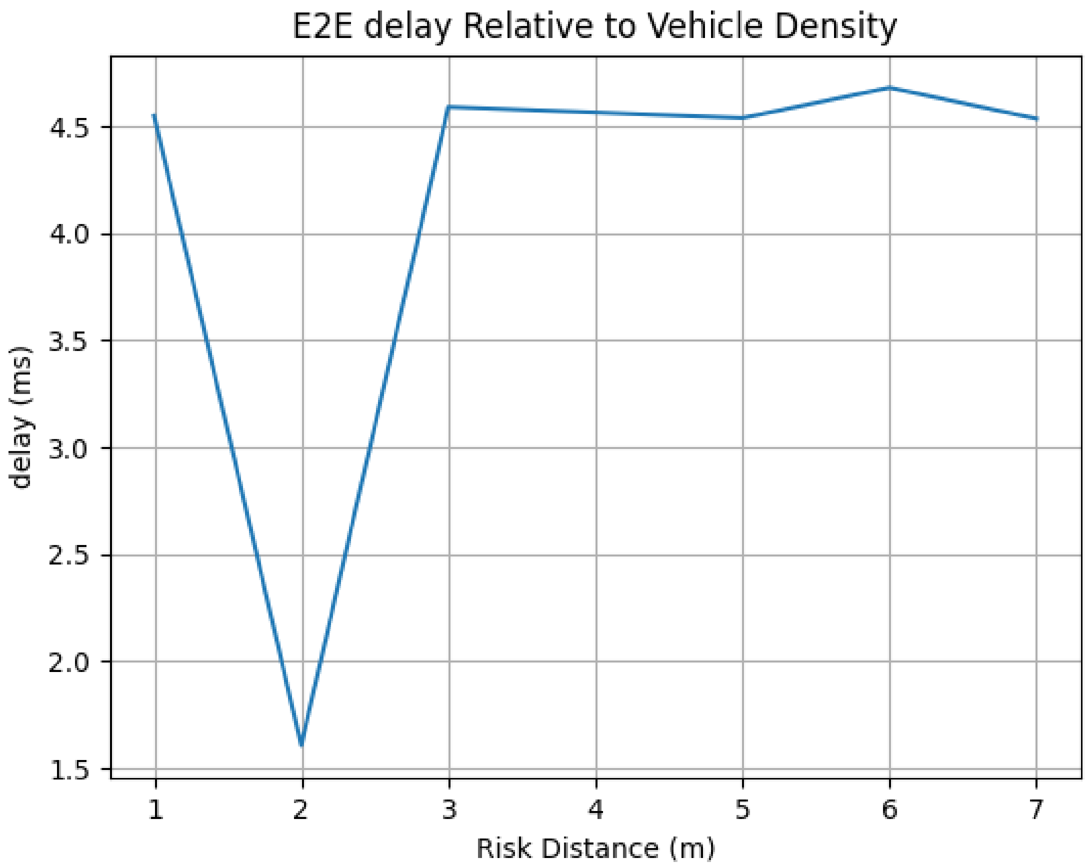


Figure 5.15: Evaluation of E2E Delay vs. $RD_{S,D}$ (relative to vehicle density)

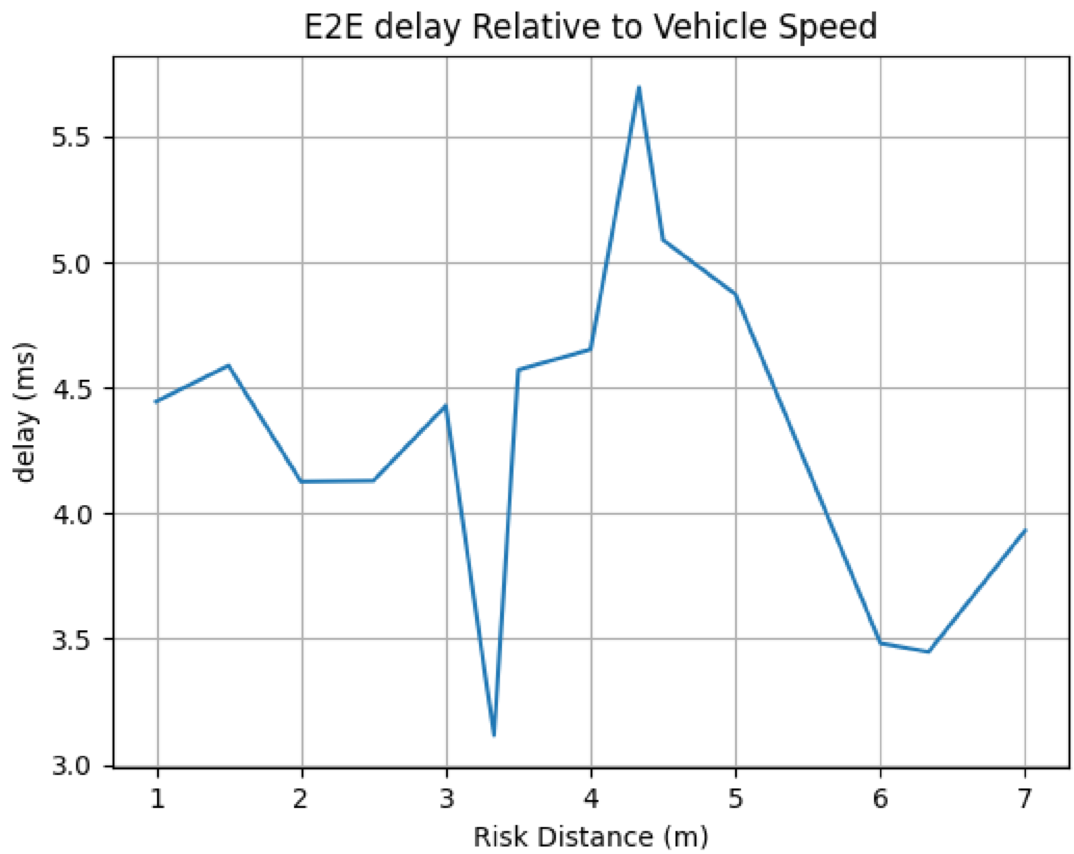


Figure 5.16: Evaluation of E2E Delay vs. $RD_{S,D}$ (relative to vehicle speed)

5.3 Summary

This chapter provides a detailed explanation of the fifth scenario that has been implemented to assess the performance of the SDNCA framework. The results of this evaluation are reported in Table 5.3, figures 5.11–5.16, Table 5.4, and Table 5.5. Based on the obtained results, the following conclusions can be drawn regarding the desired outcomes that must be reached while routing the ESM from the S to the D to keep vehicles from colliding, even when the number of vehicles and their speeds change:

1. The PDR in the SDNCA framework is consistently 0%. These results are required because routing ESMs in vehicular networks should have a PDR

of 0% to guarantee that ESMs have been received by the destination vehicles successfully. This is because the ESMs contain crucial information about vehicle actions.

2. higher values of SRR have been obtained, which ensure that the ESM travels a short distance to reach the D. This evaluation is significant since the ESMs need to cover the shortest distances to the destination vehicles.
3. Based on the observation mentioned in point 2, the SDNCA framework achieves RE averages of 0.005 ms, 4 ms, and 3.5 ms. This indicates that when the ESM is routed over the shortest distances, it takes less time to attain the D. The aspect that should be realized while routing the ESM from the S to the D.
4. The channel utilization percentages presented in the table highlight the importance of the 5G gNB in the SDNCA framework. It facilitates rapid and efficient ESM dissemination, which is essential for real-time response in emergency scenarios.
5. The choice of bandwidth can significantly influence communication performance in the SDNCA framework. The SDNCA framework finds the best balance between data capacity, delay, and overall system performance by testing and evaluating the end-to-end delay with different bandwidth values. This optimizes it for effective transmission of ESMs. Average values of 4.5 ms and 4 ms end-to-end delays are quite promising for avoiding vehicle collisions.
6. The results shown in figures 5.11-5.16, Table 5.4, and Table 5.5 indicate that the SDNCA framework can handle the varying risk distances effectively in terms of SRR, RE, CR, and E2E delay.

7. Maintaining a constant 0% packet collision rate across the simulation is crucial to ensuring seamless and reliable communication between the gNBs and destination vehicles.
8. The findings in this chapter illustrate how the SDNCA framework contributes to collision avoidance and enhanced safety in vehicular communications.

CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

6.1 Conclusions

The SDN can be a prominent technology for 5G-IoV communications, particularly for ESM transmission. This study proposes an SDNCA framework to efficiently transmit ESMs from the source vehicles to the destination vehicles and avoid vehicle collisions. The core contribution of the SDNCA is optimizing the network communication of ESMs to vehicles in terms of QoS. The SDNCA framework simulates two proposed system models. In the first and second system models, the SDNCA implements VFL algorithm, which provides the following conclusions related to research questions 1–4:

1. The proposed VFL is unaffected by the number of vehicles in terms of training accuracy, test accuracy, train loss, test loss, training latency, and test latency.
2. Desirable results are obtained when all vehicles (not some vehicles) participate in the training process.
3. The system model is stable and adaptable to the vehicular networks for any number of vehicles because it achieves load balancing according to the ESs, backbone routers, and gNBs that have been used.

Further, the research questions 5–6 have been answered through the following:

1. In the first system model, SDN algorithm is applied to calculate the QoS_{σ}, allocate the gNB_{nr_i} and gNB_{cr_i}, and select the best route to the destination vehicle. gNB algorithm then schedules the ESMs based on their priorities and configures the gNB_{nr_i} and gNB_{cr_i} of the selected gNB based on the

SDN OpenFlow control message. SDN and gNB algorithms handle each ESM independently to achieve improved V2V communication.

2. The SDNCA framework focuses on the $RD_{S,D}$ in the second system model to provide more precise analysis in terms of QoS_{λ} calculations, allocation of gNB_{nr_i} and gNB_{cr_i}, and setting up reliable and low-latency communication paths. This system model enables the achievement of collision avoidance in vehicular networks.

Finally, the SDNCA performance is validated through nine evaluation metrics, namely, Network Overhead (NO), Computational Complexity (CC), Collision Rate (CR), End-to-End (E2E) Delay, Packet (ESM) Transmission Reliability (TR), Packet Drop Ratio (PDR), Successful Routing Ratio (SRR), Routing Efficiency (RE), Channel Utilization (CU), and compared with the related study. The SDNCA framework achieves a 0% collision rate, which is an ideal value that can fulfill the stringent requirements for ESM transmission in 5G-IoV environment.

6.2 Future Research Directions

- ✓ Investigate and implement advanced model aggregation techniques to improve the accuracy and convergence speed of the proposed RS-ANN learning model.
- ✓ Develop secure aggregation methods to protect the confidentiality of individual contributions in federated learning.
- ✓ The integration of 6G technology in the SDNCA framework holds substantial promise for advancing the capabilities of vehicular communication systems. The anticipated enhancements in data rates, ultra-reliable low-latency communication (URLL), and advanced edge computing offered by 6G can significantly augment the efficiency and responsiveness of the proposed framework. Leveraging the

higher throughput of 6G can accelerate the delivery of ESMs, which is crucial for mitigating vehicular collisions. Furthermore, the emphasis on URLL in 6G aligns with the real-time requirements of safety-critical applications, presenting an opportunity to minimize communication delays. The advanced edge computing capabilities of 6G facilitate localized decision-making, further optimizing the allocation of network and computing resources within the SDNCA framework.

- ✓ Examine a scalable SDN architecture that can handle the increasing number of vehicles and their communications. This study suggests designing a more complicated network using the same proposed SDNCA framework, but on an extremely large scale. Specifically, simulating a larger network consisting of 5G or 6G with 1000 vehicles, two SDN controllers, and 20 backbone routers to enhance coverage.
- ✓ Explore sustainable and eco-friendly infrastructure solutions for deploying 5G and SDN components in the SDNCA framework.

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APPENDICES

Appendix A – Results of The Second Scenario

The simulation results presented in Table A.1 give comprehensive information on the connection of vehicles to 5G gNBs, with details such as vehicle id, cell index, vehicle frequency, gNB frequency, sector, distance, and azimuth. Each vehicle is associated with a specific gNB frequency. For example, a vehicle with id 0 is connected to a gNB with a frequency of 2.13 GHz, and so on. This frequency association is crucial for managing communication resources and ensuring proper connectivity between vehicles and 5G gNBs. The sector information indicates which sector of the site is serving the specific vehicle. Sectors are often used to divide the coverage area of a site, and each sector can serve a specific set of vehicles. For instance, a vehicle with id 1 is served by the gNB in sector 1. The "distance" parameter represents the physical distance between the vehicle and the associated gNB. The "azimuth" parameter provides the azimuth angle from the gNB to the vehicle. The combination of distance and azimuth information helps in understanding the spatial distribution of vehicles relative to their serving gNBs. Analyzing this spatial distribution is essential for optimizing cell planning, antenna beamforming, and the overall efficiency of the network.

Table A.2 provides a concise overview of vehicle application start and end times, offering useful insights into the temporal dynamics of the simulated 5G network for vehicles, along with the predicted RS_{V_i} value for each vehicle.

Table A.1: Results of the second scenario-part 2

Results of attaching UEs (vehicles) to the 5G gNBs						
Ue Id	**Cell Index**	**Ue frequency (GHz)**	**gnb frequency (GHz)**	**Sector Id**	**distance (m)**	**azimuth gnb->ue (degrees)**
0	0	2.13	2.13	0	713.257	-113.444
1	1	2.17	2.17	1	376.319	-68.2647
2	2	2.21	2.21	2	803.547	110.448
3	3	2.13	2.13	0	335.493	-129.206
4	4	2.17	2.17	1	299.431	-38.1378
5	5	2.21	2.21	2	521.172	45.1648
6	6	2.13	2.13	0	721.457	-146.386
7	7	2.17	2.17	1	591.622	-65.7942
8	8	2.21	2.21	2	1030.28	93.6672
9	9	2.13	2.13	0	233.451	-171.56
10	10	2.17	2.17	1	956.206	-45.1146
11	11	2.21	2.21	2	413.177	127.064
12	12	2.13	2.13	0	592.83	-127.075
13	13	2.17	2.17	1	188.06	-61.3911
14	14	2.21	2.21	2	518.374	93.014
15	15	2.13	2.13	0	1006.48	-147.32
16	16	2.17	2.17	1	679.933	-71.6111
17	17	2.21	2.21	2	680.365	51.1228
18	18	2.13	2.13	0	608.963	-139.106
19	19	2.17	2.17	1	495.455	-65.5914
20	20	2.21	2.21	2	547.854	67.5269
21	21	2.13	2.13	0	848.311	-146.278
22	22	2.17	2.17	1	610.09	-2.05835
23	23	2.21	2.21	2	480.485	60.6701
24	24	2.13	2.13	0	227.989	-101.463
25	25	2.17	2.17	1	545.889	-63.8433
26	26	2.21	2.21	2	728.399	69.1528
27	27	2.13	2.13	0	728.399	-165.119
28	28	2.17	2.17	1	768.138	-1.22899
29	29	2.21	2.21	2	861.886	47.1363
30	30	2.13	2.13	0	404.302	179.776
31	31	2.17	2.17	1	640.726	-38.7931
32	32	2.21	2.21	2	812.779	123.306
33	33	2.13	2.13	0	515.542	-134.687
34	34	2.17	2.17	1	597.921	-60.0048
35	35	2.21	2.21	2	791	89.4005
36	36	2.13	2.13	0	546.143	-115.92
37	37	2.17	2.17	1	326.55	-64.1379
38	38	2.21	2.21	2	725.463	115.219
39	39	2.13	2.13	0	786.442	-143.61

40	40	2.17	2.17	1	242.508	-10.591
41	41	2.21	2.21	2	506.356	61.664
42	42	2.13	2.13	0	486.631	-155.962
43	43	2.17	2.17	1	1009.45	-26.2896
44	44	2.21	2.21	2	758.913	98.2372
45	45	2.13	2.13	0	298.473	-154.342
46	46	2.17	2.17	1	862.23	12.6117
47	47	2.21	2.21	2	351.179	66.945
48	48	2.13	2.13	0	620.867	173.142
49	49	2.17	2.17	1	621.549	-36.4901
50	50	2.21	2.21	2	816.958	126.517
51	51	2.13	2.13	0	503.408	-156.397
52	52	2.17	2.17	1	296.415	1.29328
53	53	2.21	2.21	2	298.622	59.6451
54	54	2.13	2.13	0	363.894	-168.181
55	55	2.17	2.17	1	604.621	-35.3358
56	56	2.21	2.21	2	732.343	136.315
57	0	2.13	2.13	0	474.213	-115.636
58	1	2.17	2.17	1	294.06	-45.7994
59	2	2.21	2.21	2	811.997	117.539
60	3	2.13	2.13	0	255.607	-114.007
61	4	2.17	2.17	1	426.6	-41.4144
62	5	2.21	2.21	2	552.863	101.765
63	6	2.13	2.13	0	620.584	-121.169
64	7	2.17	2.17	1	346.576	-66.8329
65	8	2.21	2.21	2	505.98	46.9964
66	9	2.13	2.13	0	473.935	-113.621
67	10	2.17	2.17	1	773.927	-53.8191
68	11	2.21	2.21	2	506.672	70.0063
69	12	2.13	2.13	0	585.745	167.475
70	13	2.17	2.17	1	167.888	-62.752
71	14	2.21	2.21	2	773.196	56.1584
72	15	2.13	2.13	0	191.523	-127.942
73	16	2.17	2.17	1	677.446	11.1177
74	17	2.21	2.21	2	914.488	98.9005
75	18	2.13	2.13	0	326.85	179.705
76	19	2.17	2.17	1	796.595	-56.1609
77	20	2.21	2.21	2	800.828	123.257
78	21	2.13	2.13	0	556.632	179.477
79	22	2.17	2.17	1	357.339	-17.2512
80	23	2.21	2.21	2	920.37	75.8827
81	24	2.13	2.13	0	559.461	-117.865
82	25	2.17	2.17	1	768.297	-0.922931
83	26	2.21	2.21	2	976.993	73.7236
84	27	2.13	2.13	0	300.141	-130.423

85	28	2.17	2.17	1	306.557	17.5357
86	29	2.21	2.21	2	561.605	96.0885
87	30	2.13	2.13	0	268.027	156.726
88	31	2.17	2.17	1	130.969	-11.3385
89	32	2.21	2.21	2	305.816	129.777
90	33	2.13	2.13	0	615.423	176.378
91	34	2.17	2.17	1	744.83	-11.2479
92	35	2.21	2.21	2	637.774	48.7927
93	36	2.13	2.13	0	531.038	-131.008
94	37	2.17	2.17	1	652.326	-28.1634
95	38	2.21	2.21	2	362.496	76.3309
96	39	2.13	2.13	0	144.676	-157.869
97	40	2.17	2.17	1	378.702	-61.0939
98	41	2.21	2.21	2	915.061	77.7757
99	42	2.13	2.13	0	869.986	-140.196
100	43	2.17	2.17	1	599.817	-30.032
101	44	2.21	2.21	2	303.74	131.831
102	45	2.13	2.13	0	970.278	-169.609
103	46	2.17	2.17	1	633.521	-32.4293
104	47	2.21	2.21	2	478.468	132.091
105	48	2.13	2.13	0	702.97	171.939
106	49	2.17	2.17	1	296.032	2.50757
107	50	2.21	2.21	2	489.336	132.83
108	51	2.13	2.13	0	495.439	-141.827
109	52	2.17	2.17	1	606.244	-28.2843
110	53	2.21	2.21	2	706.002	112.394
111	54	2.13	2.13	0	467.337	-156.293
112	55	2.17	2.17	1	654.819	0.846854
113	56	2.21	2.21	2	567.391	115.06

Table A.2: Results of the second scenario-part 3

Results of application start and end times						**Results of RS_{V_i}**
Ue Id	**Cell Id**	**Sector Id**	**Site Id**	**Start time of the application**	**End time of the application**	**Predicted Risk**
0	0	0	0	+435ms	+1435ms	3
1	1	1	0	+434ms	+1434ms	4
2	2	2	0	+431ms	+1431ms	5
3	3	0	1	+444ms	+1444ms	5
4	4	1	1	+425ms	+1425ms	4
5	5	2	1	+407ms	+1407ms	5
6	6	0	2	+406ms	+1406ms	2
7	7	1	2	+410ms	+1410ms	5
8	8	2	2	+407ms	+1407ms	6
9	9	0	3	+406ms	+1406ms	6
10	10	1	3	+415ms	+1415ms	7
11	11	2	3	+429ms	+1429ms	1
12	12	0	4	+442ms	+1442ms	5
13	13	1	4	+411ms	+1411ms	5
14	14	2	4	+407ms	+1407ms	2
15	15	0	5	+415ms	+1415ms	7
16	16	1	5	+403ms	+1403ms	5
17	17	2	5	+418ms	+1418ms	6
18	18	0	6	+443ms	+1443ms	5
19	19	1	6	+444ms	+1444ms	9
20	20	2	6	+417ms	+1417ms	2
21	21	0	7	+403ms	+1403ms	4
22	22	1	7	+448ms	+1448ms	5
23	23	2	7	+437ms	+1437ms	6
24	24	0	8	+422ms	+1422ms	5
25	25	1	8	+416ms	+1416ms	5
26	26	2	8	+441ms	+1441ms	6
27	27	0	9	+413ms	+1413ms	5
28	28	1	9	+412ms	+1412ms	7
29	29	2	9	+442ms	+1442ms	5
30	30	0	10	+436ms	+1436ms	9
31	31	1	10	+402ms	+1402ms	4
32	32	2	10	+407ms	+1407ms	6
33	33	0	11	+426ms	+1426ms	6
34	34	1	11	+415ms	+1415ms	8
35	35	2	11	+419ms	+1419ms	6
36	36	0	12	+429ms	+1429ms	2
37	37	1	12	+417ms	+1417ms	7
38	38	2	12	+407ms	+1407ms	4

39	39	0	13	+400ms	+1400ms	6
40	40	1	13	+427ms	+1427ms	6
41	41	2	13	+401ms	+1401ms	6
42	42	0	14	+409ms	+1409ms	5
43	43	1	14	+414ms	+1414ms	5
44	44	2	14	+432ms	+1432ms	9
45	45	0	15	+415ms	+1415ms	6
46	46	1	15	+422ms	+1422ms	5
47	47	2	15	+439ms	+1439ms	2
48	48	0	16	+402ms	+1402ms	8
49	49	1	16	+425ms	+1425ms	2
50	50	2	16	+409ms	+1409ms	4
51	51	0	17	+427ms	+1427ms	7
52	52	1	17	+440ms	+1440ms	4
53	53	2	17	+407ms	+1407ms	4
54	54	0	18	+447ms	+1447ms	5
55	55	1	18	+434ms	+1434ms	2
56	56	2	18	+438ms	+1438ms	5
57	0	0	0	+424ms	+1424ms	2
58	1	1	0	+439ms	+1439ms	2
59	2	2	0	+404ms	+1404ms	4
60	3	0	1	+406ms	+1406ms	3
61	4	1	1	+410ms	+1410ms	5
62	5	2	1	+432ms	+1432ms	2
63	6	0	2	+407ms	+1407ms	3
64	7	1	2	+410ms	+1410ms	3
65	8	2	2	+436ms	+1436ms	3
66	9	0	3	+418ms	+1418ms	1
67	10	1	3	+414ms	+1414ms	5
68	11	2	3	+446ms	+1446ms	3
69	12	0	4	+427ms	+1427ms	5
70	13	1	4	+437ms	+1437ms	5
71	14	2	4	+429ms	+1429ms	5
72	15	0	5	+444ms	+1444ms	5
73	16	1	5	+414ms	+1414ms	7
74	17	2	5	+405ms	+1405ms	4
75	18	0	6	+440ms	+1440ms	7
76	19	1	6	+437ms	+1437ms	4
77	20	2	6	+420ms	+1420ms	5
78	21	0	7	+426ms	+1426ms	8
79	22	1	7	+428ms	+1428ms	6
80	23	2	7	+423ms	+1423ms	5
81	24	0	8	+410ms	+1410ms	6
82	25	1	8	+405ms	+1405ms	1
83	26	2	8	+400ms	+1400ms	5

84	27	0	9	+411ms	+1411ms	3
85	28	1	9	+414ms	+1414ms	7
86	29	2	9	+437ms	+1437ms	4
87	30	0	10	+416ms	+1416ms	4
88	31	1	10	+421ms	+1421ms	5
89	32	2	10	+402ms	+1402ms	2
90	33	0	11	+407ms	+1407ms	5
91	34	1	11	+402ms	+1402ms	7
92	35	2	11	+406ms	+1406ms	4
93	36	0	12	+426ms	+1426ms	6
94	37	1	12	+442ms	+1442ms	2
95	38	2	12	+400ms	+1400ms	2
96	39	0	13	+438ms	+1438ms	4
97	40	1	13	+409ms	+1409ms	5
98	41	2	13	+443ms	+1443ms	6
99	42	0	14	+423ms	+1423ms	5
100	43	1	14	+442ms	+1442ms	5
101	44	2	14	+404ms	+1404ms	6
102	45	0	15	+447ms	+1447ms	5
103	46	1	15	+441ms	+1441ms	7
104	47	2	15	+427ms	+1427ms	5
105	48	0	16	+436ms	+1436ms	9
106	49	1	16	+404ms	+1404ms	5
107	50	2	16	+436ms	+1436ms	2
108	51	0	17	+404ms	+1404ms	5
109	52	1	17	+419ms	+1419ms	7
110	53	2	17	+430ms	+1430ms	4
111	54	0	18	+400ms	+1400ms	6
112	55	1	18	+402ms	+1402ms	2
113	56	2	18	+411ms	+1411ms	9

پوختە.

تەکنەلۆژیای نوێی نەوەی پێنجەم (5G) چەندین سوود پێشکەش بە ئینتەرنێتی ئۆتۆمبێلەکان (IoV) دەکات، وەک ئاستی کەمتری دواکەوتن، و پەیوەندی بەیکبەستنەوەی جێگیرتر، و پاڵپشتیکردن بۆ جوڵەی خێراتر. بەڵام خۆبەدوورگرتن لە پێکدادانی ئۆتۆمبێل لە (IoV) ئەرکێکی قورسە بەهۆی بڵاوکردنەوەی پەیامەکانی سەلامەتی فریاگوزاری (ESMs) بەبێ دواکەوتن و پەیڕەوکردنی مەرجە تووندەکانی متمانەپێکردن. بۆ چارەسەرکردنی ئەو پرسە، ئەو توێژینەوەیە پێشنیاری چوارچێوەیەکی بەرنامەکاری نوێ و زیرەک دەکات کە بریتیە لە چوارچێوەکاری پێناسەکراو بە سۆفتوێر و بنەمادار لەسەر تۆڕبەندی ئینتەرنێتی بۆ خۆبەدوورگرتن لە پێکدادان (SDNCA) کە لەڕێگەی تەکنەلۆژیای (5G) یەوە پاڵپشتی دەکرێت. ئەو چوارچێوەکاریە پێشنیارکراوەی SDNCA دوو مۆدێلی سیستەم بەکاردەهێنێت، کە هەریەکەیان لە سێ ئەلگۆریتمی پێشنیارکراو پێکدێت. لە مۆدێلی یەکەمی سیستەمەکەدا، بە پلەی یەکەم، SDNCA ئەلگۆریتمی فێربوونی یەکانگیری ئۆتۆمبێل (VFL) دەخاتەگەڕ کە بە وردی مەودای سەختی مەترسیەکان بەردەم هەر ئۆتۆمبێلێک دەخەمڵێنێت لە ڕێگەی ڕاهێنانی مۆدێلی پێشنیارکراوی سەختی مەترسی-تۆڕی دەماری دەستکرد (RS-ANN) وبە جێبەجێکردنی فێربوونی یەکانگیر لە نێوان ئۆتۆمبێلەکان. ئەو چوارچێوەکاریە پێشنیارکراوەی SDNCA ئەلگۆریتمەکەی SDN بەکاردەهێنێت بۆ گەیشتن بە سێ ئامانجی سەرەکی. یەکەمیان بریتیە لە حیسابکردنی کوالیتی خزمەتگوزاری (QoS)ی پەیامەکانی فریاگوزاری (ESM). دووەمیان بریتیە لەوەی بە شێوەیەکی داینامیکی هەردوو تۆڕی 5G و سەرچاوە حساباتیەکان بۆ سێ تۆڕی مەجازی (VN) تەرخان دەکات. سێیەمیشیان بریتیە لەوەی کە وێستگەی بنەڕەتی 5Gی گونجاوی (gNB) هەڵدەبژێرێت بۆ ڕێڕەوکردنی پەیامەکانی فریاگوزاری (ESM) بۆ ئۆتۆمبێلی شوێنی مەبەست. بۆ دڵنیابوون لە پێشکەشکردنی خزمەتگوزاریەکی کاریگەر بۆ هەر پەیامێکی فریاگوزاری (ESM)، (SDNCA) ئەلگۆریتمی (gNB) دەخاتەگەڕ لەسەر (gNB)ی دەستنیشانکراو بۆ دانانی خشتەی کاتی بۆ ناردنی پەیامەکانی فریاگوزاری (ESM) بە لەبەرچاوگرتنی ئەولەویەتەکانیان، و سەرچاوەکانی تۆڕی (5G) و سەرچاوە حساباتیەکان لەسەر بنەمای پەیامی کۆنترۆڵکردنی (OpenFlow) کە لە (SDN) وەردەگیرێت ڕێکدەخات.

جێبەجێکردنی مۆدێلی سیستەمی دووەم ئەلگۆریتمەکانی VFL ، SDNو gNB یەکدەخات، کە گرنگی بە مەودای مەترسی نێوان ئۆتۆمبێلەکانی سەرچاوە و شوێنی مەبەست دەدات. ئامانجی مۆدێلی سیستەمی

دووەم دڵنیابوونە لە گواستنەوەی سەرکەوتووی پەیامەکانی فریاگوزاری (ESM) لەو سیناریۆیانەدا کاتێک کە مەودای مەترسییەکانی نێوان ئۆتۆمبێلەکان لەبەرچاو دەگیرێت.

هەردوو مۆدێلی سیستەمەکە بە بەکارهێنانی سێ ئامرازی هاوشێوەکردن (سمیولەیشن) جێبەجێ کراون: هاوشێوەکاری تۆڕ (NS3)، زمانی بەرنامەسازی پایتۆن و هاوشێوەکاری تۆڕی مینینێت. ئەنجامەکانی هاوشێوەکردنی کاتی ڕاستەقینە هەڵسەنگاندنی چوارچێوەکاری SDNCA لە دوو بەش نیشان دەدەن، بە بەراورد لەگەڵ لێکۆڵینەوە پەیوەندیدارەکانی ئێستادا. بەشی یەکەم هەڵسەنگاندن بۆ ئەدای چوارچێوەکاری SDNCA دەکات بە گۆڕینی چڕی و خێرایی ئۆتۆمبێلەکان. ئەنجامانەکانیش بریتین لە 17% و 20% باری زیاد لەسەر تۆڕ (NO)، 17% و 20% ئاڵۆزی حیساباتی (CC)، 0% ڕێژەی پێکدادان (CR)، 18 میلی چرکە دواکەوتنی لایەک بۆ لایەکی تر (E2E)، 89%–90% متمانەپێکراوی گواستنەوەی پاکێتی پەیامەکانی (TR) (ESM)، 99.5% و 99.4% ڕێژەی سەرکەوتووانەی ڕێڕەو (SRR)، 0.0050 میلی چرکە کارایی ڕێڕەو (RE)، 0% ڕێژەی دابەزینی پاکێت (PDR)، 10^{-4} × 0.25 و 10^{-4} × 0.5 بەکارهێنانی کەناڵ (CU)، و 4.5 میلی چرکە و 4 میلی چرکە دواکەوتنی لایەک بۆ لایەکی تر (E2E) لەگەڵ بەها جیاوازەکانی باندویزی تەرخانکراو. بەشی دووەم هەڵسەنگاندن بۆ ئەدای چوارچێوەکاری SDNCA دەکات لە مەودای نێوان ئۆتۆمبێلەکانی سەرچاوە و شوێنی مەبەستدا کە دەگاتە 30 مەتر، بە لەبەرچاوگرتنی چڕی و خێرایی جیاوازی ئۆتۆمبێلەکان. ئەنجامانەکانیش بریتین لە 97%– 99.5% و 98.4%– 99.8% SRR، 4 میلی چرکە و 3.5 میلی چرکە RE، 0% CR، و 4.5 میلی چرکە دواکەوتنی E2E.