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Enhancing V2X communication systems for cooperative perception: road users safety

Chaima Zoghلامي

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THÈSE

**En vue de l'obtention du
DOCTORAT DE L'UNIVERSITÉ DE TOULOUSE
Délivré par l'Université Toulouse 3 - Paul Sabatier**

**Présentée et soutenue par
Chaima ZOGHLAMI**

Le 13 octobre 2023

**Amélioration des systèmes de communication V2X pour la
perception coopérative : Sécurité des usagers de la route**

Ecole doctorale : **EDMITT - Ecole Doctorale Mathématiques, Informatique et
Télécommunications de Toulouse**

Spécialité : **Informatique et Télécommunications**

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Abstract

This thesis presents an in-depth investigation into cooperative safety systems in the context of smart cities and intelligent transportation systems. The research aims to enhance network performance through the use of network-assisted cooperative perception, considering the constraints of Vulnerable Road Users (VRU) protection applications. It addresses challenges in improving VRU safety and explores innovative approaches by leveraging a wide range of available data, capabilities of connected and autonomous vehicles, and advanced intelligent infrastructures. The initial phase involves a comprehensive review of existing communication standards, communication architectures, and recent research projects incorporating VRU safety use cases, providing insights into the current state of the field and identifying gaps and opportunities for exploration. We used prediction to dynamically collect awareness messages for VRU collision avoidance and improve localization accuracy while efficiently managing the signalling overhead. Additionally, we also investigated the importance of adapting the frequency of sending awareness messages, considering the surrounding context information, by giving an enhanced version of the existing standard. Lastly, we present an opportunistic approach for message collection that benefits from the variety of the existing types of cooperative messages by jointly adapting their type, size, and transmission frequency.

Keywords: cooperative safety systems, intelligent transportation systems, smart cities, vulnerable road users, 5G network, collision detection, multi-access edge com-

puting (MEC), frequency adaptation, resource optimization, trajectory predictions, reinforcement learning.

Résumé

Cette thèse explore le domaine des systèmes de sécurité coopératifs dans les systèmes de transport intelligents et les villes intelligentes. L'objectif est d'améliorer la sécurité des usagers vulnérables de la route en utilisant la sécurité coopérative assistée par le réseau. La recherche aborde les défis liés à cette amélioration et propose des approches innovantes en exploitant les données disponibles, les véhicules connectés et autonomes, ainsi que les infrastructures intelligentes.

La thèse commence par une revue des normes de communication existantes et des projets de recherche récents sur la sécurité des usagers vulnérables de la route. Cette revue identifie les lacunes et les opportunités à explorer. En se basant sur cette revue, la thèse détaille l'architecture de communication nécessaire, en se concentrant sur le réseau 5G.

Une contribution clé de cette thèse est le développement d'un système de détection de collision assistée par un réseau défini par logiciel (SDN). Ce système prédit les dangers de la route en collectant et en traitant des messages spécifiques des usagers de la route, permettant ainsi la détection des risques de collision. Une solution est proposée pour optimiser l'utilisation des ressources en adaptant la fréquence des messages en fonction des niveaux de risque et des contraintes d'énergie.

Une autre contribution importante concerne l'optimisation de la sélection des ressources dans le système de sécurité coopératif. Les véhicules et les usagers vulnérables de la route peuvent adapter la fréquence des messages en fonction des variations de

localisation et des informations contextuelles. Cette approche réduit la signalisation inutile du réseau tout en préservant l'énergie des appareils connectés.

En conclusion, cette thèse fournit une exploration approfondie du domaine des systèmes de sécurité coopératifs pour les usagers vulnérables de la route. Elle propose des solutions innovantes pour améliorer la sécurité dans les villes intelligentes en utilisant des architectures de communication optimales, des schémas adaptatifs et opportunistes, des prédictions de trajectoire et l'apprentissage par renforcement.

Mots clés : systèmes de sécurité coopératifs, transport intelligent, villes intelligentes, usagers vulnérables de la route, réseau 5G, détection de collision, calcul en bordure multi-accès (MEC), adaptation de fréquence, optimisation des ressources, prédictions de trajectoire, apprentissage par renforcement.

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[2] Chaima Zoghlami, Rahim Kacimi, Riadh Dhaou: 5G-enabled V2X communications for vulnerable road users safety applications: a review. *Wirel. Networks* 29(3): 1237-1267

[3] Chaima Zoghlami, Rahim Kacimi, Riadh Dhaou: Dynamics of Cooperative and Vulnerable Awareness Messages in V2X Safety Applications. *IWCMC 2022*: 853-858

[4] Chaima Zoghlami, Rahim Kacimi, Riadh Dhaou: A Study on Dynamic Collection of Cooperative Awareness Messages in V2X Safety Applications. *CCNC 2022*: 723-724

Submitted:

[5] Chaima Zoghlami, Rahim Kacimi, Riadh Dhaou: RL-based Adaptive Collection of Cooperative Messages in V2X Networks. Submitted article.

Abbreviations

3GPP 3rd Generation Partnership Project

5GAA 5G Automotive Association

5GCAR 5G Communication Automotive Research and Innovation

ADAS Advanced Driver Assistance Systems

AF Application Function

AI Artificial Intelligence

AMF Access and Mobility Management Function

AP Application Plane

API Application Programming Interface

ASN1 Abstract Syntax Notation 1

AUSF Authentication Server Function

BS Base Station

BSM Basic Safety Message

CAM Cooperative Awareness Message

- CAV** Connected Autonomous Vehicles
- CNN** Convolution Neural Network
- C-ITS** Cooperative-ITS
- C-V2X** Cellular-V2X
- CP** Control Plane
- CPM** Cooperative Perception Messages
- DP** Data Plane
- CPU** Central Processing Unit
- DCC** Decentralized Congestion Control
- DENM** Decentralized Environmental Notification Messages
- DSRC** Dedicated Short Range Communication
- EKF** Extended Kalman Filter
- eMBB** enhanced Mobile Broadband
- ETSI** European Telecommunications Standards Institute
- GNSS** Global Navigation Satellite System
- GPS** Global Positioning System
- HD** High Definition
- IEEE** Institute of Electrical and Electronics Engineers
- ITS** Intelligent Transportation Systems

KF	Kalman Filter
KPI	Key Performance Indicator
LDM	Local Dynamic Map
LTE	Long Term Evolution
LOS	Line Of Sight
MEC	Multi-Access Edge Computing
mMTC	massive Machine Type Communications
NEF	Network Exposure Function
NBS	Neighbouring Based Scheme
NFV	Network Function Virtualization
NSSF	Network Slice Selection Function
NLOS	Non Line Of Sight
NR	New Radio
NR-V2X	New Radio-V2X
ns3	Network Simulator 3
NWDAF	Network Data Analytic Function
OBU	On Board Unit
PSM	Personal Safety Message
PDU	Packet Data Unit

QoS	Quality of Service
RAN	Radio Access Network
RAT	Radio Access Technology
RL	Reinforcement Learning
RSU	Road Side Unit
SAE	Society of Automotive Engineers
SDN	Software Defined Networks
SMF	Session Management Function
SPS	Semi Persisting Scheduling
SSP	Service Specific Permissions
SUMO	Simulation of Urban Mobility
TBS	Terrestrial Beacon Systems
UE	User Equipement
UDM	Unified Data Management
UDP	User Datagram Protocol
UPF	User Plane Function
uRLLC	ultra-Reliable Low-Latency Communication
Uu	UMTS Air Interface
UPS	Paul Sabatier University

V2I Vehicle-to-Infrastructure

V2P Vehicle-to-Pedestrian

V2N Vehicle-to-Network

V2V Vehicle-to-Vehicle

V2VRU Vehicle-to-Vulnerable Road User

V2X Vehicle-to-Everything

VAM VRU Awareness Message

VANET Vehicular Ad hoc Networks

VLC Visual Light Communication

VRU Vulnerable Road Users

Introduction

1.1 Context

1.1.1 Intelligent transport system (ITS)

In the context of Intelligent Transportation Systems (ITS), the current research focuses on enhancing the safety of Vulnerable Road Users (VRU) through the development of technologies that mitigate accidents caused by poor visibility. VRU include pedestrians, cyclists, individuals with disabilities, motorcyclists, and others. Accidents involving VRU in urban areas are often severe, and they can occur due to various factors such as distractions, both on the part of VRU using smartphones, and drivers failing to detect their presence due to factors like age, alcohol, fatigue, etc.

To address this challenge, research and standardization actors propose the utilization of Vehicle-to-Everything (V2X) communications. V2X refers to the exchange of cooperative messages wirelessly between vehicles, infrastructure, pedestrians and other entities. By equipping vehicles with onboard sensors and Radio Access Technology (RAT), they can perceive their surroundings using perceptual features and communicate with other users to share information and build a cooperative knowl-

edge of the network.

The goal is to leverage **V2X** communications to improve the safety of **VRU** by enabling vehicles and infrastructure to exchange vital information about their presence, location, and intentions. This real-time exchange of information helps to alert drivers to the presence of **VRU**, even in situations where visibility is poor, reducing the risk of accidents and ultimately saving lives.

By combining sensor technology, wireless communication, and intelligent algorithms, the research aims to create an environment where **VRU** are better protected on urban roads, minimizing the occurrence of tragic incidents caused by limited visibility and various factors affecting both **VRU** and drivers.

1.1.2 Perception based ITS applications

Cooperative perception in the smart city enhances the collective intelligence of vehicles and infrastructure, leading to safer and more efficient transportation systems. Through collaboration and information exchange, vehicles can establish a comprehensive and accurate perception of the surrounding environment. This cooperative perception enables several applications that have been classified by the 5G Automotive Association (**5GAA**) [6] and by the 5G Communication Automotive Research and Innovation (**5GCAR**) [7; 8; 9; 10] according to the application service and their technical requirements as follows:

Cooperative maneuver: vehicles share their driving intentions to negotiate the planned trajectories and efficiently coordinate them, to increase awareness and avoid collisions.

Examples of cooperative maneuver include lane merging, lane changing, convoy driving, and cooperative intersection management, which rely on coordinated actions between vehicles to enhance driver safety and optimize road capacity.

Autonomous navigation: based on the collected data of the cooperative perception and other sources of information, an intelligent map is updated with more accurate context information. This updated map is then distributed among other vehicles depending on their location. The real-time High Definition (**HD**) map is used to increase road users' awareness of their environment, helping them to avoid accidents and react quickly in emergency situations. Additionally, it aids in optimizing traffic flow by selecting the best trajectory to the destination.

Remote driving: in this use case, the vehicle utilizes sensors, an **HD** map, and infrastructure information to remotely control its actuators (steering wheel, brake, and throttle) through wireless communication. Examples of remote driving include remote parking, public transport, and other scenarios where a remote server controls the vehicles.

Collective perception: vehicles exchange raw or processed data with other connected road users and infrastructure, merging them to extract useful information and build collective awareness. This includes relative position information, see-through or Bird's eye view at an intersection, and 3D video composition.

Cooperative safety: vehicles exchange data about the detected road elements (using sensors, cameras, positioning system, communication system, etc.) directly, with other road users, or via the infrastructure. On Board Unit (**OBU**) in vehicles, Road Side Unit (**RSU**) and edge/remote servers are responsible for processing the received data, extracting useful information and making decisions. If a danger is detected, alert messages are generated. The vehicle can then avoid the danger by reducing speed, changing trajectories, or braking.

In this thesis, our research focuses on exploring the specific usefulness and benefits offered by the cooperative safety and cooperative perception use case classes, with a particular emphasis on the protection of **VRU**. We can harness the capabilities

of establishing robust communication networks by leveraging advanced technologies such as Multi-Access Edge Computing ([MEC](#))-enabled infrastructures and Connected Autonomous Vehicles ([CAV](#)). This enables real-time information exchange and rapid response to potential dangers.

Moreover, the cooperative perception and safety classes enhance situational awareness by opportunistically collecting necessary data from various sources, including Vehicle-to-Vehicle ([V2V](#)), Vehicle-to-Infrastructure ([V2I](#)), Vehicle-to-Network ([V2N](#)) and Vehicle-to-Vulnerable Road User ([V2VRU](#)) communication. By merging the advantages of perception and data sharing through communication, we can address the limitations of traditional sensor or vision-based perception systems, which may struggle to accurately detect and respond to complex urban environments, varying weather conditions, and unexpected scenarios.

In the next section, we will explore the analysis of recent collision statistics in France, with a specific emphasis on accidents involving [VRU](#), which serves as our primary motivation for studying VRU protection in this thesis. By examining real-world data and evaluating the effectiveness of cooperative safety measures, we aim to gain valuable insights into the impact of these technologies on reducing accidents and improving [VRU](#) safety.

1.1.3 Vulnerable Road Users Safety

In France, more than three thousand people have lost their lives in road accidents in the year 2021 [[11](#)]. In Metropolitan France alone, approximately 53,540 instances of traffic-related bodily injuries were reported. Out of these incidents, nearly two thousand nine hundred and fifty accidents occurred within a month after an accident, with four hundred fourteen being pedestrians, and around five-hundred eighty-six being riders, drivers, motorcyclists in different parts of the country. Minors aged up

to seventeen years old as well as elderly individuals aged sixty-five and above also fell victims to fatal crashes on roads. Furthermore, reports from local authorities indicate that even individuals operating personal mobility vehicles like e-scooters or commercial trucks faced fatalities.

As shown in the pie chart 1.1, approximately 50% of deadly crashes are related to passenger cars, while vulnerable users account for almost 40% of all fatal accidents.

These statistics clearly demonstrate the need to propose new solutions to ensure the safety of VRU. Throughout this thesis, the safeguarding of VRU is achieved through a communication-based cooperative perception system, designed to detect hazardous events. The primary requirement of our system is the ability to detect potential collisions well in advance using the exchanged data, to provide enough time for both vehicle drivers and VRU to take appropriate actions to ensure their safety.

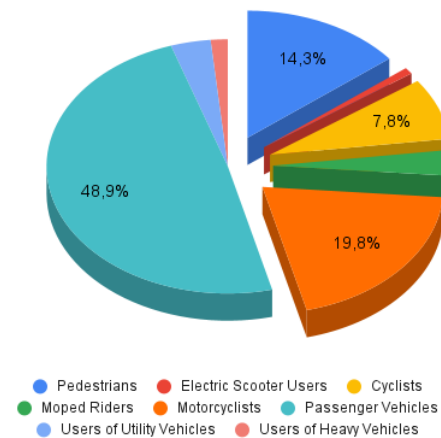


Figure 1.1: Distribution of Accident Deaths in France by User Class.

Vision-based perception, relying solely on cameras and visual inputs, faces limitations in adverse conditions such as low visibility at night, unfavorable weather, and obstructed views. This leads to difficulties in detecting objects, with visibility-related problems being responsible for approximately 20% of fatal accidents between 2019 and 2021 based on the same statistics resource. Additionally, the penetration level of sensor-equipped vehicles is not high enough for reliable object detection. This leads to consider solving the visibility and Non Line Of Sight (NLOS) situations through taking advantage of communication architectures.

Hence, in this thesis, we propose a network-based solution to overcome these challenges, where we consider perception as the collection of a wide range of data to understand the network in its entirety, enabling us to gain a holistic understanding of the network dynamics and components. Moreover, we acknowledge the inherent advantages of network-based perception and propose the utilization of Cooperative Awareness Message (**CAM**), VRU Awareness Message (**VAM**), Decentralized Environmental Notification Messages (**DENM**) and Cooperative Perception Messages (**CPM**) to gather comprehensive information regarding the dynamics of the vehicular network.

1.2 Motivation

According to the statistics cited in [11], visibility and traffic conditions play a crucial role in road safety. They indicate that a significant portion of accidents occurs during peak hours when the volume of road users is high, making the identification of potentially hazardous situations more challenging. Furthermore, fatal accidents tend to occur under circumstances where vehicles are operating at high speeds, further complicating the detection of **VRU**, particularly in adverse conditions such as nighttime or inclement weather characterized by rain or reduced visibility. Despite regulatory efforts, traffic accidents remain as causes for the loss of many lives. Individuals who are not directly involved in these incidents may also endure lasting physical and psychological effects, among other possible outcomes. Consequently, through this thesis, we consider vulnerable road users as active participants using smartphones and connected devices to help mitigate road fatalities. Instead of being a source of distraction, these devices have the potential to alert users about possible accidents. Currently, various approaches exist to enhance **VRU** protection, including the use of Lidar and camera technologies. However, we choose communication-based technology over vision-based

technology (camera) due to the limitations of vision-based approaches in adverse weather conditions, **NLOS** and low-light situations. Communication-based technology relies on **V2V**, **V2I**, and **V2VRU** communication to improve situational awareness and provide timely warnings. This approach, known as Network-Centric, utilizes a communication system that collects and distributes real-time data to all connected vehicles and infrastructure. In this thesis, the use of a centralized approach is justified due to the increased reliability and consistency of the communication system, the global vision of the network, and a solution to **RAT** heterogeneity problems, resulting in a higher level of safety for all **VRU** on the road. Although several research works have been conducted to improve the performance of these networks or propose new mechanisms, certain aspects such as scalability, heterogeneity of vehicular networks, energy consumption when considering **VRU** as active participants, complexity of collision detection algorithms, and reliability and latency in relation to application requirements, remain relatively unexplored.

1.3 Methodology

1.3.1 Identified Issues

Vehicular network exhibits heterogeneity characterized by variations in velocity, mobility types, and radio access technologies among vehicles and **VRU**. Moreover, the effectiveness of safety applications aimed at protecting vulnerable road users may be compromised by the scalability issue. This refers to the system capacity to maintain communication despite an increasing number of vehicles and **VRU**, which poses a challenge. The frequency of cooperative messages generations may be inadequate for collision risk notification systems that follow the standard. For instance, a single message transmission every second can be appropriate in lower-risk areas, whereas a

transmission every 100 *ms* can be unnecessary in low risk situations. Smartphones, due to their limited battery energy consumption and inherent limitations, are generally unable of achieving high location-sampling rates necessary for precise measurements. Furthermore, with a high concentration of vehicles and vulnerable road users, the traffic safety architecture faces the challenge of network congestion when all road users sending their position and other information to edge servers through wireless communication channels at a high rate. This continuous stream of data transmission results in network overload. Consequently, congestion can lead to transmission errors and significantly drain the energy of **VRU** devices. Indeed, an increased overhead can hinder the timely dissemination of safety messages and reduce the effectiveness of safety applications.

1.3.2 Holistic approach

To tackle the difficulties in ensuring safety for **VRU**, a holistic approach was adopted to address the issue from a wider angle. The initial phase consisted of examining the communication messages employed within **VRU** applications, which were exploited to satisfy particular needs like minimized latency and maximum energy efficiency while guaranteeing high reliability. Furthermore, the heterogeneous nature of the network and the computing placement was taken into account by selecting an architecture that supports multi-radio access technologies and allows seamless integration with different communication protocols.

Furthermore, in order to improve the accuracy of collision detection algorithms, an effort was made to provide up-to-date messages. This involved adapting the frequency of the communication messages, respecting the data freshness. By continuously updating the messages with the latest information, the collision detection algorithm could respond more effectively to dynamic road conditions, increasing the overall

safety of **VRU**. The diagram depicted in figure 1.2 illustrates the integral role that our contributions have played in addressing several issues simultaneously. Notably, the first contribution, represented by a circled number one, primarily focused on resolving the accuracy problem using the prediction. This contribution also addressed other concerns, such as reliability and latency. Our approach to tackling the research topic involved examining it from various angles through an extensive review (circle number 4) that we referred to. The choice of the architecture is present in the four contributions, and it aims to solve the problem of message collection and collision avoidance algorithm computing placement, in addition to solving the heterogeneity of road users and their **RAT**. By embracing this holistic approach, the **VRU** safety application was able to address the challenges posed by communication messages, latency, reliability, energy consumption, and heterogeneity. It provided not only a robust and reliable communication framework, but also enhanced the accuracy of collision detection algorithms by leveraging real-time data. This comprehensive solution aimed to improve the overall safety application **VRU** in an increasingly complex and interconnected **V2X** transportation environment.

1.3.3 Process Validation

During the thesis, the process validation phase involved the utilization of various tools and techniques. Simulation played a crucial role, with the Simulation of Urban Mobility (**SUMO**) simulator [12] being employed for generating realistic mobility traffic scenarios based on OpenStreetMap data. Additionally, the Network Simulator 3 (**ns3**) [13] was utilized to simulate and evaluate vehicular networks' protocols, while the **ms-van3t** framework [14] facilitated the analysis of vehicular communication and networking aspects. Python and C++ programming language was utilized in conjunction with automation scripts to streamline and optimize simulation workflows.

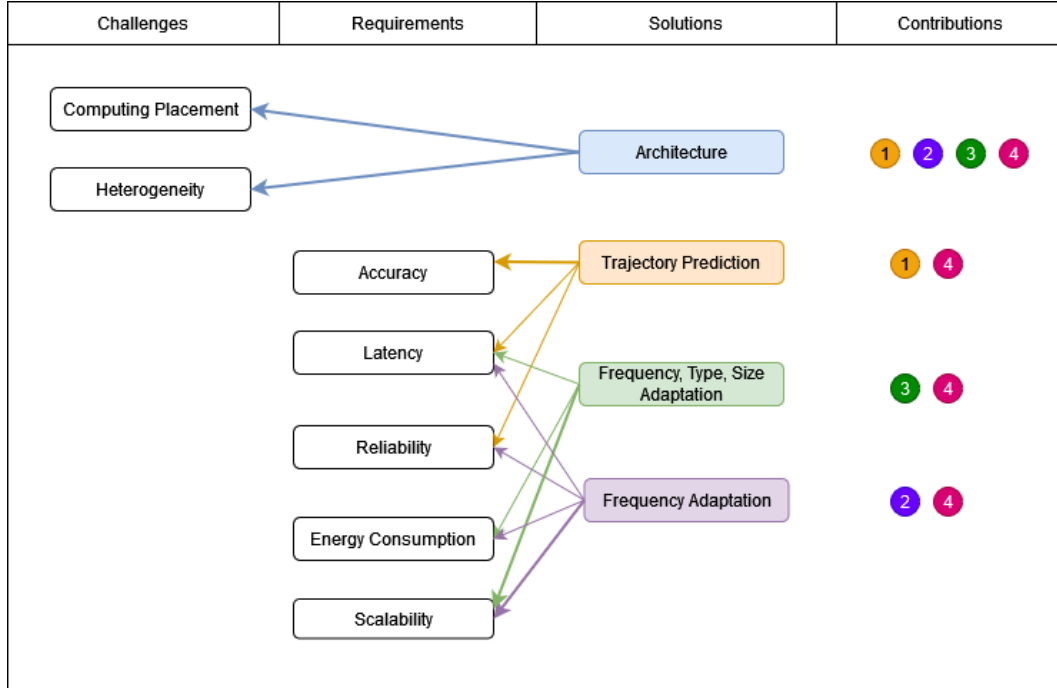


Figure 1.2: Diagram of contributions.



Moreover, to enhance the learning process, the use of the Grid5000 [15] super calculator provided valuable computational resources for executing complex simulations and data analysis tasks. These tools and resources collectively supported the thorough validation process of the research findings, ensuring their reliability and applicability in real-world vehicular environments.

1.4 Thesis contributions

This thesis provides three main contribution with a comprehensive literature review, critically examining existing works, identifying their limitations and providing a comprehensive analysis. Each part is dealing with a crucial problem for vehicular networks and providing answers to the raised challenges.

The initial phase of the research involves a thorough review [2] of existing com-

munication standards and recent research projects that incorporate the VRU safety use case. This literature review provides insights into the current state of the domain and identifies gaps and opportunities for further exploration. Building upon the literature review, the thesis proceeds to detail the required communication architecture, specifically discussing the placement of functions within a 5G network environment. Chapter 2 and 3 serve as important components within the manuscript since they facilitate the comprehension of key notions.

Chapter 4 focuses on a significant contribution of this thesis, which involves the development of a collision detection system aided by the implementation of a Software-Defined Network [3]. This system predicts road hazards by collecting and processing specific messages from road users, enabling the detection of collision risks. To enhance the accuracy of trajectory prediction and optimize resource utilization, a solution is proposed that allows vehicles and VRU (e.g, pedestrians, cyclists) to intelligently adapt the frequency of awareness messages, considering risk levels and energy consumption constraints. Simulation results demonstrate the effectiveness of frequency adaptation in improving energy consumption and network signalling without compromising trajectory prediction accuracy and collision detection reliability.

Chapter 5 delves into another contribution of our research, which focuses on the optimization of resource selection within the cooperative safety system. By considering quality of service and energy consumption constraints, vehicles and VRU can efficiently adapt the frequency of awareness messages based on not only dynamic localization variations but also contextual environmental information. This approach enhances the current version of the standard and reduces unnecessary network signalling while conserving the energy of connected VRU devices. Additionally, the thesis investigates the impact of adaptation on safety application constrains in terms of reliability and latency, revealing promising gains in network and application-related

metrics with optimal message periodicity configurations.

Furthermore, a novel Q-learning technique is introduced in chapter 6 to enhance the selection of cooperative message types, sizes, and frequencies. Leveraging the diversity of existing messages in vehicular networks, this methodology determines the most suitable message type with appropriate size while adjusting its transmission frequency based on the environmental context. Beyond mitigating network overload and reducing simultaneous message transmission, the proposed method can result in significant energy savings when applied to VRU identified by CAV.

In conclusion, this thesis contributes to the field of cooperative safety systems for VRU by providing an in-depth exploration of the relevant literature, proposing innovative solutions, and evaluating their performance through extensive simulations. A key point of emphasis in our study was the use of communication-based perception to build the collective knowledge of the network. The research outcomes contribute to improve VRU safety in smart cities in a holistic approach that entails identifying optimal architectures, employing adaptive and opportunistic schemes, making predictions and integrating artificial intelligence. Furthermore, these outcomes establish a foundation for potential breakthroughs in this area of research, which will be discussed at the end of each contribution chapters and in the future perspectives outlined in the final chapter 7.

Context and preliminaries

2.1 Introduction

As many technological contexts, the [ITS](#) benefits from a large panel of communications standards and constantly brings out new application use cases. We present in this chapter the recent projects and studies considering a [VRU](#) safety use case. Then, we introduce the general context where we present the communication standards and technologies. Finally, we explore the safety application system based on the use of communication messages.

2.1.1 Projects and Studies

In this thesis, we delve into various research projects and studies to examine their focus and accomplishments, specifically exploring their relevance to the protection of [VRU](#). These international initiatives have primarily centred around [V2X](#) services and architectures, aiming to enhance the safety of transportation systems. The insights gained from these projects and studies have played a significant role in advancing standardization efforts and developing comprehensive end-to-end solutions for intelligent

transportation systems.

By analysing their outcomes, we identified potential areas for improvement and proposed avenues for further enhancement in this field [2]. For instance, the PROSPECT [16] and InDeV [17] projects studied VRU scenarios to understand the causes of the accidents. PROSPECT provided testing in realistic traffic scenarios. However, it relied on sensing without communication when considering the VRU as a passive actor. The vehicle, equipped with sensors, actively takes necessary actions in risky situations. TIMON project [18] provided a unified cloud-based platform to process data intelligently for real-time VRU protection through smartphone applications. The project considered hybrid communication technologies (802.11p and Long Term Evolution (LTE)); however, the integration of 5G is lacking. Similarly, the XCYCLE project [19; 20] was based on the use of 802.11p technology, which no longer responds to the new requirements of today's needs. Moreover, the project considered only studying one type of VRU (cyclists). Transmitting positioning data to an external server can raise security and privacy problems not explored by the projects mentioned above. 5GCAR [7; 8; 9], a H2020 European project started in 2017, proposed a 5G system architecture, providing enhancements to optimize the network and to meet the service requirements. VRU detection is handled by combining data from their connected devices with vehicle onboard sensor readings and the communication system.

5GinFIRE [21] and 5G-Transformer [22; 23; 24] supported different communication technologies in centralized and decentralized architectures. Throughout merging sensing with communication data, 5G-Routes [25], 5G-Croco [26], and 5G-Heart [27] projects enhanced VRU safety by anticipating potential risks. BiDiMoVe [28] increased the safety and efficiency of road traffic by providing a test field which prevents cyclists and pedestrians from colliding with buses. CSCRS [29] investigated VRU road

fatalities, applied Artificial Intelligence (AI) to improve Vehicle-to-Pedestrian (V2P) interactions, analysed data to examine VRU injuries, and proposed and evaluated safe systems approaches. In Europe, [30] focused on modelling driver behaviour during pedestrian-overtaking manoeuvres on rural roads. Another study conducted in the USA [31] evaluated collision avoidance systems for low-speed autonomous shuttles using V2P communication. Similarly, an analysis of fatally injured pedestrians' data [32] aimed to identify crash characteristics and propose countermeasures. SAKURA project, in Japan [33; 34], provides scenario generation and traffic data analysis and acquisition. It focuses on autonomous driving services and VRU safety. 5G OPEN ROAD [35] enhances the safety of high-risk exposed areas such as intersections and decreases traffic congestion through real-life experiments. Table 2.1 provides more details on the aforementioned projects. While the cited projects approached VRU protection from various perspectives, there remains a need to delve deeper into the automation level of vehicles and the adoption rate of CAV. This exploration not only presents an opportunity to harness the intelligence of cars but also to effectively utilize existing messages and infrastructure architectures, leveraging communication opportunistically to enhance network performance and improve the effectiveness of related applications.

2.2 Standards and regulations

2.2.1 The European strategy towards cooperative, connected, and automated mobility ETSI C-ITS

The European Telecommunications Standards Institute (ETSI) working group is responsible for supporting regulations and developing Cooperative-ITS (C-ITS) systems' technical standards. The ETSI-ITS defines reference architectures, V2X com-

Table 2.1: List of projects implicated in VRU safety application.

Project	Coverage	Reference	Use case scenario	Technology	Contribution
PROSPECT	2015-2018	[16]	VRU protection: pedestrians and cyclists	–	Developed the next generation active safety systems to protect VRU by improving VRU sensing and situational analysis, as well as enhancing vehicle control strategies. Test in realistic traffic scenarios.
InDev	2015-2018	[17]	VRU protection: pedestrians and cyclists	–	Provided a better understanding of road accident causes and their costs, while focusing on vulnerable road users such as pedestrians and cyclists.
TIMON	2015-2018	[18]	Cooperative real-time VRU and vehicles safety prediction	802.11p, LTE	Proposed a cloud-based platform using the road users data and V2X hybrid communications, then processing it with AI to provide real-time services to all the users through a smartphone application.
XCYCLE	2015-2018	[19; 20]	Bicycle interaction with vehicles at intersections. Cyclists approaching traffic signals.	802.11p	Developed technologies improving active and passive detection of cyclists, as well as cooperative systems to inform both drivers and cyclists of a hazard at intersections.
5GCAR	2017-2019	[7; 8; 9]	VRU protection: road user detection	5G	Proposed a 5G system architecture providing enhancements to optimize the network and to meet the service requirements. VRU detection is handled by combining data from their connected devices with vehicle on-board sensor readings and the communication system.
5GinFIRE	2017-2019	[21]	VRU protection	802.11p, LTE, 5G	Developed an open source Management and Orchestration 5G NFV-enabled platform (MANO) to support different technologies and critical safety requirements.
5G-Transformer	2017-2019	[22; 23; 24]	Pedestrian Collision Avoidance	802.11p, LTE, 5G	Developed virtualized 5G network for uR-RLC services, a prototype 5G RAN orchestrator, 5G network slicing, NFV, and MEC integration mechanisms, connected cars, and traffic flow control.
BiDiMoVe	2018-2021	[28]	Cyclists and Pedestrians protection	ITS-5G	Increase the safety and efficiency of road traffic by providing a test field that prevents cyclists and pedestrians from colliding with buses.
5G-Croco	2018-2021	[26]	Anticipated Cooperative Collision Avoidance (ACCA)	5G	Extended the ITS architecture using Cellular infrastructure and Interoperability as well as C-ITS Security areas.
5G-ACIA	2018-2022	[36]	Support of Functional Safety	5G	The project aims to implement functional safety as a native network service to determine the target safety provisioning.
CSCRS	2018-2022	[29]	VRU protection	–	The Collaborative Sciences Center for Road Safety provides numerous projects regarding VRU safety systems: (Investigating VRU road fatalities, applying AI to improve V2P interactions, analyzing data to examine VRU injuries, proposing and evaluating safe systems approaches, etc.)
5G-HEART	2019-2022	[27]	Smart junctions and network assisted cooperative collision avoidance	5G	Provide 5G uRLLC with data fusion of detected objects so that the vehicles can anticipate what is ahead and react in real-time to avoid the collision.
5G-ROUTES	2020-2024	[25]	Sensing Driving: Vulnerable road user collision avoidance	5G	Enhance the VRU safety using sensor gathered information and communication exchanged data between VRU and vehicles to warn them in advance against collision risks.
SAKURA	2018-2025	[33; 34]	V2VRU interactions to support the development of AV.	–	The project provides scenario generation and traffic data analysis and acquisition. It focuses on autonomous driving services and VRU safety.
5G OPEN ROAD	2022-2024	[35]	VRU protection	5G	Enhance the safety of high-risk exposed areas such as intersections and decrease the traffic congestion through real-life experiments

munication technologies, and studies on **ITS** use cases such as cooperative road safety traffic efficiency, etc. More specifically, the **ETSI-ITS** release two addresses **VRU** protection use-case [37].

The **ETSI** is a partner in the 3rd Generation Partnership Project (**3GPP**), where it helps to study and develop mobile communications. In the United States, the Society of Automotive Engineers (**SAE**) is responsible for developing and updating standards to advance automotive engineering [38]. Despite the **SAE** International and **ETSI** have different names for **ITS** awareness messages, their function may be the same.

2.2.2 IEEE 802.11p

The 802.11p is the first Wi-Fi based standard specifically designed for vehicular communications [39]. It works in the licensed **ITS** band of 5.9 GHz (5.85–5.925 GHz). Institute of Electrical and Electronics Engineers (**IEEE**) 802.11p supports mobility and dynamic topology of the vehicular network by reducing the association time between communicating nodes. To this aim, it is considered as the best candidate in Vehicular Ad hoc Networks (**VANET**) while allowing **V2V** and **V2I** communications.

The **ITS-G5** in Europe [40] is a radio access technology based on the **IEEE** 802.11p standard that enable **V2X** communication, and it is called Dedicated Short Range Communication (**DSRC**) in the United States. It guarantees privileged access for critical applications by differentiating channel access according to the application type and the priority level of the messages sent between **ITS-G5** stations (vehicles and **RSU**) in a purely distributed network operating without a coordinator. Further, the **ITS-G5** provides new features as the Decentralized Congestion Control (**DCC**) mechanism to control the network load. The messages transmission is based on Carrier-Sense Multiple Access with Collision Avoidance (**CSMA/CA**) algorithm, where only one frame can be transmitted at the time [41]. To support technological advancements and **V2X**

requirements, 802.11p is followed by its successor 802.11bd. The latter presents physical layer enhancements to improve the throughput and the transmission range while guaranteeing the interoperability with legacy 802.11p [39]. 802.11bd can certainly improve **VRU** safety applications.

2.2.3 3GPP standards

In addition to defining use cases for **V2V** and **V2I** communication, **3GPP** also investigates **V2P** communications for **VRU** safety [42]. The key features of **3GPP** use cases are centered on Cellular-V2X (**C-V2X**). They cover the settings of the transmission periodicity of cooperative safety messages, warnings for the driver and the **VRU**, the definition of end-to-end latency, and the reliability requirements. For instance, releases 14 and 15 studied the **LTE** support of **V2X** services such as road safety via infrastructure where servers and **RSU** generate traffic safety messages for road users and warn the pedestrians against hazardous events in **NLOS** scenarios. **3GPP** worked on ultra-Reliable Low-Latency Communication (**uRLLC**) to meet the stringent reliability and latency requirements of critical use cases [43]. In release 14, **3GPP** have defined two types of **V2V** resource reservation for **C-V2X**: (i) *mode 3* that requires the cellular coverage where the resource are allocated by the eNB, and (ii) *mode 4* where vehicles select autonomously their resources using Semi Persisting Scheduling (**SPS**) scheme, independently of cellular infrastructure. Further, in **C-V2X** vehicles communicate through two interfaces: (i) *PC5 interface* used for side-link **V2V** direct communication and (ii) *Uu interface* used by vehicles to communicate with eNB to request transmission resources on PC5 channel. In release 15, the group introduces enhancements to support 5G-**V2X** safety (e.g., autonomous driving, platooning, etc.) and non-safety services (e.g., high data rate comfort services and map updating). Further, in release 16 they introduced New Radio-V2X (**NR-V2X**) and physical layer

improvements to fulfil more rigorous 5G Quality of Service (QoS) requirements and support interoperability with multiple RAT (e.g., 3GPP RAT: LTE-V2X, NR-V2X, and non-3GPP RAT: ITS-G5, DSRC).

Undoubtedly, these standards significantly contributed to the format definition of the messages and harmonized the specifications for each use-case and set requirements for the upcoming ITS.

2.3 ETSI protocol stack

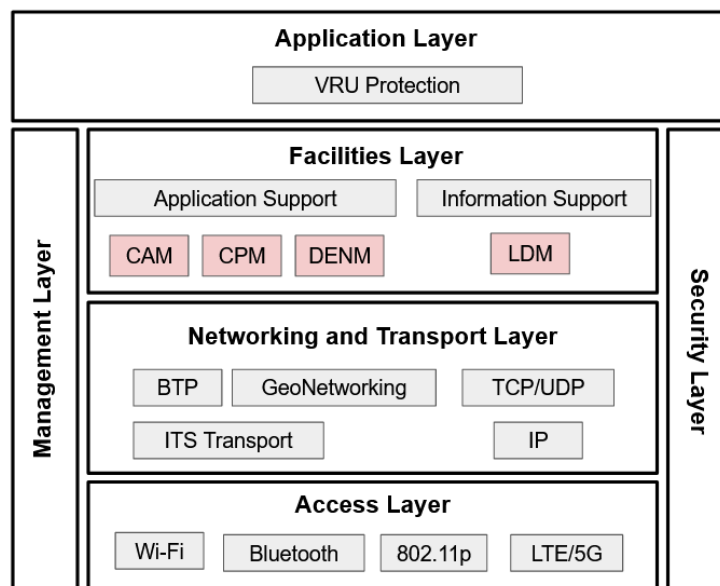


Figure 2.1: ETSI protocol stack.

The figure 2.1 depicts the layered model of ETSI for vehicular communication. The application layer contains the ITS applications that require information exchange. In our case, the targeted application is the protection of vulnerable road users. The "facilities" layer is an application support that provides assistance for vehicular communication. This layer offers support to applications by defining common message formats for various services and organizing information for easy access from the appli-

cation and network layers. The Local Dynamic Map (**LDM**) is an information support that plays a crucial role in supporting **ITS** applications by actively storing and updating information regarding moving or stationary objects that are either influenced by or have an influence on road traffic. The network and transport layer include protocols that ensure the dissemination of messages from the source to the destination. The access layer includes protocols that facilitate access to the physical channel and the transmission and reception over that channel. **ITS** stations can be equipped with various technologies such as Wi-Fi standards, 4G/5G, and **IEEE** 802.11p. Two cross-layer management and security layers are responsible for providing support to each of the preceding layers and ensuring secure communication.

2.4 Types of communication messages

- Cooperative Awareness Message (**CAM**): road users send safety-specific messages periodically to an application server. These messages, called **CAM** in the **ETSI** standard or Basic Safety Message (Basic Safety Message (**BSM**)) in Society of Automotive Engineers (**SAE**) standard, enclose context-awareness (i.e. vehicle ID, type and role in the road traffic, length, width, position, speed, heading angle, lateral and vertical acceleration, etc.) [44]. They are triggered with $1 - 10$ Hz frequency that depends on vehicle characteristics: speed, position, heading angle, etc.
- **VRU** Awareness Message (**VAM**): **VRU** with Smartphones can send another message type more flexible than **CAM**. It is characterized with a shorter length and it is context-specific. This **VAM** message is introduced by the **ETSI** standard [37] and Personal Safety Message (Personal Safety Message (**PSM**)) in the **SAE** standard. It includes location information, **VRU** type, speed, direc-

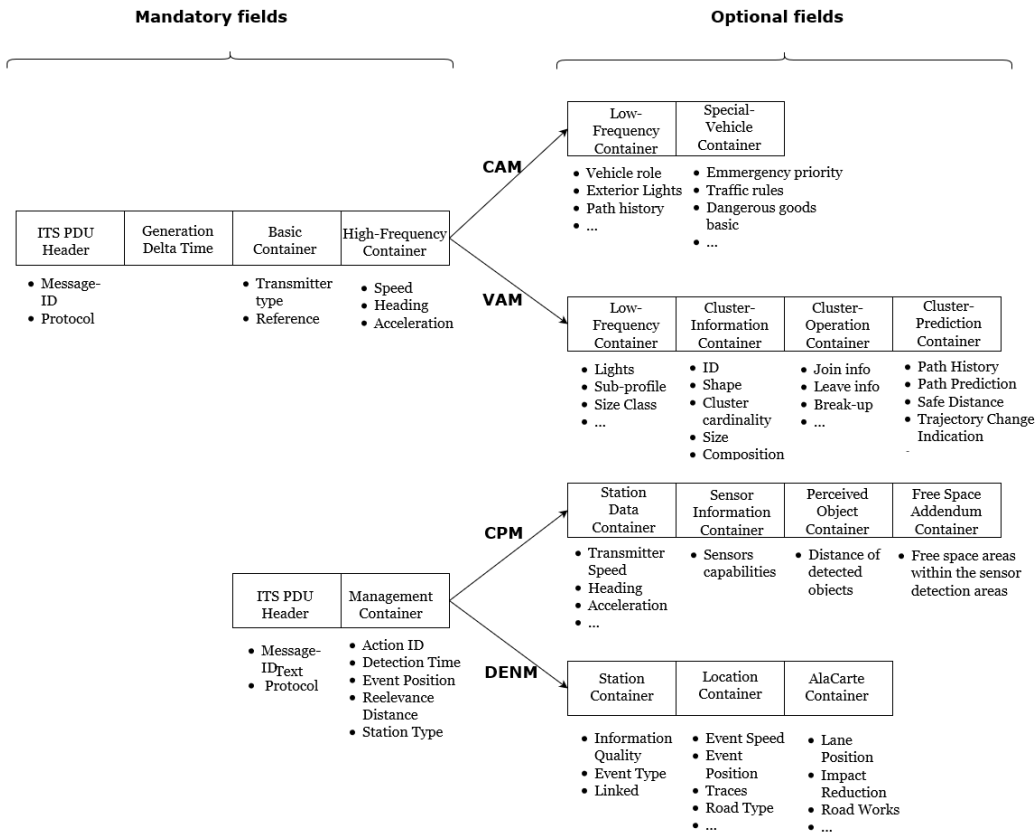


Figure 2.2: Type of communication messages.

tion, etc. **VRU** devices are in charge of generation and construction of **VAM** while including motion prediction and other context information to improve the positioning accuracy.

- Decentralized Environmental Notification Messages (**DENM**): composed of four containers, they are used to alert road users when a triggering application detects a dangerous event [45].
- Cooperative Perception Messages (**CPM**): vehicles exchange sensing information to improve driving environment perception using **CPM**. They contain information about surrounding detected objects. **ETSI** standard defines their format, generation and transmission rules [46]. They are updated every 1 s

or if any change in the detected object conditions occurs. The current **ETSI-CPM** implementation is characterized by high **CPM** transmissions, while the **CPM** contain small Information about detected objects. In [47], authors have proposed a new **CPM** generation algorithm that predicts the behavior of the detected objects to optimize the generation rules.

The different fields of the messages cited above are depicted in figure 2.2. It is worth to note that **VAM** and **CPM** messages have similar mandatory fields to **CAM** and **DENM** respectively.

2.5 The Use of Communication Messages by the Collision Detection System

This section strives to highlight the types of communication messages and describe a collision-avoidance system's key components in **VRU** protection use case. Based on our related work-study, a collision-avoidance system comprises many parts (data-collection, message processing, collision detection algorithm, alert dissemination, etc.). It effectively operates thanks to the received communication messages.

The first step in **ITS VRU** safety application is data collection. It provides the capability to gather essential data (e.g., location, speed, neighboring vehicles or **VRU**, surrounding objects, road traffic conditions, etc.) encapsulated in vehicles and **VRU** messages (cf. 2.4). Further, it can be extended to collect information from multiple data sources (e.g., road cameras and sensors data, network functions data, **VRU** self-positioning, etc.). In this survey, we consider the **ITS** messages as the essential information source that should be provided to the collision avoidance algorithm to operate correctly.

2.5.1 Message processing

After the server receives the messages correctly, it verifies their freshness and stores them in a table before being forwarded to the Collision avoidance algorithm; otherwise, it discards them. For instance, authors in [22] set the up-to-date threshold equal to 0.8 s. Furthermore, the process differentiates the types of the received messages based on their characteristics [24]. It determines whether they are received from pedestrian VAM/PSM or vehicles CAM. This phase gives the advantages of avoiding the computation of pedestrian to pedestrian collision and adapting the algorithm according to the available information.

2.5.2 Collision detection

Regardless of the server type or location (cloud or Edge), the server's role is twofold: the detection of a risky situation and the identification of the involved users.

Several collision avoidance algorithms have been proposed in the literature. We group them as follows:

- Benchmark Algorithm: it predicts future positions of the entities function of their current position, velocity or acceleration information. [22; 48; 49] then compute the distance between two nodes to deduce the minimum distance or time between the two nodes and compare it to a threshold. Or it can compute the collision probability ($P_{collision}$) as in [50; 51; 52]. Finally, it selects the group of endangered vehicles and VRU to be alerted if the minimum distance and the time before collision are less than the defined threshold.
- Multi-Threshold based Algorithm: this type proposes multiple thresholds to improve the detection system performance, as in [21]. Instead of using a single

threshold to detect collision, three types of thresholds have been defined to improve the performance of the algorithms: *Collision Threshold*: for each possible collision event a collision counter is incremented, if this counter exceeds the predefined collision threshold, an Alert is generated. It is used to control false positive alerts. *Tolerance Threshold*: to avoid the impact of prediction errors or a change in vehicle velocity. *Immediate Threshold*: used to ignore the collision counter and send an immediate alert if a collision is predicted for an immediate event. It controls the false-negative alerts.

- Risk level based Algorithm: Instead of only relying on thresholds to determine the collision possibilities, authors of [49; 53; 54; 55] proposed to evaluate the risk level related to the danger area. The risk level depends on several parameters such as the proximity to vehicles, the location (e.g. urban or rural, intersections). In this way, the driver awareness is increased in NLOS scenarios by visualizing invisible pedestrians according to the danger zone evaluation.

2.5.3 Alert dissemination

After the collision detection step, if a collision risk is detected, a warning must be sent to the identified VRU and vehicles. It can be encapsulated into a DENM or a CPM message. The alert can stay active as long as the triggering conditions remains valid. Once the alert is received, there are various ways to present it to the user depending on the device being used. For instance, on a vehicle’s dashboard, the alert can be displayed visually. On a smartphone, it can be adapted dynamically based on the user’s current state of engagement, utilizing methods such as displaying a message on the screen, providing a voice alert, or even combining both modalities to effectively capture the pedestrian’s attention [56]. To target the alert only for the concerned users, risk filtering algorithms can be used, for instance by evaluating the collision

risk for the specified vehicle or [VRU](#) [57].

2.6 Conclusion

During this chapter, we introduced the general context of [VRU](#) protection in a [V2X](#) communication system. To begin with, we initiated the chapter by providing an overview of the most pertinent projects and studies in our research domain, specifically focusing on accidents involving vulnerable road users. The objective was to identify potential avenues for improvement and enhancement in order to address the identified challenges. Subsequently, we elucidated the establishment of standards and regulations pertaining to a cooperative awareness system dedicated to safeguarding vulnerable users. This involved outlining the rules for message generation, diverse communication message types, the [ETSI](#) protocol stack, and the specific roles played by each layer within the system. Finally, we provided an extensive outline of the collision detection system by outlining its procedures and explaining the specific roles carried out in each step.

The objective of this thesis revolves around exploring the effective utilization of environmental perception to improve the efficiency and effectiveness of vehicular networks. Our main goal is to utilize network communications and cooperative messages to develop an intelligent understanding of the surrounding environment. The following chapter of this thesis will delve into different communication architectures and their strengths and constraints. We will also present a categorization of network performance metrics while examining how they relate to the safety requirements of [VRU](#). Furthermore, an overview of previous works conducted during the literature review phase will be provided, highlighting areas that still need to be explored or adequately investigated to tackle existing challenges.

State of the Art

3.1 Introduction

The advancement of technology has led to the proposal of various active and passive safety systems aimed at enhancing the safety of vulnerable road users. Among these solutions, the integration of mobile devices that presents both opportunities and challenges. Their wide proliferation, coupled with their increased computing power, storage capacity, network connectivity, and sensing capabilities, positions them as promising candidates for numerous applications, including traffic safety. By harnessing the potential of innovative computing and offloading paradigms that bring cloud capabilities closer to end users, the latency requirements of traffic safety applications can be effectively addressed, leading to improved safety outcomes for vulnerable road users. This chapter provides an overview of vulnerable road users' safety applications, focusing on the network and communication architectures that facilitate their operation. Furthermore, it examines the architectural and network-related challenges that arise in deploying these applications, as well as the specific challenges associated with their implementation.

3.2 Communication Architectures for VRU protection

Two communication architectures are available to back a VRU safety system. Their distinction lies in employing or not the network infrastructure, depending on the communication technology and the availability of the network to fulfil the crucial prerequisites for ensuring safety application.

3.2.1 Infrastructure based architecture

3.2.1.1 Software Defined Networks (SDN)

In order to deal with the problems of incompatibility of network elements due to the variety of properties of hardware equipment, operators have designed the virtualization of network functions by defining a Software Defined Networks (SDN) managed by a unified interface, which simplifies the integration of heterogeneous vehicular networks [58]. SDN allows the use of less expensive equipment and to guarantee the automatic and dynamic management, configuration and control of all network elements thanks to a global and centralized view. SDN is based on the concept of decoupling between the control plane and the data plane. Thus, its logical structure is composed of three main planes: (i) *The Control Plane (CP)*: is made up of the central SDN controller and the Base Station (BS) controllers. The purpose of using SDN in a vehicular context is to allow network resources to be allocated efficiently by the logical, centralized control plane responsible for making packet routing decisions and quickly and automatically configuring the network. In addition, it allows the implementation of control applications. (ii) *The Data Plane (DP)*: The network elements are considered as switches, and they are managed by a unified interface (OpenFlow

Application Programming Interface (**API**) which simplifies the integration of heterogeneous vehicular networks. The data plane is responsible for collecting, quantifying, and sending information to the control plane. *(iii) The Application Plane (AP)*: The application plane is responsible for generating the policies used by the control plane. The network management request, the access control, the service priority implementation, the mobility management and the updating routing rules are some examples of **SDN** applications.

In our initial contribution, we employed **SDN** to address heterogeneity challenges and leverage its inherent benefits, particularly the holistic network perspective. However, we subsequently transitioned towards adopting a 5G-based architecture integrated with **MEC** due to the limitations encountered with **SDN**-based architectures. In fact, the centralized controller used in **SDN** could cause network failure should it malfunction. This is due to heavy dependence on a single point of control. Moreover, security risks are higher, as an intruder can manipulate the compromised controller to access sensitive data illegally. As well, scalability issues arise when too many devices flood controllers with traffic exceeding their capacity limit, which may hinder functionality and operation efficiency. Furthermore, **SDN** introduces an additional layer of abstraction and packet processing overhead compared to traditional network architectures, this can introduce latency causing performance degradation especially in real-time applications or high-traffic environments.

3.2.1.2 5G-enabled MEC-based Network Architecture

The components of an infrastructure-based architecture are depicted in figure 3.1. As shown in this figure, there are two main parts: the 5G core network and the Radio Access Network (**RAN**). Notably, this architecture counts connected **VRU** and vehicles, Cloud and Edge servers, base-stations, **RSU**, etc. Further, **V2X** communication

links exist possible (V2V, V2I, V2N, V2VRU).

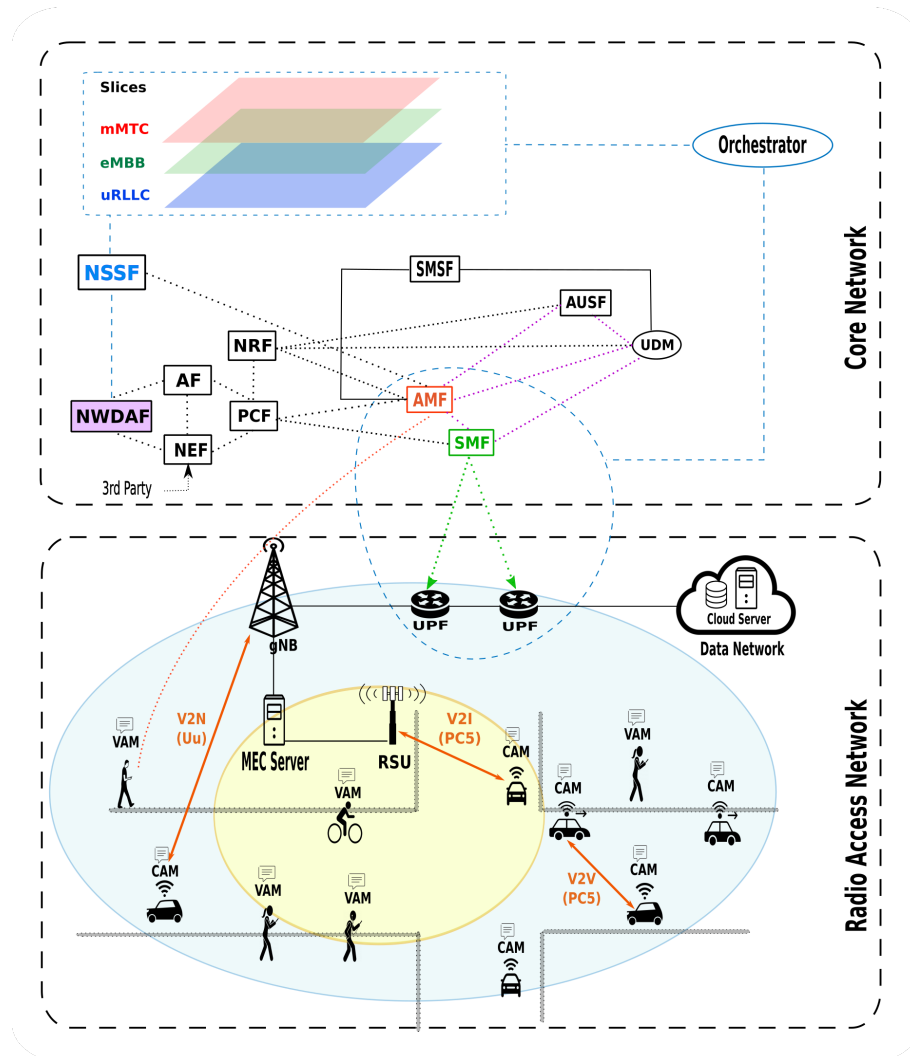


Figure 3.1: In this 5G Communication architecture, an orchestrator coordinates the core network functions and slices to support the safety application. The road users exchange safety messages in the RAN. The gNB cellular coverage is defined by the blue circle when the yellow circle delimits the RSU coverage.

Radio Access Network :

The key elements of the Radio Access Network are as follows:

- **VRU:** vulnerable road users can be classified according to their characteristics. For instance, pedestrians are characterized by their average walking speed 5km/h, that can vary with age and physical ability. The cyclists speed is around

15 km/h, and for motorized two wheels (e.g. scooters), it is about 50 km/h in urban area [37].

VRU can use gadgets to communicate such as connected Helmets, Tags, etc. However, exploiting the fact that smartphones are very used and widespread [59] among VRU instead of buying specific gadgets is more relevant. In addition to their intelligent capabilities in terms of computation and communication, they have multiple sensors (motion, Global Positioning System (GPS), magnetometer, accelerometer, gyroscope, etc) that can provide useful raw data to enrich context information. The VRU send periodically specific messages namely PSM or VAM using cellular communication to exchange context-awareness information with other road users or servers as explained in chapter 2.

- Vehicles: the vehicles are characterized with their high mobility. Their Advanced Driver Assistance Systems (ADAS) helps to improve safety and to decrease human driver errors. It reduces the reaction time by assisting the drivers to take the appropriate action and avoid road accidents. Besides, the cars are equipped with Lidars, Radars, and cameras to detect road users and increase its surrounding environment awareness. Nevertheless, in NLOS scenarios (e.g., buildings in urban areas, intersection corners, bad weather conditions that deteriorate camera performance) the vehicle relies on cooperative communication via its OBU. Indeed, the vehicle exchanges safety-related information encapsulated in specific messages (DENM or CAM) with its neighbors or with VRU or the network infrastructure using Vehicle to everything communication technology V2X. They can communicate under the cellular coverage using C-V2X or 5G NR-V2X communication directly using the mode-3 PC5 interface or indirectly via the cellular infrastructure employing the UMTS Air Interface (Uu) interface. With the advent of CAV, human driver errors and reaction time can be heavily

reduced thanks to advanced intelligence and high automation. However, their penetration rate is still in progress which puts the system in a transition phase. Many studies have proved that autonomous vehicles in mixed traffic enhance smooth driving and improve traffic safety, increasing their penetration rate [60], [61].

- **BS-RSU**: **BS** or **RSU** forward the received packets to a fog or a cloud server when they do not process them locally with their Edge server. As well as that, they also disseminate messages and alerts from the network to the cars and the **VRU** through downlink transmission.
- **Servers**: Once a server receives the packets, it uses them to compute collision events. If any danger is detected, alerts are sent to involved vehicles and **VRU**. Undoubtedly, the server placement impacts the application performance in terms of latency and the expected outputs. Thus, the configuration should be carefully chosen according to the application requirements [21]:
 - (i) *Cloud server*: placed in the cloud, it benefits from the high storage and processing capacities [54],[21]. However, the transmission of data to and from a far situated cloud server increases the bandwidth and latency, making it unsuitable for critical application requirements.
 - (ii) *Fog server*: to alleviate the additional delay, Fog computing is introduced to bring computing, storage, and network services down to the data plane. Unlike the centralized cloud, Fog servers can be placed anywhere, thereby providing distributed services to reduce the network traffic load and the latency thanks to its placement [62].
 - (iii) *Edge server*: If the server is placed on the edge of the network, it allows **MEC**. **MEC** brings cloud computing capabilities and **V2X** services closer to vehicles and **VRU** [63; 23]. By getting more computational power closer to the users, the goal of **MEC** is to reduce the latency as well as decrease the signaling overhead in the cloud core

and the task offloading time [22].

5G Core Network: The introduced network functions offer efficient use of network services that helps to improve the safety applications compared to classical 4G architectures. As shown in figure 3.1, several network functions have been introduced in the 5G architecture. Hereinafter, we present them:

- The User Plane Function (**UPF**) relays the packets, identifies the application according to the flow structure, interconnects with a data network, and adds or removes the packet headers.
- The Access and Mobility Management Function (**AMF**) communicates with the non-access stratum to manage access mobility.
- The Session Management Function (**SMF**) controls the Packet Data Unit (**PDU**) sessions and allocates IP addresses.
- The Authentication Server Function (**AUSF**) manages the authentication keys.
- The Unified Data Management (**UDM**) is responsible for user identification and subscription.
- The introduction of the Network Slice Selection Function (**NSSF**) determines, for each UE, the network slices that are allowed to access. In the context of collision avoidance application, **NSSF** associates the User Equipment (**UE**) to **uRLLC** slice to guarantee high reliability and reduced latency, to massive Machine Type Communications (**mMTC**) to optimize the energy consumption and to enhanced Mobile Broadband (**eMBB**) to high throughput experience.
- Another important function is the Network Data Analytic Function (**NWDAF**), which provides other network functions with load level information on the

slice level which can be helpful to adapt the application to network condition.

- The Application Function (AF) interconnects with the control plane and the 5G core network. It implements procedures such as traffic routing and interacts with the core network via the Network Exposure Function (NEF).
- The NEF is in charge of exposing network functionalities and data collected from the control plane and other sources (e.g., location information, channel quality, achievable QoS, estimated or predicted latency, etc.).

The network orchestrator is responsible for slice orchestration and controlling the SMF and AMF to guarantee resource allocation flexibility. Mainly, it enables or disables the SMF and AMF instances and reduces the number of UPF, leading to energy saving and load balancing.

It offers the opportunity to meet a large set of V2X application requirements. Network functions are defined instead of network entities, and the control plane is centered around services instead of interfaces. Moreover, the introduction of network slicing and virtualization offers more flexibility and raises intelligence [64] in the network management. Aside from securing the network via logic isolation where the failure on one slice does not affect the operation of the others, network slicing reduces the cost by sharing the same physical infrastructure. Additionally, it enhances the flexibility by enabling customized network slices for different scenarios and managing the network resources in real-time. Slicing is extended from only resource slicing to service and function slicing to satisfy the requirements of V2X critical applications. Service slicing improves the service access efficiency, where the function slicing enables dynamic monitoring and scheduling [65].

3.2.2 Infrastructure-less architecture

In an infrastructure-less architecture, VRU safety applications can be supported without the need of cellular coverage when road users autonomously select their communication resources. Moreover, VRU can be protected using perception based solutions that ensure its tracking and detection.

3.2.2.1 Communication based cooperative perception

When the communication infrastructure is not available, direct communication between the nodes could be the solution. The technologies that offer direct transmissions in vehicular communications are DSRC via 802.11p and C-V2X mode-4 or NR-V2X mode-4 in 5G. Visual Light Communication (VLC) can also be used for direct communication. With the introduction of 6G, it is expected that the achievable data rate of VLC will reach hundreds of Gbps [66]. Undoubtedly, this improves the signal robustness and enhances the communication quality. If the network function discussed above are not more available, thus an autonomous and distributed collision avoidance system is needed to avoid accidents.

The RSU enables the road to communicate with users, namely, vehicles and pedestrians, through vehicle to vehicle V2V, vehicle to RSU (V2RSU), and pedestrian to RSU (P2RSU), as shown in figure 3.2. In [56], hardware and software architectures for vehicle and pedestrian collision avoidance have been presented. Different warning modes fitting to the current state of use have been described to attract pedestrians' attention.

The proposed architecture is composed of vehicles with 802.11p enabled OBU. They can exchange road information about detected objects via 802.11p with the surrounding vehicles and run an application that can predict collisions. Moreover, the OBU is also equipped with Wi-Fi to communicate with the pedestrian smartphone,

which contains a safety application that communicates with [OBU](#) through Wi-Fi and alerts them if a risk arises.

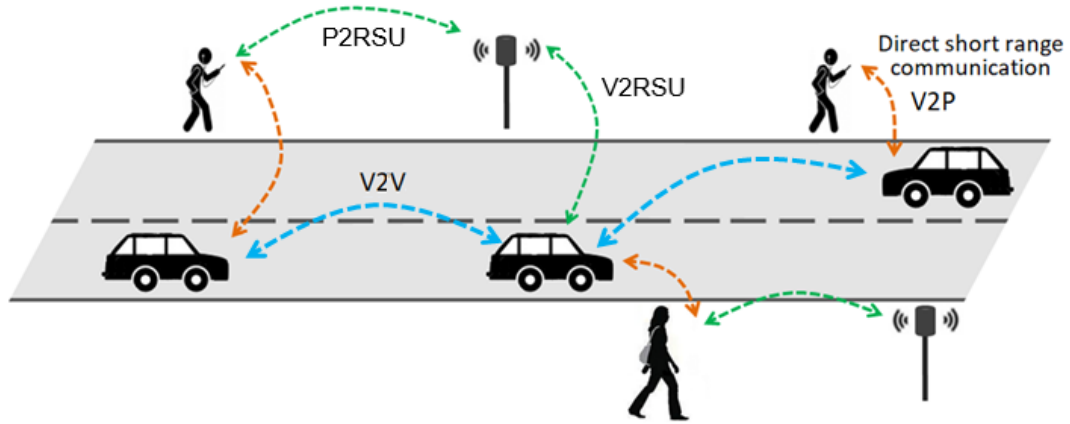


Figure 3.2: Communication-based cooperative perception.

When cellular communication is not possible, the use of WiFi in pedestrian smartphones can introduce latency. Otherwise, another device (tags, gadgets, etc.), with 802.11p or other technology, is proposed instead of a smartphone to communicate with the [VRU](#) [67].

Likewise, [C-V2X](#) Mode-4 is a direct short-range communication technology with enhanced performance for vehicular communication [68]. [C-V2X](#) mode-4, where vehicles can communicate directly via PC5 interface, selects and manages their resources autonomously without the network infrastructure support or cellular coverage using their [SPS](#) scheme. This communication mode outperforms the IEEE-802.11p, especially in high load conditions [69]. Inevitably, this makes it suitable for critical safety applications where reliability and maintaining the connectivity under heavy traffic is paramount [70]. Moreover, it offers interoperability with the future 5G communication standards such as [NR-V2X](#) [71; 39]. It is expected that future smartphones will communicate via 802.11p and [C-V2X](#) [72]. However, to the best of our knowledge, current smartphones in the market are still not equipped yet with side-link communication. The penetration of [LTE-V2X](#) PC5 in smartphones is by no mean sure, and

the incorporation of 802.11p is considered unlikely [73].

3.2.2.2 Vision-based cooperative perception

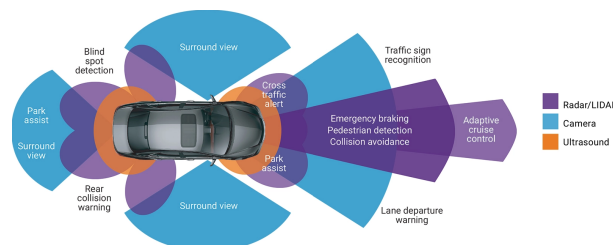


Figure 3.3: Vision based cooperative perception [1].

The freestanding solutions do not require an exchange with the pedestrians, as the vehicles rely on cooperative perception. These solutions utilize a combination of vehicle sensors, including cameras and other sensing technologies, to collect data about the detected elements in the surrounding environment, as shown in figure 3.3. This data is then shared with neighbouring vehicles, enabling analysis and the creation of a comprehensive global view. Informed by this view, vehicles are capable of making decisions and undertaking various actions, such as adjusting velocity, initiating stops, changing trajectory, applying brakes, or even issuing warnings to other vehicles. The collection of this essential data is made possible through the integration of vision sensors and radio sensors within the vehicle's ADAS system. Then, the data is analysed to extract useful information to be fed as an input to an intelligent collision avoidance algorithm implemented inside the vehicle. This algorithm builds a perception of the environment to detect and track VRU, predicts their future trajectories, and computes the collision risks to make the appropriate decision. For instance, in [74], authors have proposed a real-time pedestrian detection system based on Convolution Neural Network (CNN) for autonomous vehicles equipped with cameras. The camera video stream is fed into the CNN to be processed and to extract features in real-time. The obtained recognition accuracy is more significant than 96.73%. In [75],

the authors proposed a vision-based approach using a camera. A 4 step state-of-the-art tracking algorithm has been exploited to analyse a signalized intersection video collected in Ningbo, China. They obtained real-time trajectories and estimated the vehicle-to-pedestrian collision probability at intersections. They defined the critical time before collision based on different collision patterns of perception-reaction failure and evasive action failure. An architecture is proposed in [76], called safeVRU platform, involving the vehicle localization module, the environment perception, the motion planning, and the control. Unlike the other solutions, the objective is to prevent arising from the beginning where the vehicle can plan real-time collision-free trajectories in the presence of VRU.

3.2.2.3 Hybrid Architecture

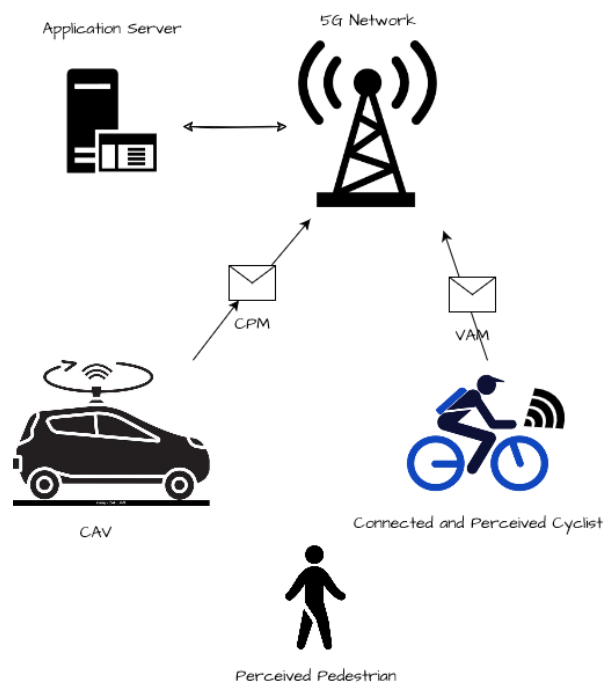


Figure 3.4: Hybrid Architecture.

A hybrid approach consists of over-passing the limits of communication-based as

well as vision-based methods as shown in figure 3.4. In [77], the authors proposed a cooperative system that combines communication and the perception to benefit from the advantages of both approaches and build a more reliable system. They used a WiFi-enabled distributed communication protocol to exchange CAM messages, including GPS data, and vehicles equipped with laser range finders to track the VRU. This approach improves the system performance in terms of localization accuracy and VRU detection in NLOS compared to a system based only on perception or WiFi communication. IEEE-802.11ac have been used in [78] as a V2I communication technology and combined with vehicle's sensors to build a robust collision avoidance system. Similarly, authors of [79] combined 5G and LTE communication with smart-phone sensors data to detect the VRU stepping onto the road.

3.3 VRU safety requirements

As depicted in figure 3.5 we classified VRU safety-related requirements to application-related challenges: (position accuracy, energy consumption for VRU smartphones, collision detection algorithm complexity and reliability) and architecture-related challenges: (communication reliability, latency, and network scalability). For each requirement, we present the most relevant state-of-the-art solutions.

3.3.1 Network related requirements

- **Communication latency:** one of the most paramount requirements of VRU safety applications is the highly reduced system latency. The latency requirement is the longest period that the application can tolerate meeting the safety context's reliability. The messages must be up-to-date, sent, and received in a bounded time interval; otherwise, they will no longer help compute collision

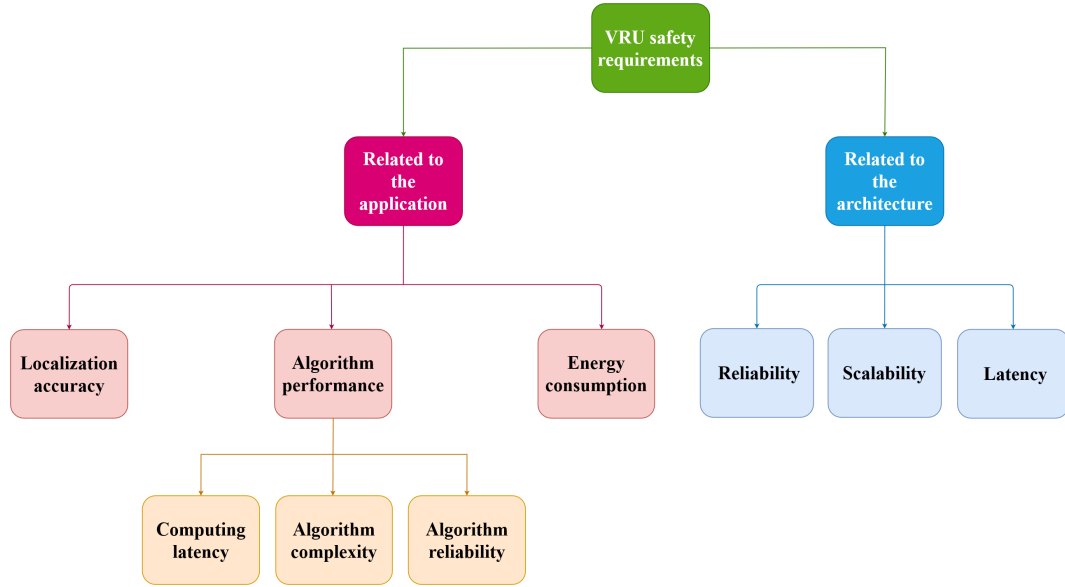


Figure 3.5: VRU protection requirements' classification.

risk. Indeed, to determine if there is a collision risk, the collision detection algorithm should use these timely messages. The algorithm could be deployed either on a server, on the VRU's smartphone, or the vehicle's OBU depending on the system architecture. The latency includes the processing time taken by the collision avoidance application. Therefore, it could be related to different factors: (i) *Communication delay* affected by the propagation time, the physical channel conditions, and the network congestion. It is also impacted by the routing time, type of communication (direct or indirect), and the server's location. According to 5GCAR [9; 8], the end-to-end communication latency should be less than 60ms. Indeed, direct communication takes less time than indirect communication via network infrastructure. Authors of [21] proposed a 5G-based lightweight and low complexity algorithm that predicts trajectories and detects in real-time potential collisions while addressing critical 5G requirements in terms of low end-to-end latency and high reliability. Moreover, they have proposed a hybrid architecture that exploits MEC and cloud computing

resources in a coordinated manner to optimize the end-to-end latency.

A MEC-based architecture has been presented in [22], where vehicles and vulnerable road users can exploit different network technologies to send CAM toward a centralized collision detector and receive collision alert messages. A distributed and IEEE-802.11p V2V communication-based approach where every vehicle runs its own collision detection system has been compared to a centralized approach where the computation is placed on a MEC server to determine which approach better guarantees minor delay. The performance evaluation shows that the MEC architecture adopted for the centralized implementation has very low delay and 100% of collisions involving vulnerable users can be detected in time to be avoided, compared to distributed approaches. In [80; 81], authors investigated the impact of the processing placement of VRU context information, whether to offload to a server or to compute locally, then the effect of the two approaches on the latency. They also studied the local processing time of pedestrian movement detection with a machine learning algorithm-enabled smartphone and the average end-to-end delay if the offloading to a MEC server is selected. They studied in [52] the impact of pedestrian activity detection and the communication delay in a collision detection use case. In [70], authors compared the performance of MEC-based architecture and the conventional cloud-based architecture. They studied through extensive simulations the impact of the two approaches in the end-to-end latency of the VRU communication.

- **Communication reliability:** protecting VRU from potential collision risk is a mission-critical safety application that requires high reliability and high service availability. It reflects the ratio of the packets successfully received within a bounded delay. A maximum packet delivery ratio and a weak congestion are crucial for a proper system operation. Indeed, the reliability should be higher

than 99%, particularly in **VRU** safety use cases [9]. A maximum packet delivery ratio indicates a minimum packet collision and thus a good communication and connectivity quality. The high communication range, without degradation of connectivity with the increase of the traffic load or the distance, is an index of reliability. The evolution of communication technology plays an essential role in the enhancement of reliability. **3GPP** Release 16 defined the latency in the range of milliseconds and the reliability as high up as 99.999%, thanks to the introduction of physical improvements to 5G New Radio technology for **uRLLC** [43]. For instance, [3] provided reasoning for the utilization of **C-V2X** communication technology, citing its ability to meet safety application requirements through superior reliability performance.

- **Network scalability:** to avoid or reduce the impact of network congestion, the network capacity should be dimensioned to support a massive number of road users to avoid packet loss. Indeed, the **ETSI** standard has estimated the scalability being 5000 users in the same 300m-radius communication area [37].

In [21] a dynamic and hybrid resource selection architecture between **MEC** and the cloud is proposed depending on the collision avoidance scenario's specification. Precisely, it shows that the **MEC** operation outperforms in specific scenarios with a small number of **OBU**. In contrast, the cloud-based operation could be more valuable in up-scaled scenarios and showed overall robust and stable performance. The authors proved that a dynamic resource selection approach depending on real-time network resource availability and network state information could lead to high gains.

On the other hand, clustering can be an effective technique to group road users when their number in a specific area gets high. It can increase the network capacity without additional infrastructure by considering the **VRU**' cluster as

a single object and electing a cluster-head to transmit a **VAM**. The **VAM** contains the cluster's total dimension and other information (e.g. velocity, reference position) instead of individual **VRU** transmissions. For instance, in [82], the authors create low-power small cells called clusters that allow the frequency reuse in other clusters while decreasing the interference and increasing the capacity. The scheme starts with the first phase to define the clusters using K-means algorithm, then a second phase to select the best link quality node as a cluster-head to relay the cluster members' data to the **BS**.

Authors of [83] proposed a Multi-channel Clustering-based Congestion Control (MC-COCO4V2P) algorithm to mitigate the congestion caused by the high number of pedestrian safety messages. The clustering mechanism groups pedestrians based on their location and direction. It reduces the signalling overhead by separating the clustering and safety messages while saving the energy consumption of pedestrians' devices. The efficient use of radio resources is considered as another challenge that needs to be properly addressed, given the size of **CPM** messages and the wireless channel's limited bandwidth. **CPM** can contain many perceived objects and can be generated frequently, which can lead to exceed the channel capacity or increase the channel load. In [84], the authors introduced the filtering that exploits the communication redundancy and discards objects with low kinetics status as an effective technique to reduce the number of detected objects included in a message while keeping a good perception quality. Although there are many possible alternatives to manage scalability challenges, it is expected that by 2030, the number of connected devices will reach 125 Billion [85], which will increase the network load and the high demand for bandwidth. The introduction of 6G will extend the network capacity to support high connected device density and guarantee ubiquitous

connectivity [86; 87].

3.3.2 Application related challenges

- **Power consumption:** vulnerable road users often utilize smartphones or connected gadgets that can communicate with the V2X communication system. To ensure safety on the road, it is necessary to continuously monitor sensors and process data through safety applications. However, this could lead to battery drainage, affecting their ability to function during crucial moments. It is imperative not to excessively consume the power of these devices since they have limited battery life capacity; thus optimizing power consumption remains a top priority for extending battery lifetime and maintaining an efficient safety system. [54]. Different research directions have been proposed to minimize the average end-to-end delay and the mobile devices' energy consumption. In [54], the authors developed an energy-efficient solution based on wireless V2P communication to avoid collision and save smartphones' battery lifetime. This paper's main contribution is to adapt the frequency of sending beaconing messages of smartphones with the situation risk level. They defined a full rate beaconing for vehicles and smartphones in a high-risk situation and a low rate beaconing for mobile smartphones in a low-risk case. The solution runs in a server placed at the cloud level. When the algorithm detects a risky situation, a request to switch to full rate beaconing mode is sent to increase precision and obtain up-to-date Geo-location information. In case of accident detection, it sends an alert to concerned elements. Results show that the proposed solution enhances the total battery lifetime compared to a full rate beaconing case. Authors of [88] have also suggested the adaptation of the beaconing rate ac-

according to the predicted collision risk level. They proposed an energy-efficient fuzzy logic adaptive beaconing rate management system to overcome the mobile devices' energy consumption limitations. The prediction is computed based on minimum information exchange distance while considering various source of information and risk-pulling factors. Results reflect that their system reduced the energy consumption to half while having an insignificant energy overhead compared to full-rate beaconing schemes. The energy consumption could be affected by vehicle arrival rates and risk pulling factors. The difference between the two previous works is that the method based on fuzzy logic model considers many types of factors that affect collision risks that have been neglected in [54]. Moreover, three collision risk levels (high, medium, low) have been defined in [88] instead of two in [54].

The authors of [89], proposed a best-effort application called V2PSense that notifies road users if any nearby danger is detected. The authors investigated an energy-efficient consumption positioning method instead of greedy GPS for the limited battery life smartphones. A potential arrival area is calculated for each pedestrian using intermittent GPS information and mobile sensing data to determine if he is close to a dangerous spot. Results indicate that the proposed mechanism saves 20.8 % energy compared to always-activated GPS.

Other research directions focus on studying the impact of collision risk processing placement on the smartphone's energy consumption, whether to locally compute the safety-related tasks on a smartphone versus offloading to a MEC server. For this purpose, the authors of [80; 81] examined the two modes' performance separately and suggested a heterogeneous scheme that combines the two modes. They proposed an adaptive system architecture with two levels. At the data level, smartphones can compute context information locally or with

the MEC server support by offloading raw data collected by their sensors. At the service level, they process the collision avoidance algorithm locally or offload it to the server. The decision should be made while considering the situation's risk rate and the smartphone's available resources to make a trade-off between latency and energy consumption optimization [80].

In [55], the authors have implemented a collision-avoidance system that adapts the transmission rate to control the congestion of the wireless channel and reduce the energy consumption of VRU smartphones. Their approach consists of minimizing GPS receiver's active duty cycle by turning off the GPS and even the DSRC radio based on the context information (e.g., indoor, stationary, inside the vehicle, etc). Moreover, the smartphone stays on listening mode to the channel. If a BSM transmission is needed, the transmission range should be controlled according to the surrounding environment (e.g., risk level, number of nearby vehicles).

- **Localization accuracy:** collision avoidance systems between vehicles and pedestrians are based on processing and predicting the spatial proximity between cars and pedestrians. Therefore, a certain level of localization precision is needed to ensure the proper functioning of the system. Accordingly, ETSI standard [37] set up that safety applications require precision error not exceeding 1 m for vehicles. In VRU use cases involving pedestrians and bikes, higher positioning accuracy is necessary. Indeed, the precision error should be less than 0.5 m [90], and 25 cm accuracy would be the ideal case [9]. Nevertheless, current positioning systems do not provide the required precision. For instance, GPS accuracy varies between (1 m to 5 m). Moreover, VRU smartphones cannot meet the positioning requirements (3–10 m precision). They are equipped with low-performance Global Navigation Satellite System (GNSS) antennas charac-

terized by a noise measurement phase that introduces inaccuracy [90]. With the evolution of 5G and the introduction of 3GPP 5G-New Radio (NR) in Release 16, the localization will be based on the signals of the NR transmission links as well as new GNSS technologies (BeiDou, Galileo, GLONASS, GPS), Terrestrial Beacon Systems (TBS), Bluetooth, WLAN, RFID, and sensors [91]. Moreover, NR-V2X communication will enable the possibility of cooperative localization in dense networks where nodes inter-communicate to exchange measurements related information.

The use of mmWave in 5G brings the advantage of large bandwidth that improves the robustness to multi-path and exploit it to obtain additional position information from radio signals. In this context, LOCUS and IoRL projects have focused on providing location accuracy for less than 10 cm for safety concerns[92] [93]. Besides, with 5G, localization involves infusing data and measurements collected from heterogeneous sensors with contextual information. Moreover, the 6G will improve the localization and, consequently, the accuracy of the application. For instance, with the 3D localization, the number of false-positive alerts will decrease when VRU are on a footbridge crossing a road [66].

Authors in [7] developed a smartphone-based collision avoidance system for pedestrians called "WSB" that exploits the smartphones' context information and the user activity to improve the collision detection accuracy and accurately detect the direction of the dynamic movement of the pedestrian. They demonstrated that even with exact estimation of speed and direction, a position error more than 1m could deteriorate the system performance. Besides, their approach based on curb detection improves the warning system.

A similar approach is in [52], where the authors demonstrate the benefit from additional contextual information to decrease positioning inaccuracy. Authors

of [94], used Kalman filter to enhance the GPS positioning accuracy and reduce its error. The collision avoidance algorithm reliability was significantly improved by their approach. In [26], the bikes send periodically CAM messages that will be exploited to estimate high localization accuracy. They developed a hybrid pilot to perform a high-precision localization system based on the fusion of different information sources. They have combined multi-sensor hybrid solution to estimate position, velocity, and altitude.

In [53], the authors proposed a smartphone-based warning system with three phases for activation, prediction, and warning. They have evaluated their system's performance on detecting the correct risk level warning under the impact of the position and direction inaccuracy.

The authors of [95] investigated the required accuracy to recognize VRU movement in a cooperative collision avoidance system. They evaluated the collision detection performance in terms of missed and false alarms depending on the measurement error distribution of position, speed, and direction. They determined for different pedestrian's crossing angle scenarios, the corresponding accuracy of the required position, direction, and speed to keep the probability of a missed alarm low in a defined time before the collision.

The following approaches focus on improving the localization accuracy for pedestrian detection and activity recognition.

In [50], the authors proved that NLOS scenarios influence camera-based systems. Even in LOS scenarios, they can detect a pedestrian while a bike is not detectable if its speed is higher than 15 km/h. Nonetheless, the cooperative communication system is not influenced by Line Of Sight (LOS) situations, and it proved its ability to detect both pedestrians and cyclists. It also presents a higher probability of collision detection, but it depends on positioning accuracy

that should be less than 1m.

To improve activity recognition and support context filter in identifying VRU stepping onto the road, [79] focused on short and non-periodic activities. They used the combination of context filter, 5G and LTE communications, and smart-phone sensors' data to solve the challenges of inconsistent sensor data, over-representation of periodic activities, and the evaluation of the recognition. They evaluated their solution using precision and recall metrics.

In NLOS scenario, the detection of VRU becomes a challenging task. Authors of [50] used the camera to detect future collision between vehicles with variable speeds and distinct road users' types (pedestrian, cyclist), having different speeds. They compared the probability of collision detection of a camera-based solution and a cooperative-based system in NLOS scenario.

To anticipate the pedestrians' intention and future behavior, [96] proposed a bio-LSTM for 3D pedestrian pose and gait prediction to foretell the global location and 3D full-body mesh with articulated body pose inside the metric space. This ability allows vehicles to avoid collisions and improve ride safety and quality.

- **Algorithm performance:**
 1. **Algorithm complexity:** Optimizing the algorithm's complexity is paramount to ensure efficient performance without adversely impacting other important application metrics, such as latency and reliability. The algorithm compares the trajectories of all road users in a binary manner to identify potential collisions. However, the complexity increases exponentially as each trajectory of a vulnerable road user is checked against the trajectories of all other moving vehicles, resulting in a computational bur-

den. Balancing the need for accurate collision detection while managing the computational complexity is a crucial challenge to handle [2]. Moreover, depending on the implementation of the algorithm and the inputs it receives, additional challenges may arise. For instance, considering the extraction of other types of communication messages, such as cooperative perception messages that provide sensor data from neighbouring vehicles or infrastructure, adds complexity to the algorithm. Incorporating these additional sources of information requires processing and integration, which may increase the computational resources required. Furthermore, leveraging infrastructure data such as accessing information from traffic cameras, road sensors can also need additional computing resources to analyse and incorporate this information into the algorithm's decision-making process. Authors of [21] proposed detecting hazardous events by identifying potential intersections of the predicted trajectories while each trajectory is computed and stored in a data element. In this way, they reduced the algorithm running time and complexity from $O(n^2)$ to $O(n)$.

To relieve the complexity, authors in [24] exploited the fact that the server can distinguish between the received CAM transmitters and skip analysis for the pedestrian-to-pedestrian collisions.

2. **Algorithm delay:** The algorithm needs to process sensor data, compute collision probabilities, and generate appropriate alerts or control actions within strict time constraints. Delays in the algorithm can lead to missed collision warnings or delayed interventions, compromising the safety of vulnerable road users. Achieving the required delay requirements involves optimizing the algorithm's computational efficiency. The processing delay can be impacted by several parameters, such as the server type and its

Central Processing Unit (CPU) performance. A high number of parallel processes (batch processing) can significantly reduce the computing load and make the application run faster. Further, it is essential to mention that the complexity of the application algorithm should be low to minimize the processing time. For instance, in [97], an algorithm that can parallelize computations by separating coupling constraints and decision variables is presented. The proposed synchronous parallel approach enables each vehicle to undergo iterations simultaneously. Additionally, an asynchronous version of the same algorithm allows vehicles to update their respective variables independently in a computational network. In [80; 81], the authors studied the local processing time of pedestrian movement detection with a machine learning algorithm-enabled smartphone and the average end-to-end delay if the offloading to a MEC server is selected.

3. **Algorithm reliability:** The reliability requirements of a collision avoidance algorithm have a significant impact on its performance and effectiveness. To ensure the safety of vulnerable road users, accurate detection of potential collisions is paramount. The algorithm must be able to identify and predict collision scenarios with a high level of precision, minimizing false negatives. False positive messages, on the other hand, can result in unnecessary alerts and disruptions, potentially leading to driver or pedestrian confusion and reduced trust in the system. Therefore, striking the right balance between accurate detection and minimizing false positive messages is crucial. False positives and false negatives characterize the reliability, and their percent reflect the inaccuracy of the system.

A false negative happens when the road users do not receive the relevant warning, do collide. On the other hand, false positives mean that the users

receive an alert, when they are not actually at risk, think that they are in a risky situation, and an imminent reaction is needed. Authors of [22] considered that false positives could be as harmful as false negatives because they can decrease the driver's confidence in the system's effectiveness. To handle this issue, they have evaluated the collision avoidance system's effectiveness by studying the variation of the time and space to collision and their impact on reducing the false positives and increasing the overall reliability. They have focused, in [24], on the safety application for automotive collision avoidance at intersections and study the effectiveness of its deployment in a C-V2I-based infrastructure. They also accounted for the server's location running the application as a reliability-enhancing factor in the system design. The simulation-based results, derived in real-world scenarios, indicate the reliability of car-to-car and car-to-pedestrian collision avoidance algorithms, both when a human driver is considered and when automated vehicles (with faster reaction times) populate the streets. Authors of [21] have also studied the impact of missed collisions and false positives to evaluate the performance of their proposed algorithm for VRU protection in identifying imminent road hazards between vehicles and VRU. They used the accuracy parameter, precision, recall, and F1-score as a Key Performance Indicator (KPI) to study the reliability of their proposed MEC and 5G Network Function Virtualization (NFV) based architecture, the network communication (deadline respect, MEC and cloud operations), and the validity of the algorithm under different thresholds. In [98], the authors proposed a communication model based on collision probability between vehicles and cyclists. They designed an application that takes periodic CAM and informs car drivers to take action in colli-

sion risk. To evaluate their proposed solution's reliability, they compared two scenarios with and without collision avoidance application, and they assessed the collision probability and the obtained false positives and false negatives. As pointed by [51], the insufficiency of the limited information (speed, position, direction) used to estimate pedestrian's trajectory and the effect of the NLOS could lead to false collision detection. To handle this problem and improve the detection inaccuracy, additional context data is used to adjust warning thresholds or to correct the measurement data concerning missed and false collision warnings.

3.4 Conclusion

In this chapter, we have studied V2X communication architectures for the VRU safety use case, given their importance in protecting people's lives. Among existing solutions, we focused on exploring communication-based approaches where road users exchange data between them and with the infrastructure to increase awareness and avoid road fatalities. We detailed the collision avoidance system architecture and possible communication architectures in the 5G network with MEC capabilities, while projecting possible enhancements to support the technical evolution. We depicted the most critical challenges, and we classified them to both network and application related requirements. Based on the comprehensive analysis of the state-of-the-art solutions and their inherent limitations in addressing the critical challenges, the subsequent chapter will thoroughly investigate and present novel approaches that effectively tackle scalability and accuracy issues while meeting the other requirements.

Enhancing Road Safety: Harnessing Prediction and Communication Messages

4.1 Introduction and Problem Statement

Smartphones play a crucial role in the functioning of intelligent transportation systems due to their widespread accessibility, extensive storage and processing capabilities, as well as their ability to accurately determine users' locations. For smartphone-based traffic safety functions, it is crucial for the detected positions to be extremely accurate in order to avoid road accidents. However, due to the insufficient accuracy of [GPS](#) localization, we suggest addressing this issue by incorporating prediction methods to anticipate the future positions and compensate for any inaccuracies.

In addition, vehicular networks exhibit diverse characteristics in their radio access communication, road users' categories, and types of communication messages. To address this challenge, we propose utilizing an [SDN](#)-enabled communication-based architecture, previously discussed in the literature review chapter in [3](#). This type of architecture provides several benefits, including managing cases with [NLOS](#) conditions

and effectively handling a diverse range of available network information. Despite its merits, it is worth noting that issues with scalability may emerge as the number of road users surges, thereby impacting both application performance and network operations. Consequently, we conducted an experiment to evaluate the impact of scaling on signaling overhead. Further details are provided in the next sections.

4.2 A SDN-based collision Avoidance

4.2.1 System Architecture

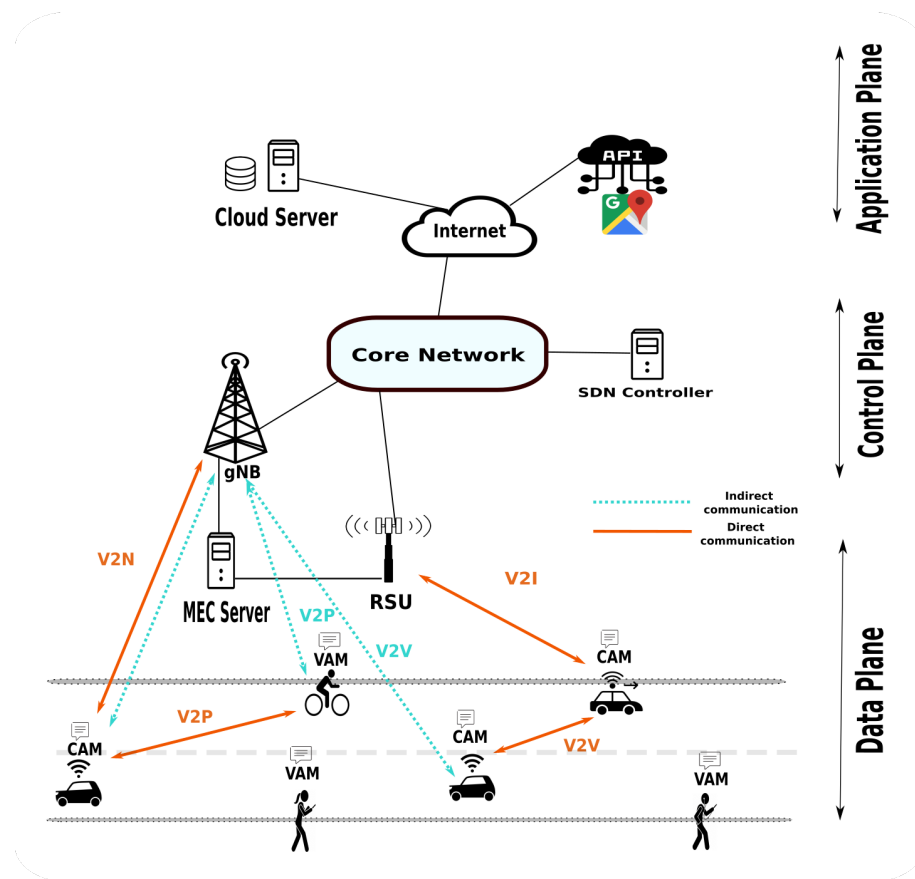


Figure 4.1: SDN based Architecture

The rise in the number of accident deaths emphasizes the significant importance

of protecting such as pedestrians and cyclists [17]. Nevertheless, technological advances alone cannot meet the requirements of such critical applications. It is essential to combine them with architectural revolutions, particularly cloud computing, edge computing, **NFV**, and **SDN**. The latter supports highly dynamic mobility and heterogeneity by integrating the logic of the network at a central controller level to dynamically manage network resources. Furthermore, **SDN** decouples the **DP** from the **CP** to ensure independent and flexible configuration.

This approach offers the ability to unify multiple **RAT** and manage them cooperatively to enhance the **QoS**. Decoupling **CP** and **DP** functionalities allows for flexible displacement of them to convenient locations. [99]. **CP** functions can be placed in a central site, which makes management and operation less complex. On the other hand, **DP** functions can be distributed close to the user to reduce service access latency. For example, **MEC** servers can be placed closer to road users to guarantee quick offloading. The **AP** is responsible for generating strategies and policies used by the control plane, such as access control, multi-access edge management, service priority, network slicing, adaptive protocol deployment, and more.

In the control plane, road users exchange awareness messages through different communication technologies to perceive the environment. When vehicles transmit **CAM** messages, **VRU** equipped with smartphones have the capability to send **VAM** messages. **VAM** messages are characterized by a shorter length, context-specific, and are introduced by the **ETSI** standard [37]. However, both **CAM** and **VAM** include essential information such as position, speed, direction, etc. In this chapter, we present a multi-**RAT SDN**-assisted collision detection system designed to protect **VRU** by predicting road collisions. The system leverages network function virtualization and software defined network technologies. It incorporates a collision detection service that collects specific messages from road users and processes them to detect colli-

sion risks. Our proposed solution enables vehicles and VRU to intelligently adapt the rate of awareness messages. As illustrated in Figure 4.1, in the DP, the base station and the RSU provide connectivity over the geographical area and facilitate data communication between vehicles and VRU. The VRU exchange safety-related information encapsulated in CAM or VAM messages directly or indirectly through the infrastructure.

The network is characterized by its heterogeneity, where different communication technologies coexist, such as 802.11p, C-V2X, 5G-V2X, 802.11b, etc. [8] and are supported by SDN and MEC. In the CP, the SDN controller manages network slices and functions using AP policies. It has a global view of the network and controls the DP via the Southbound Interface OpenFlow.

The trajectory prediction and collision risk anticipation algorithm can be deployed in either the cloud or the MEC servers, depending on the situation. The cloud provides ample computational and storage resources, while MEC guarantees low latency due to its proximity to road users.

4.2.2 Impact of signalling overhead on the SDN controller

We studied the impact of adapting the frequency of sending awareness messages on the network to validate our hypothesis. To this end, we emulated a large-scale network using Mininet-WiFi and the Pox SDN controller, with nodes representing road users moving at different velocities as described in algorithm 1. Figure 4.2 is a screenshot of a scenario of the emulation network with 10 road users.

In order to achieve optimal solutions, we conducted the experiment iteratively for the three granularity (500 *ms*, 1000 *ms* and 5000 *ms*) while varying the number of road users (1, 5, 10, 15, and 20). We recorded the data obtained from each emulation and subsequently computed the average of all the tests.

Algorithm 1: Mininet-WiFi network emulation

Result: SDN-based vehicular network emulation
Initialisation: Initialize Mininet-WiFi packages;
 Create Mininet-WiFi stations;
 Add POX controller;
 Add access point;
 Associate controller with access point.;
for *each station* **do**
 | Associate station with access point;
end
 Configure SUMO mobility for stations;
 Build network;
 Start controller and access point;
 Run Simulation;

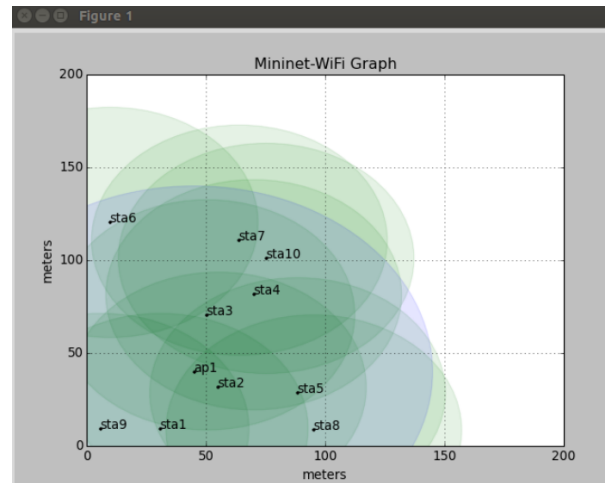


Figure 4.2: Mininet-WiFi emulation.

The results obtained confirm our initial expectations. As depicted in figure 4.3, the signaling overhead increases with both the density of road users and the messages' periodicity.

4.2.3 Adaptive collision detection algorithm

As described in figure 4.4, the first step in VRU safety application is data collection from network functions and the exchanged awareness messages.

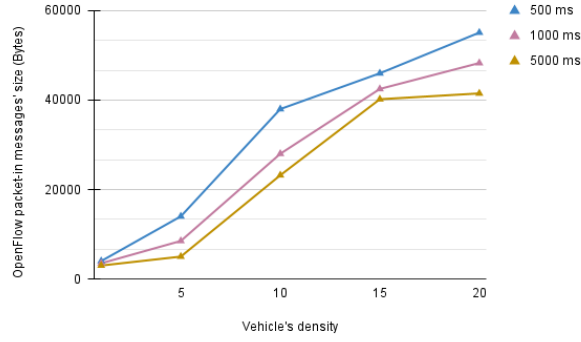


Figure 4.3: Open-Flow Signalling Variation.

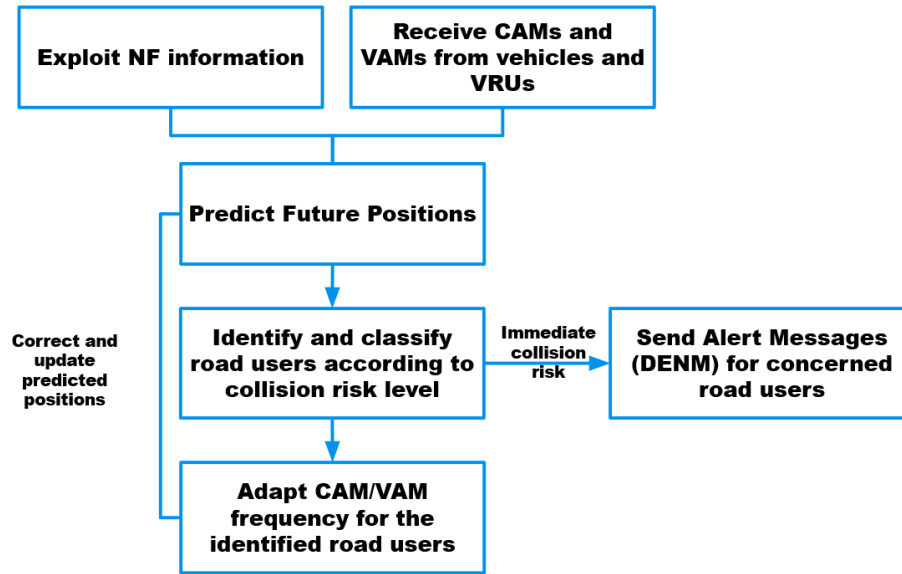


Figure 4.4: Adaptive Collision Detection Algorithm

In this work, we considered (CAM/VAM) as the primary sources of information that should be provided to the collision detection application to operate correctly. Inspired by [22], a server processed these messages to check their freshness and then used them in the adaptive collision detection algorithm. The latter predicts future road users' positions based on their current position, velocity or acceleration information. We implemented a Kalman Filter (KF) to estimate the location of the VRU and vehicles based on the former history of the received user positions. Then, it computes the minimum distance and the time between each two nodes and compares it to a

threshold D_{min} used in [88].

The algorithm selects a group of vehicles and **VRU** to be alerted, if they are at immediate collision risk via **DENM**. Otherwise, the algorithm goes through to the next iteration and configure the **CAM/VAM** frequency to be used by the concerned nodes based on risk area and the computed time before collision. Once the algorithm receives new positions, it updates the **KF** to correct the estimated positions' accuracy.

4.2.4 Kalman filter for position prediction

KF is a mathematical algorithm that can be applied to determine the state of a dynamic system by utilizing imprecise and incomplete measurements. Its applications extend to several fields such as navigation and guidance for aviation, vehicle control, as well as inertial measurement unit-based position estimation applications. When it comes to vehicular trajectory prediction, this tool can help in approximating parameters like the acceleration, the velocity or the location through input from sensors such as accelerometers, **GPS** or gyroscopes. One of its advantages lies with its ability of confronting noisy signals and ambiguities present within input measurements, which makes precise positioning estimations challenging in dynamically changing conditions of vehicular networks. The algorithm integrates previous readings and predicted measurements alongside current observations for quick estimates regarding positional changes at each time interval.

Several studies have explored the use of **KF** in vehicular position estimation. For instance, authors of [100] proposed a **KF**-based algorithm for vehicle position estimation using **GPS** and accelerometer measurements. The algorithm was able to estimate the vehicle's position with high accuracy even in the presence of noisy sensor measurements. They developed an analytical framework based on the Extended Kalman Filter (**EKF**) to evaluate a vehicle tracking systems. In [101; 102] authors used **EKF**,

an extension to Kalman Filters for vehicle tracking. Authors of [103] established effective and robust vehicle tracking algorithm based on the use of **KF**. They introduced an innovative technique that combines prior knowledge from Kalman filtering to facilitate background updates, refine morphological operations, and identify occlusion. It relies on merging prior data with observations to isolate vehicles even under challenging occlusion conditions.

In this research, **KF** comes into action to predict future positions based on the history of the received data encapsulated in **CAM/VAM** messages, to anticipate potential risky events.

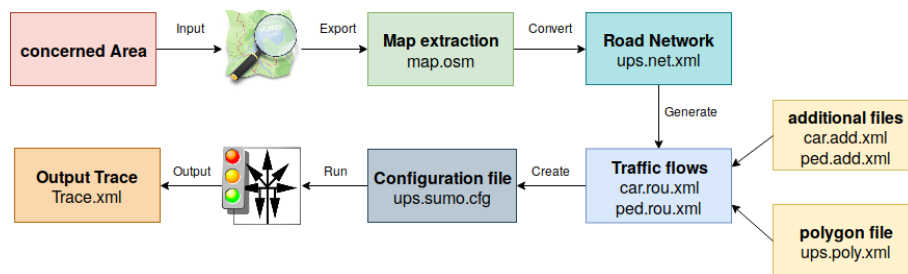


Figure 4.5: Map extraction steps

The steps of the mobility scenario generation to extract trajectories are described in figure 4.5. Firstly, the initial step involves exporting the campus map by utilizing the open-source tool OpenStreetMap. This tool enables the creation of editable geographical maps, yielding an "map.osm" file. Subsequently, the NETCONVERT tool is employed to generate the road network, encompassing vehicle and pedestrian routes. This tool imports digital road networks from the map and converts them into a format compatible with **SUMO**, specifically "ups.net.xml". Moreover, polygon data from the osm dataset is imported to produce a "ups.poly.xml" file, which will be further utilized in the mapping process. Furthermore, additional files need to be prepared, containing pertinent traffic characteristics and simulation parameters for each element. Once the road network has been adequately prepared, the subsequent

step involves generating traffic for vehicles and pedestrians, accomplished via the "randomTrip.py" script. This script initiates the generation of trajectories, flows, and routes, ultimately producing "cars.rou.xml" and "peds.rou.xml" files. Finally, to execute the simulation and subsequently extract a trace file, a SUMO configuration file, namely "ups.sumo.cfg", is created, using the various generated files.

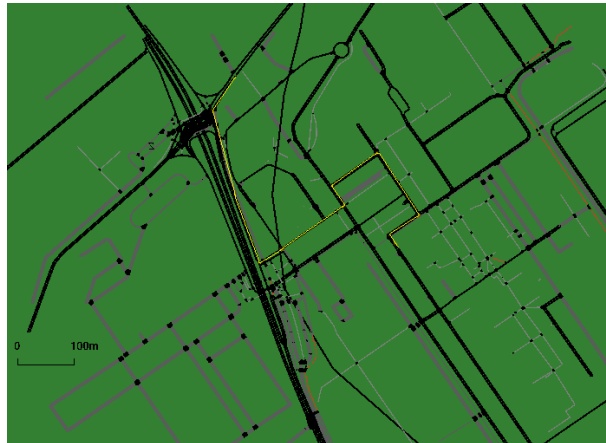


Figure 4.6: Screenshot of SUMO simulation on the campus of Paul Sabatier University

Figure 4.6 is a screenshot of the simulation carried out by SUMO on the campus of Paul Sabatier University (UPS).

As shown in figure 4.7, we conducted an experiment to analyse the effects of Kalman filtering on three different time prediction windows 500 *ms*, 1000 *ms*, 5000 *ms* referred to as "*dt*". These time windows represent varying levels of periods, determining how frequently the filter receives updates that we inject from the mobility trace to refine its estimated values based on different time scales.

Results show the impact of prediction window on the accuracy of the prediction. The period of 5 *s* is the least accurate in terms of prediction accuracy. The algorithm used for prediction relies on periodic updates at this timescale, resulting in relatively larger errors compared to the finer granularities. The prediction window with a period of 1 *s* yields a reasonably accurate estimation of the position, whereas the period of 500 *ms* provides the highest accuracy. It is important to highlight that at the initial

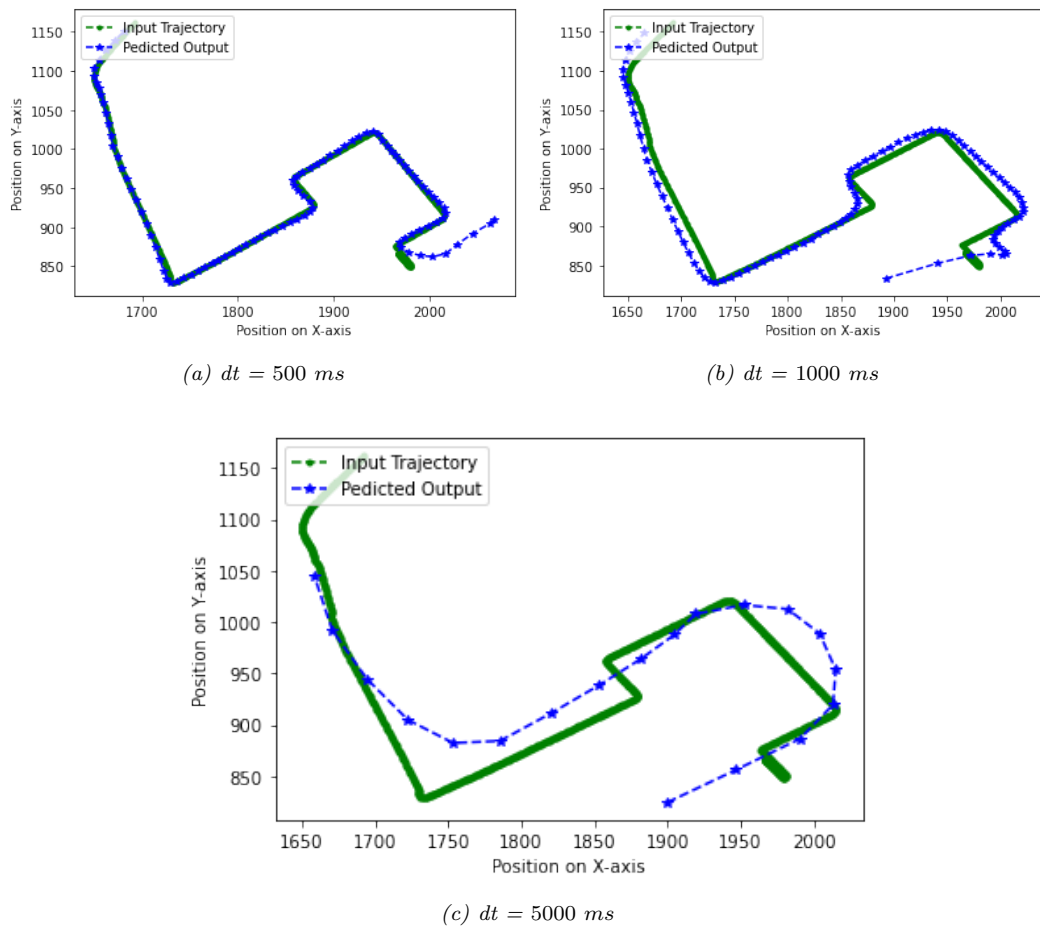


Figure 4.7: Kalman Filter: Predicted vs actual trajectory

stage, it is necessary to consider historical data in order to anticipate future actions. It should be noted that when not providing the Kalman filter with position information from time $t - 1$, the first set of predictions may appear unconventional or peculiar, as evidenced by the observations made in the three predictions in figure 4.7.

This section provided a thorough analysis to understand how different prediction window settings affect the accuracy of the localization process, the subsequent section will explore the effects of the adaptive algorithm on system reliability, latency, and energy consumption.

4.3 System Validation

In order to validate our proposed algorithm, we have evaluated the impact of the frequency adaptation in the prediction and the reliability of detecting collision risks. We compared our approach with different frequencies (0.5 Hz , 1 Hz , 5 Hz). We generated the traffic mobility using **SUMO** and implemented the adaptive collision detection algorithm in MATLAB. The algorithm with fixed periodicity equal to 5000 ms operates as follows: it takes a position, predicts the next position within a 5-second timeframe, checks for collisions, waits for the next update after 5 seconds, and continues this cycle. While the algorithm offers two advantages, namely moderate energy consumption on smartphones due to fewer update messages and avoidance of controller overload, there are significant limitations. Specifically, the chosen granularity of 5 seconds leads to inaccurate position estimations and statistics from the simulation reveal missed accident events. These shortcomings arise due to the limited number of updates and corrections at this granularity, hindering the algorithm's ability to capture directional changes effectively. However, 500 ms and 1000 ms granularities have better reliability, and are more accurate in position anticipation.

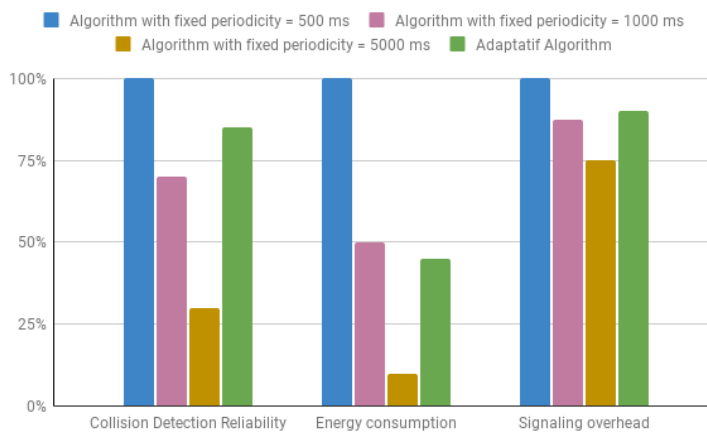


Figure 4.8: Performance Evaluation: Comparative Analysis of Adaptive Algorithm and Fixed Periodicity Algorithms

The adaptive algorithm effectively addresses these limitations by dynamically switching between different granularities based on the risk area and time before a collision. This approach ensures reliable risk detection without overloading the network. Figure 4.8 showcases the performance evaluation of the adaptive algorithm compared to three fixed periodicity algorithms. Additionally, we collected data on the number of detected accidents using four different algorithms, comparing them to a reference scenario where the total number of events was known, to evaluate their reliability in accurately identifying and detecting accidents. This analysis allowed us to gain insights into the performance and effectiveness of the algorithms in terms of energy efficiency and accurate accident detection. The adaptive approach gains accuracy using low frequencies in risky contexts, while stretching the granularity in low-risk situations.

4.4 Conclusion

Within this chapter, we justified our architectural choice by implementing an SDN approach, which effectively facilitates the attainment of our objectives. We employed emulation to demonstrate the impact of signaling on the controller, and we utilized these results to extract the values of the interval between two consecutive position messages. These values will be used in our adaptive algorithm in the next chapter. Additionally, we showcased how frequency adaptation can enhance the overall performance of the VRU protection system in predicting future trajectories and detecting potential collision risks. By adjusting the up-link traffic of CAM and VAM accordingly, we update the prediction accuracy and efficiently send alert messages. This approach helps reduce network traffic load and preserves the battery level of VRU's smartphones.

However, as we delve further into this thesis, some particular aspects that pique our curiosity are:

- How to adapt and improve the process of gathering messages opportunistically?

Relying exclusively on collision risk events for frequency adaptation and resource optimization can be susceptible to inaccuracies and false positives, especially considering the dependence on the accuracy of the collision detection algorithm.

- Is a centralized approach utilizing **SDN** the most optimal architectural choice?

Indeed, implementing of **SDN** in an entirely centralized manner has shown its vulnerability to signaling overhead and increased system susceptibility due to its heavy reliance on a central controller. It introduces a single point of failure, which poses significant limitations. Exploring alternative architectural options to mitigate these concerns related to signaling overhead and system vulnerability is essential. One promising approach is adopting a hybrid architecture combining centralized control elements with distributed decision-making within individual **MEC** servers, each assigned to oversee a specific geographical area. This architecture model aims to balance between leveraging the advantages of centralization while prioritizing resilience and scalability.

- What are the consequences of frequency adaptation on both the network and application prerequisites? Our research proposes an extension to the adaptive algorithm to answer these inquiries. This extension involves incorporating the kinematics of movements and the contextual information obtained from the perceived environment. By considering both aspects, we aim to create a more comprehensive and robust approach to resource selection within the cooperative safety system. The details of this enhanced approach will be discussed in the subsequent chapter.

Enhancing Road Safety: A Context-Aware Adaptive Scheme

5.1 Introduction and Problem Statement

The main objective of this chapter is to establish a strategy that enables the **V2X** system to enhance network resources' allocation while considering various constraints associated with quality of service and energy consumption concerning **VRU** transmitting devices and also computing servers. Several studies that explored the topic of **VRU** safety application [23; 54; 88; 55; 26] have employed a fixed and high frequency beaconing rate to transmit awareness messages. However, we contend that it is important to intelligently adjust the message periodicity by considering the context in which they are delivered before resorting to maximum transmission rate. Moreover, the dynamic nature of the vehicular network environment, including factors such as changes in network density, number of surrounding vehicles and **VRU**, and potential hazardous situations, prompt us to consider that following only the **ETSI** standard may not efficiently utilize network resources based solely on location dynamics. Fur-

thermore, the latter adversely affects energy consumption for vulnerable road users who rely on their battery-powered smartphones.

By addressing these limitations and challenges proactively, we design a novel Neighbouring Based Scheme (**NBS**) to enhance the existent standard version of awareness messages transmission. **VRU** and vehicles will be able to efficiently adapt the frequency of sending awareness messages based not only on the variation in location dynamics (e.g. velocity, position and direction) but also on the surrounding environmental context. We believe that context-aware and dynamic adaptation of the transmission periodicity undoubtedly helps in reducing unnecessary network signaling and saving the energy of the **VRU**' connected devices.

Initially, we begin by providing a detailed account of the employed architecture. Then, we introduce the **NBS** algorithm as a means to adjust periodicity in order to alleviate network load and conserve energy resources. In the second phase of our investigation, we study the impact of frequency adaptation on the application requirements with regard to evaluating our solution using simulation techniques.

5.2 Architecture Definition

In this chapter, to overcome the limitations associated with a global **SDN** architecture where a single centralized controller executes the collision detection algorithm and takes decisions for a large scalable network, we explore an alternative approach that involves the deployment of multiple **MEC** servers, where each server is responsible for a specific geographical area. Using this architecture, we aim to distribute the control and decision-making tasks across multiple **MEC** servers, thereby alleviating the signalling overhead and reducing the vulnerability to system failures. Then, the central controller will be responsible for managing the communication between all the

MEC servers, to guarantee the service continuity. For instance, charging road users' data transitioning from one region under the supervision of an **MEC** server to another region monitored by a different **MEC** server. In this work, by narrowing our study to a single zone under the supervision of one **MEC** server, we can thoroughly investigate the scalability and accuracy challenges within this specific context, paving the way for targeted solutions that effectively address the requirements and characteristics of the selected area. In order to ensure the required responsiveness of safety services, we leveraged the functionalities offered by multi-access edge computing. This technology allows for an increased processing power and brings computing capabilities closer to road users [63; 22]. Additionally, **MEC** enables the integration of various Radio Access Technologies through its multi-access feature, as we explained in chapter 3.

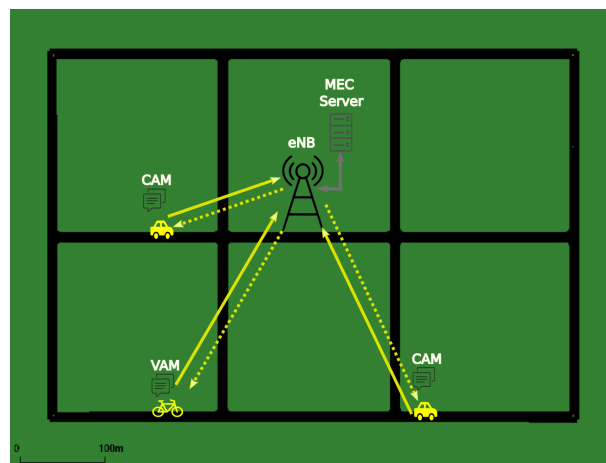


Figure 5.1: System Architecture (on a screenshot from SUMO simulation)

As shown in figure 5.1, this architecture counts connected vehicles, **VRU**, an Edge server, and a base station.

- **VRU**: Smartphones are used by **VRU** to exchange **VAM** with the **MEC** server. In this part of the thesis, we chose to study cyclists as **VRU** since they are exposed to danger when they share the road with vehicles.
- Vehicles: connected vehicle exchanges safety-related information encapsulated

in specific messages (**DENM** or **CAM**) to a **MEC** server that covers the area. Vehicles and cyclists transmit the **CAM** (**VAM** respectively) carrying the transceiver related speed, acceleration, position, heading, identifier (ID) and other information every period configured by the **MEC** server. The centralized architecture is more favorable in multi-**RAT** context as it solves heterogeneity issues, enables vehicles and **VRU** to use different communication technologies and benefits from the global knowledge of the network.

- The Base station is related to the **MEC** server. It is responsible for allocating resources for road users and transmitting messages between the server and the communicating entities.
- **MEC** server: it brings computing, storage capabilities and **V2X** services closer to vehicles by providing more computational power closer to the users. The goal of a **MEC** server within this architecture is to reduce the latency by avoiding the need to traverse through the core network, thereby reducing infrastructure delays. Moreover, it is used to support multi-access through different technologies and to take benefit from the centralized approach to collect more **CAM** without experiencing **NLOS** limitations [22]. The **MEC** Server is the key element of this architecture, where **CAM** and **VAM** periodicity is computed. It analyses and extracts valuable information from the received messages. It adapts the transmission frequency by considering the environment's context.

For the purpose of simplification, we opt to position both the **MEC** server and **BS** at the center of the grid in this study. This choice is deemed reasonable because it facilitates our research.

5.3 Neighboring Based scheme

5.3.1 Neighborhood discovery

As observed in figure 5.2, we chose a simplified model where a vehicle and a VRU are considered as neighbors when the distance between them is shorter than the sum of their radius. This scheme can be applied for two vehicles as well. Initially, we conducted experiments using a static radius of 6 m for all scenarios. However, upon further analysis, we realized that it would not be equitable to expect cyclists and vehicles with varying velocities to adhere to the same fixed distance criterion. Therefore, we introduce a modified formula for calculating the radius R as a function

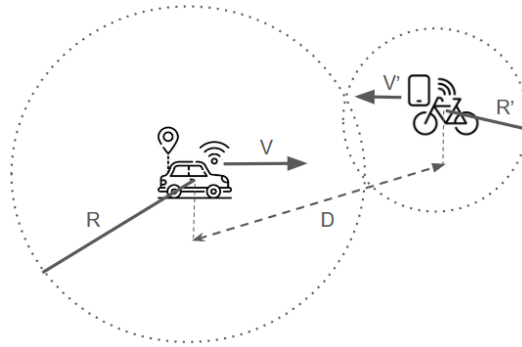


Figure 5.2: Neighborhood discovery procedure.

of the velocity V as follows: $R = r_0 + \frac{V}{10} \times 6$ where r_0 is the gap of one car's length in case of stopping behind another vehicle (e.g. at traffic lights, an intersection, a pedestrian crossing, an emergency braking, in stop-start rush hour traffic, etc.). The second term $\frac{V}{10} \times 6$ aligns with safety distances specified by traffic laws[104]. It should be noticed that this formula allows adjustments based on different velocities while maintaining consistent safety standards. As we mentioned earlier, this is a simplified neighboring discovery model that suffers from limitations like 3D localization. For instance, the case when a vehicle is on a bridge and a VRU is below it. There are

possibilities to extend it beyond simply incorporating velocity into calculating R . Environmental factors such as weather conditions could also be taken into account by adding braking distance parameters.

5.3.2 Implementation

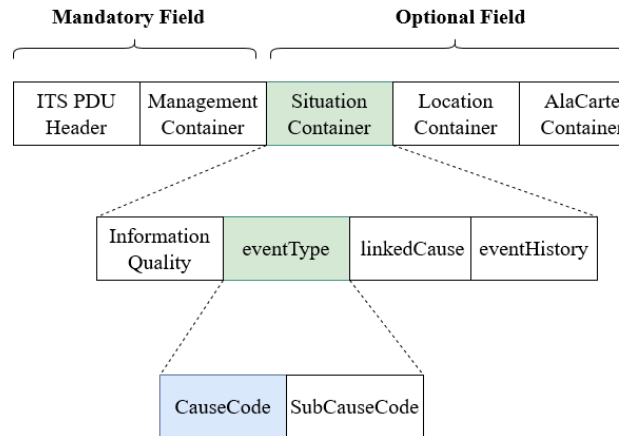


Figure 5.3: DENM message format.

In this work, we used the optional field of the DENM, which includes the situation container, that contains the event type repository. The latter provides a description of the detected event, with each event type assigned a unique code. It is composed of two data elements: causeCode and subCauseCode [105]. The causeCode represents a high-level description of the event type, while the subCauseCode offers more detailed information about the event associated with the causeCode. In our case, we assign flag 1 in the bit value to the CauseCode number 97 that corresponds to collision risk type, when the server finds out there are neighbors otherwise the flag is set to 0.

To enhance this simplified version further, we can introduce an optional field within the CauseCodeType container that corresponds to neighborhood density as an example. Subsequently, in the subCauseCode section, different codes could be assigned to represent various levels of density. This enhancement is feasible since the

current Abstract Syntax Notation 1 (ASN1) implementation of the ETSI standard messages' specification only used 4 octets as stated; octet #0 for Service Specific Permissions (SSP) version control, octets #1 – 3 for service specific parameters and finally octets #4 – 30 reserved for future use.

5.3.3 Algorithm

The NBS is based on the standard. It mainly runs two processes: one on the MEC server, where the server controls road users' CAM transmission frequencies, and the other one is on the client (on the vehicle or on the cyclist smartphone), as illustrated by the diagram in figure 5.4.

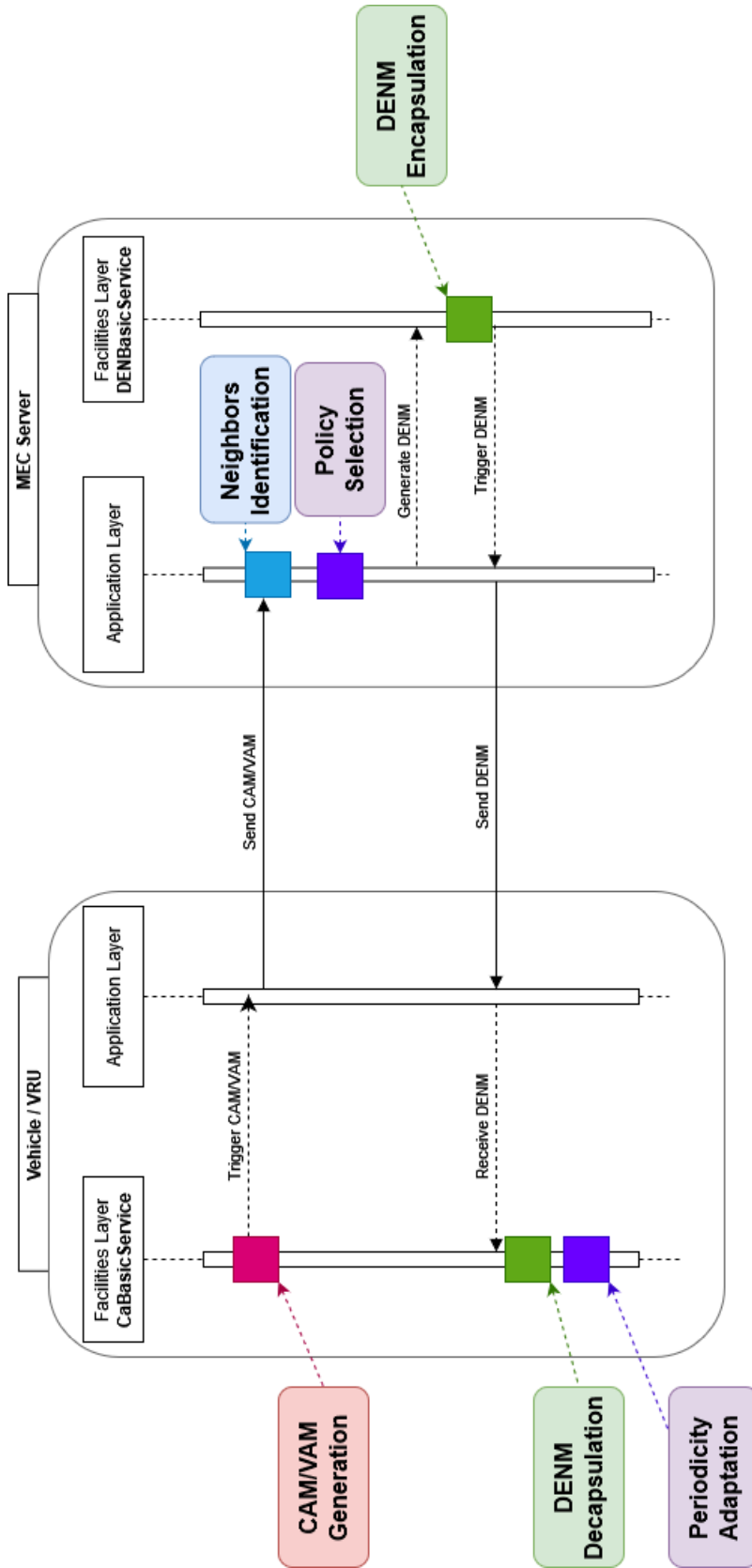


Figure 5.4: Diagram of the proposed Adaptive and Dynamic CAM and VAM collection scheme.

Detailed steps are described as follows: As soon as the node is created in the simulation and the first **CAM** or **VAM** is received, the server extracts the needed data from the packet: it gets the message ID and all the information fields related to the node such as the speed, the direction, the position, etc. The next step is neighbors discovery, where the server uses the velocity to compute the radius used to search if the node has neighbors, as explained in figure 5.2. If it does, it triggers a **DENM** to the client with a flag of value one and stores its ID in a vector that corresponds to the list of IDs where the standard is activated, otherwise it just sends the **DENM** with a flag of value zero, which means that the node needs to send a message using the defined period P_s . In the following steps, the server continues listening to the clients. When a new **CAM** or **VAM** arrives, the server extracts the information and updates them to the corresponding node ID. After the update, it returns the list of neighbors at the message arrival timestamp. Then for each stored node ID, it verifies the condition of triggering a **DENM** as described by the pseudocode of Algorithm 2.

On the client algorithm, the vehicle or the **VRU** starts by sending the first **CAM** or **VAM** to notify the server about its presence. Then, it receives the first response via the **DENM** to set its initial state (activate the standard or not) as shown in Algorithm 3. Depending on this state, two scenarios could occur: if the flag in the received **DENM** is equal to one, the standard is activated. Its policy is respected to send the awareness messages periodically to the server. Otherwise, the node sends the message periodically with a specific periodicity P_s that we define in the `caBasicService` of the facilities layer. The transition between these two cases is triggered by the arrival time of the **DENM**.

Algorithm 2: NBS Algorithm (MEC Server side)

Result: Controlling CAM and VAM periodicity

```

while True do
    Receive CAM or VAM from ITS-Stations ;
    Extract IDs, positions, speeds, timestamps, etc. ;
    for each ID in IDs do
        Compute Radiusi;
        Find neighbors;
    end
    for each ID in IDs do
        if ID in neighbors and standard not activated then
            Send DENM with flag = 1;
        end
        if ID not in neighbors and standard activated then
            Send DENM with flag = 0;
        end
    end
end
end

```

Algorithm 3: NBS Algorithm (VRU/vehicle side)

Result: Applying CAM or VAM transmission policy**Initialisation:** ITS-Stations initially send CAM or VAM to the server;

```

while True do
    Receive DENM;
    if flag = 1 then
        Send awareness messages using standard
    else
        Send awareness messages using specified periodicity Ps
    end
end
end

```

5.4 Performance Evaluation

In this section, we evaluate the performance of the **NBS** under various periodicity P_s and network size configurations.

5.4.1 Comparison and performance criteria

We carried out a performance comparison between fixed periodicity method, the **ETSI** standard and the proposed **NBS** scheme. The evaluation focuses on two main aspects: *(i)* how reliable the policy is at detecting events in time, *(ii)* its impact on traffic load and energy consumption.

The scheme should optimize the traffic load and the energy consumption by minimizing the transmission rate. However, the **CAM** or **VAM** periodicity should not impact the system reliability at detecting events, especially for safety applications characterized by high reliability and low latency requirements. Accordingly, we present the impact of varying the transmission periodicity on the system performance in this section.

5.4.2 Simulation set-up

Simulations have been conducted for a urban scenario of $400 \times 600 \text{ m}^2$. As we mentioned earlier, in this simulation we choose cyclists as **VRU** because they are more exposed to danger when they share the road with vehicles. We considered **VRU** as mobile nodes with low velocity, where the maximum speed is 50 km/h for vehicles and 15 km/h for cyclists. We simulated three traffic scenarios 5, 10, 20 and 30 nodes containing 2, 4, 8 and 12 **VRU** respectively.

Simulation step length is equal to $0.01s$ which corresponds to mobility updates granularity. As **VRU**' smartphones are equipped with cellular technology, and to

simplify the heterogeneity aspects, we considered in this simulation the use of cellular **V2X** communication by all the nodes to exchange **CAM** and **VAM** with the network infrastructure. As we are only interested on exchanging essential information, **VAM** and **CAM** have the same mandatory fields.

The size of the **CAM** message is 101 *Bytes* considering data of High-Frequency container following the **ASN1** decoder and encoder implementation. We simulate the scenario described in figure 5.1 for 300 *s* duration and repeated the experiment multiple times for different nodes trajectories.

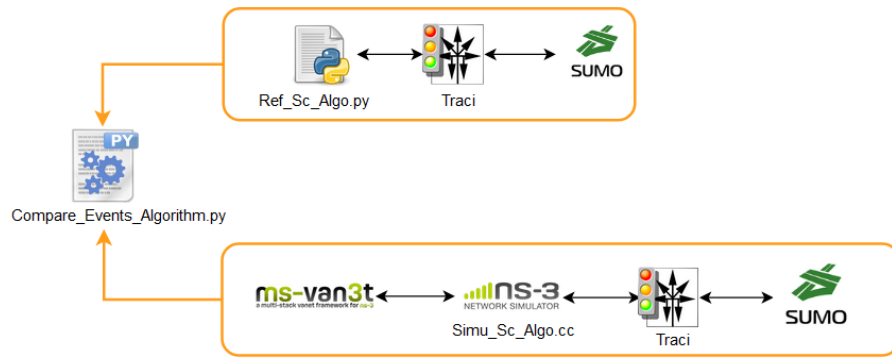


Figure 5.5: Simulation Framework.

To assess the performance of the proposed scheme, we used ns3 [13] which is a C++ based network simulator with a framework to simulate **V2X** communications [14]. The network simulator is coupled with the microscopic road traffic simulator **SUMO** to model the traffic and node mobility. As depicted in figure 5.5, we implemented a collision-avoidance simulation scenario similar to [23]. Road users send their awareness messages to a central **MEC** server with a fixed periodicity, following the standard, or the proposed scheme. The event starts when there is a collision risk and ends when **VRU** or vehicles are no longer at risk. We compare the simulation results with a reference scenario where we implement a python script to extract real-time events that occurred on **SUMO** [12].

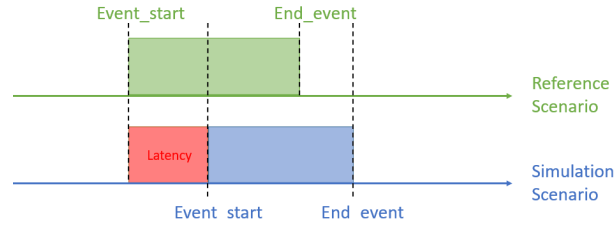


Figure 5.6: Reference and simulation scenario.

By comparing the starting time of an event, we can obtain the latency of events detection as shown in figure 5.6. If the event is not seen or is caught late in a time greater than the periodicity used to send an awareness message, we consider it as non-detected.

5.4.3 Simulation results

In this section, we study and compare the performance of the three policies, in terms of both network and application related metrics namely (energy consumption, global transmission rate, and event detection latency and reliability). To improve the efficiency and precision of our experiments, we have designed an automated script that greatly simplifies the simulation process. It allows us to conduct numerous simulations by changing policies for different node numbers across various periodicity.

5.4.3.1 ETSI standard limitations

As presented in figure 5.7 the standard tends to operate with low periods from 100 *ms* to 400 *ms* and especially 200 *ms* and 300 *ms*. This observation affirms the justification for implementing our **NBS** approach.

The results plotted in figure 5.8 shows that the standard performance in terms of (i) event detection latency is approximately around 100 *ms*, (ii) the global rate in terms of the total successfully received messages by the **MEC** server when mobile nodes use the standard policy, (iii) and the reliability of event detection that is close

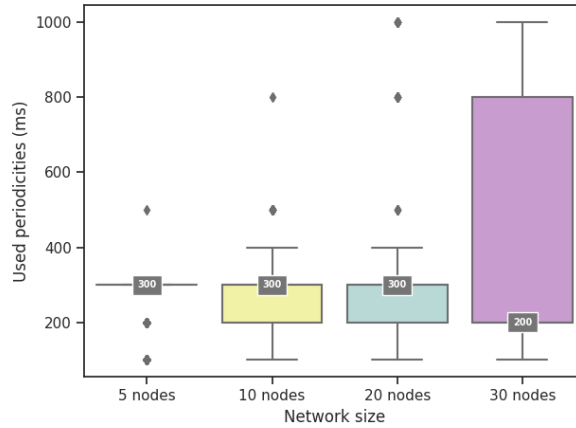


Figure 5.7: Box plot of the periodicity distribution used by the standard.

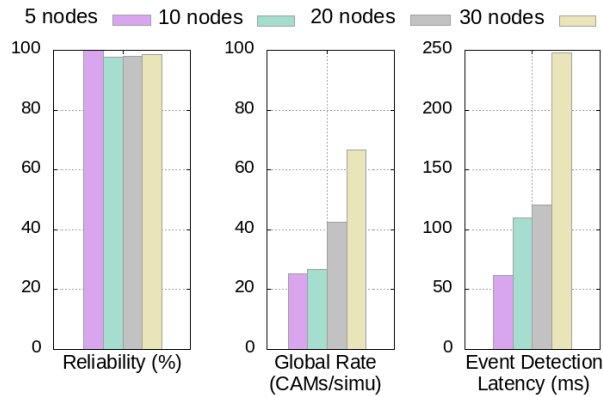


Figure 5.8: ETSI Standard Performance.

to 100% except for high-density scenarios when it starts to miss events.

5.4.3.2 Impact on global transmission rate and energy consumption

Figure 5.9 illustrates the comparison between the fixed periodicity and neighboring-based approaches in terms of the global rate. In this context, the global rate refers to the total number of received awareness messages during simulation time. As expected, an increase in the number of nodes leads to a higher global rate. However, our results demonstrate that for periods exceeding 100 *ms*, our proposed approach can significantly optimize the number of exchanged messages. Contrarily, when the beaconing rates are fixed, there is a correlation between periodicity and global rate.

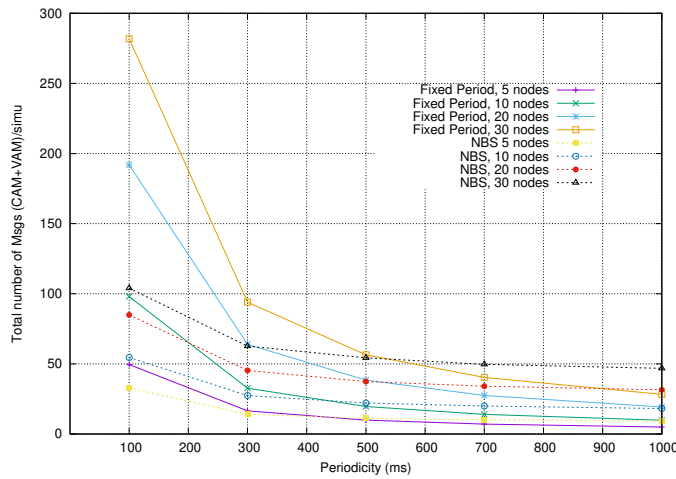


Figure 5.9: The global rate in terms of CAM and VAM collected per simulation function of periodicity.

This means that as the period increases, the global rate decreases. In particular, we observed a remarkable improvement with our NBS compared to the standard for P_s values greater than 100 ms. We cannot choose the period P_s equal to 100 ms because this period corresponds to the standard maximum beaconing rate, which is used when mobile nodes change frequently their location dynamics.

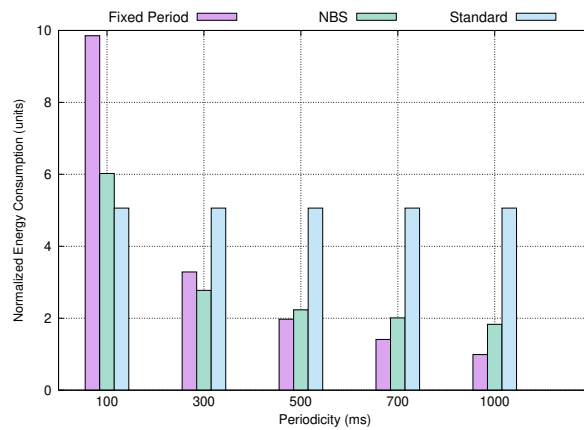


Figure 5.10: Energy Consumption.

The energy consumption was inferred by considering the average number of messages transmitted per second by a single VRU. The unit of measurement used to quantify this energy is defined as the energy consumed when transmitting an awareness

message. In Figure 5.10, the graph illustrates the comparison in terms of energy consumption for a VRU node among three different policies implemented for generating awareness messages on a VRU node: namely, the standard policy, neighboring-based scheme, and fixed periodicity. It should be noted that except for P_s equal to 100 ms which corresponds to a high beaconing rate, employing NBS demonstrates significant reduction in power consumption across varying values of P_s compared to using only the standard policy. For instance, for 300 ms , power consumption is reduced by half compared to solely relying on the standard policy, while for 1 s it is reduced to third. Moreover, fixed periodicity with intervals equal or greater than 300 ms saves energy, while intervals equivalent to 100 ms experience more substantial energy consumption compared to the standard policy.

5.4.3.3 Impact on event detection latency and reliability

After studying the gain of the NBS scheme under different values of P_s , it is paramount to study the impact of the period selection on event detection latency and reliability.

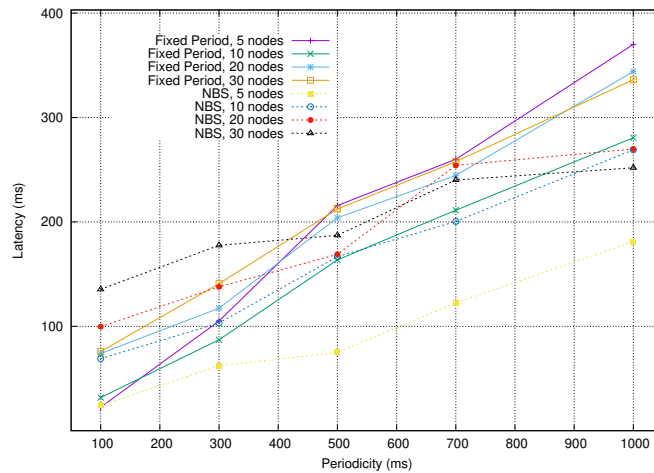


Figure 5.11: Event Detection Latency.

Figure 5.11 shows the mean latency of events detection and table 5.1 presents the event detection reliability, while comparing the fixed periodicity scheme with the

proposed **NBS** scheme under four densities.

Table 5.1: EVENT DETECTION RELIABILITY (%)

Period (ms)	Fixed Periodicity				NBS			
	5 nodes	10 nodes	20 nodes	30 nodes	5 nodes	10 nodes	20 nodes	30 nodes
100	100	100	100	100	100	100	100	99,487
300	100	97,777	97,029	100	100	98,360	98,019	98,974
500	100	97,777	96,039	98,974	100	98,360	97,029	98,461
700	100	97,777	92,079	97,435	100	98,360	96,039	98,461
1000	100	93,333	92,079	97,435	100	98,360	96,039	98,461

In the 5 nodes scenarios, all the events are detected by both approaches, guaranteeing a 100% reliability similar to the standard performance in figure 5.8. However, the **NBS** scheme outperforms the fixed rate policy in terms of latency for all the periodicity and outperforms the standard for periods equal or less than 500ms. Nevertheless, for 10 nodes scenarios, all policies have similar performances where they skip some events when the periodicity increases. The **NBS** scheme detects events with the lowest latency for P_s equal or less than 300ms. For the scenario with 20 nodes, **NBS** has better reliability and latency than the standard for P_s equal or less than 300ms. The scenarios with 30 nodes, the **NBS** with high periods and the standard have comparable results. The **NBS** with low periods achieve low latency and better reliability than the standard. The latter operates with high periodicity as shown in figure 5.7. In fact, this is because the mobility scenario is overcrowded, and some slow cyclists slow down the vehicles behind them in **SUMO**. We then note a slow evolution of the nodes' dynamics (low variation of position and speed at each time-step). Thus, most of the events were detected despite the high density and the use of large periods by the standard but with high latency.

5.4.4 Discussion

By analyzing the obtained results, we establish that the **NBS** improves significantly the global rate and thus the energy consumption compared to fixed periodicity schemes and the standard using periodicity greater than 100 *ms*. To study the impact of the specific periodicity P_s in the case of having no neighbors, we evaluated the performance of the **NBS** on detecting risky events in a road safety application. The average latency of event detection does not exceed 500 *ms*, and reliability is close to the standard. This work evaluates the scheme under different values of P_s and presents their impacts. It can be enhanced by introducing prediction in periodicity selection by choosing different proximity levels with different radius. This way, intelligence can help in selecting the best frequency configuration according to the environment state and thus compensate the latency.

5.5 The Path Forward: Expanding the research landscape

In order to broaden the scope of our investigation and make further progress, we have the opportunity to explore a multitude of different paths. In the context of **VRU** and its connection to 5G cellular communication, a possible approach to reduce energy consumption is by allowing smartphones to enter an idle mode. This means that when not actively in use, the smartphone can conserve power by minimizing its activity. Moreover, to enhance the system reliability, we can also define dynamic risk zones when vehicular activity is present in the vicinity. Within this zone, our research can be expanded to accommodate varying levels of neighboring density. As a result, the radius used for calculating neighboring procedures can be modified based on the

density of nearby objects.

5.6 Conclusion

In this chapter, we focused on examining a [V2X](#) communication system that is specifically designed for the road user safety use case. Our main contribution was the development of a centralized scheme to regulate the collection of awareness messages. We strongly believe that relying solely on changes in location dynamics is not sufficient when it comes to adjusting transmission periods. Instead, it is crucial to take into account the surrounding context as well.

Environmental context comprises numerous elements that encompass various factors, such as meteorological conditions, the state of roads, levels of traffic congestion, the presence of obstacles and ongoing construction sites, accessibility to infrastructure facilities, and the timing during rush hour or non-peak times. In this work, our focus was on the utilization of neighboring information as a contextual framework for enhancing transmission control. We proposed a novel approach called [NBS](#), which leverages the detection of nearby nodes to optimize the effectiveness of data transmission.

This study demonstrates the efficacy of adaptive schemes that strategically choose the most suitable periodicity configuration based on the surrounding context, by surpassing the limitations of current policies and capitalizing on their advantages. In fact, we have highlighted the limitations of the current standard policy when it fails to consider contextual information, wasting network and energy resources. Furthermore, we have demonstrated how fixed periodicity schemes can save energy by using longer periods, but at the cost of increased latency and reduced reliability in detecting dangerous events. On the other hand, setting low fixed periodicities

improves performance and reliability; however, it comes with a trade-off of higher energy consumption and inefficient utilization of network resources.

This research is not the final contribution to evaluating the effectiveness of collecting awareness data in [V2X](#) safety applications. There are still opportunities to further investigate and assess its performance. This could include investigating different aspects, such as examining various sizes of data packets and utilizing different types of existing communication messages. In the subsequent chapter, we present an [AI](#)-based approach that utilizes reinforcement learning techniques to determine the optimal periodicity configuration and ideal environmental conditions for transmitting the most appropriate message type.

Leveraging AI for Optimal Message

Formats: Expanding Possibilities

6.1 Introduction and Problem Statement

In the preceding chapter, we demonstrated the effectiveness of adaptive schemes to select the optimal periodicity configuration, relying on environmental context. These schemes have demonstrated promising outcomes by surpassing existing policies limitations and leveraging their benefits. In this chapter, our aim is to further enhance network resources optimization and management to address scalability problems and meet safety application requirements. Moreover, while continuing to consider VRU as an active participant, we focus on achieving even greater optimization. To this end, we aim to take advantage of the diversity of existing messages in vehicular networks and try to minimize transmissions whenever possible. This involves determining the best message type with the appropriate size and adjusting its transmission frequency based on network conditions.

Additionally, through communication-based perception, we aim to mitigate the

network load and intelligently reduce the number and the size of messages transmitted simultaneously by harnessing the collective knowledge within the network. This approach also leads to substantial energy conservation when applied to vulnerable road users detected by **CAV** equipped with cameras and sensors, and are able to send **CPM**. In the next sections, we present a Q-Learning technique to opportunistically address the emerging challenges and meet the evolving requirements in vehicular networks.

6.2 Distinctive Positioning in Comparison to Existing Literature

The existing regulations for generating collective perception messages raise an issue, as they result in excessive messages because each message only addresses a limited number of detected objects. This increases communication overhead and reduces **V2X** communications reliability and perception capabilities. To tackle this issue, the authors of [106; 107] proposed an approach to reduce redundancy and lighten the communication burden. In fact, if a vehicle receives updated information about an object from another vehicle, it will not need to rebroadcast the same information.

In [108], the authors proposed an algorithm that reorganizes the transmission of information about detected objects, and reduces the frequency of **CPM** per second to decrease communication load and overhead by modifying the content of **CPM** using prediction. In addition to prediction techniques, Q-learning is a widely used method of learning in vehicular networks. It can be employed to improve the beaconing rates of data exchanged between vehicles. The article [109] explores the application of machine learning to understand the dynamics of vehicular networks and make informed decisions to enhance network performance. Specifically, it delves deeper into the use

of reinforcement learning as a potential replacement for existing optimization techniques for managing network resources. A collaborative edge computing framework is developed in [110] to reduce service latency and improve reliability for vehicular networks. The paper proposes a task partition algorithm to allocate workload and schedule execution order of offloaded tasks, as well as an artificial intelligence-based approach to determine task policies. The learning predicts network traffic demands based on network performance metrics (such as latency, packet delivery rate, channel utilization rate, etc.) to orchestrate the radio resources efficiently and solve congestion problems. Authors of [111] used Reinforcement Learning (RL) to determine transmission parameters according to present channel conditions, offering an adaptive remedy for congestion control. The work showcased how RL can create an appropriate reward system that balances the conflicting goals of congestion control and recognizing surrounding circumstances.

This chapter contribution is inspired by the aforementioned research as well as the previous chapter. In fact, after studying the effectiveness of adaptive approaches and having a deep understanding of the use of communication messages, we had the idea to opportunistically take advantage of the variety of messages in an intelligent adaptive approach that meets the safety application requirements. To the best of our knowledge, there exists a wide range of message types that facilitate the communication of vehicles' relevant information. However, while regulations are in place for each type individually, there is a dearth of specific guidelines addressing their collective utilization due to the similar data they share. Therefore, we believe that this study represents an initial effort in proposing the utilization of various existing messages with an adaptive approach. The aim behind this suggestion is to effectively reduce network congestion and overcome scalability challenges by opportunistically leveraging different message types based on their suitability to the current network state.

This involves identifying the appropriate message type with optimal size and adjusting transmission frequency based on network conditions to minimize network load and also energy consumption, particularly when applied to VRU. We have selected reinforcement learning as our methodology. This decision was made based on the fact that our problem involves decision-making in various network contexts, where we are seeking the optimal choice for improving safety application-related metrics. Consequently, we employ Q-learning as a RL tool in this chapter to improve resource allocation by leveraging the range of available awareness messages.

6.3 System Model

In this section, we introduce the reinforcement learning algorithm for joint message type, size and frequency adaptation.

6.3.1 Q-Learning Framework

The Q-learning update equation is given by:

$$Q_t(s_t, a_t) \leftarrow (1 - \alpha)Q_{t-1}(s_t, a_t) + \alpha \left[r_t + \gamma \min_{a \in A} Q(s_{t+1}, a) \right] \quad (6.1)$$

where $Q_t(s_t, a_t)$ is the Q-value [112] for state-action pair (s_t, a_t) , r_t is the reward obtained after taking action a_t in state s_t and transitioning to state s_{t+1} , α is the learning rate, and γ is the discount factor.

The discount factor γ , which falls between 0 and 1, is used to weight the importance of immediate versus future rewards. The learning rate α , also within the range of 0 to 1, determines how much weight should be given to new knowledge as opposed

to old information (e.g. when α equals to 1 only the latest new information will be considered).

6.3.2 Overview of Q-Learning-Based Adaptive Algorithm

As shown in figure 6.1, the framework of reinforcement learning consists of the agent interacting with the environment. The details of this proposed framework are outlined below:

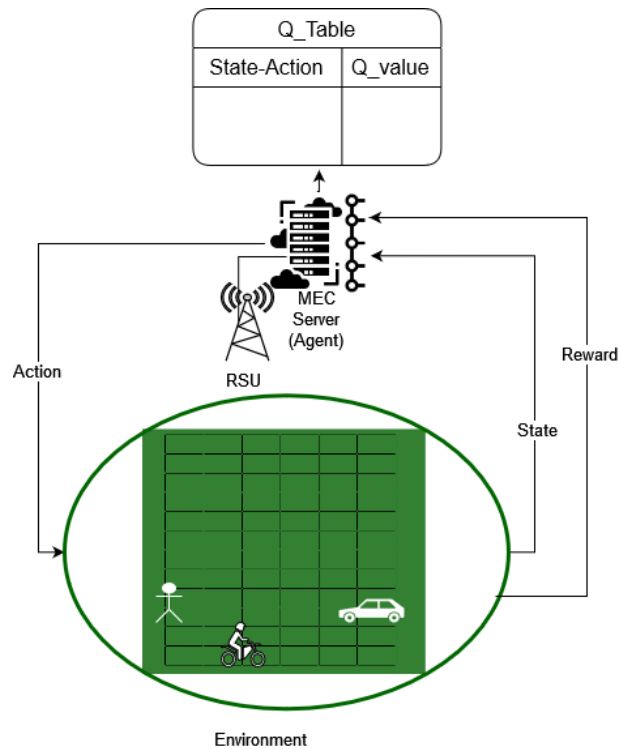


Figure 6.1: An illustration of the RL framework for joint message type, size and frequency adaptation

Optimization function: In this work, a centralized RL-based message type and size with frequency adaptation is designed to handle the scalability problem by minimizing the network overload while not impacting the performance of the road safety application. The constrained minimization problem is defined as follow:

$$\begin{aligned}
& \min \sum_{i=1}^N b_{i \rightarrow mec} \\
& \text{s.t.} \begin{cases} \sum_{i=1}^N th_{i \rightarrow mec} * b_{i \rightarrow mec} \leq C \\ \sum_{i=1}^N d_{i \rightarrow mec} * b_{i \rightarrow mec} \leq D \\ b_{i \rightarrow mec} \in \{0, 1\} \end{cases} \quad (6.2)
\end{aligned}$$

where: N is the total number of road users; $b_{i \rightarrow mec}$ is a binary decision variable that indicates whether a vehicle i sends a message to the MEC server or no; $th_{i \rightarrow mec}$ is the individual throughput sent from a vehicle i to the MEC server; C is the maximum aggregated throughput that can be handled by the MEC server, taking into account the network bandwidth and processing capacity; $d_{i \rightarrow mec}$ represents the maximum allowable delay for transmitting a message from a vehicle i to the server; D represents the maximum allowable delay for transmitting a message, taking into account the QoS requirements of the network.

The objective function is the total network overhead by summing up the number of messages sent by all vehicles. The first constraint limits the aggregated throughput which is the sum of all the individual throughputs considering the used periodicity that can be transmitted by reporting vehicles, ensuring that the network capacity is not exceeded. The second constraint limits the delay for transmitting a message from any road user to the server, ensuring that the QoS requirements are met. The third constraint limits the values of $b_{i \rightarrow mec}$ to either 0 or 1, indicating whether a vehicle will send a cooperative message (CAM if it is not perceived by a vehicle in the V2P neighborhood, CPM if it is identified as a reporting vehicle), or not in case its data is reported in a CPM by another reporting vehicle. Therefore, the proposed algorithm tends to find the best message type, size and frequency configuration to

balance the network load considering the environment context. It should be noted that this model is still simplified and presupposes that the mode of communication used involves vehicle/[VRU](#) to the infrastructure. Additional variables are needed for accurate modelling of complex network topology, capacity, and [QoS](#) constraints.

Agent: is a central [MEC](#) server that covers a part of the network. It takes advantages of the global view of the network with access to traffic history, road users messages, infrastructure sensors and cameras collected data. It can capture the network state to take actions based on a policy, which is a mapping from the state space S to the action space A .

Environment: The environment is the overall vehicular network system containing [RSU](#), [MEC](#) servers, vehicles and vulnerable road users communicating via their smartphones. This environment takes at time t the state s_t and calculates from the action taken by the agent the new state s_{t+1} and the corresponding reward, which is transmitted to the agent and so on. This succession of events is a step. At each step, the agent observes the state s_t from S and accordingly takes action a_t from A .

States: The state space is a collection of information that uniquely identify the situation of the environment. In our case, it is defined as a 3-tuple including a combination of three of the surrounding context information: *(i) the velocity variation:* is the average velocity of all the road users in the coverage area of the [MEC](#) server divided by the maximum allowed velocity, *(ii) the neighboring rate:* is the average neighbors divided by the maximum number of perceived vehicles/[VRU](#) to be included in a [CPM](#) message, and *(iii) the network density:* is the current number of road users divided by the maximum supported number by the [MEC](#) server.

Actions: The action space represents all the possible agent actions for each state when interacting with the environment. The action space is discretized and indexed. On the application layer, each step, the agent takes an action, consisting

of a two-dimensional matrix that combines the period at which cooperative messages are sent, and a threshold representing the minimum number of approximate road users a vehicle must have to be designed as a reporting vehicle. The threshold is used to group vehicles and/or VRU according to their proximity in their communication range, where the elements inside the same group won't send either CAM or VAM because the reporting selected vehicle will send a CPM instead containing the data (relative position, speed, etc.) of its neighbors. The other vehicles or VRU that do not belong to any group will send a CAM. Thus, the threshold is used to not only select the message type, but also the message size by defining the minimum number of perceived objects to include in a CPM.

The exploration of the solution search space is ensured by choosing the periodicity and the number of perceived objects that have a minimum Q-value, following the epsilon-greedy strategy. Thus, given a probability value of epsilon, ϵ in $[0, 1]$ and a random number r in $[0, 1]$ generated in each learning round, the action a_t is selected as:

$$a_t = \begin{cases} \text{Random action,} & \text{if } r > 1 - \epsilon \\ \operatorname{argmin}_a Q_t(s, a), & \text{otherwise} \end{cases} \quad (6.3)$$

Reward: The reward is the reward function that guides the learning, and it should be consistent with the learning objectives. The agent selects the best frequency parameter according to the overall network context information while respecting the safety application constraints. The goal of our proposed approach is to minimize the network load, considering the environmental context information, without degrading the safety application requirements by reducing simultaneous message sending while providing necessary road user data through CPM or CAM for a reliable collision

avoidance algorithm used by the MEC server.

$$reward_t = w_1 * N_{th} + w_2 * N_d \quad (6.4)$$

$$N_d = S_p / Max_p \quad (6.5)$$

$$N_{th} = A_{th} / Max_{th} \quad (6.6)$$

where S_p is the selected periodicity and Max_p is the maximum period that corresponds to 1000 *ms*. A_{th} is the aggregated throughput which is the sum of all individual throughput, Max_{th} is the maximum throughput if the maximum number of vehicles handled by the same MEC server send individual CAM in each selected periodicity. $w_1 \in [0, 1]$ represents the weight of the normalized aggregated throughput N_{th} , and w_2 represents the weight of the normalized average end-to-end delay N_d . For safety applications, we can set w_2 relative higher than w_1 , since applications require lower delay time. For non-safety applications or to avoid congestion problems, we can set w_1 higher.

Episode: An episode represents a period of trial when an agent makes decisions and gets feedback from its environment. It ends when the simulation time is reached.

Hyperparameters: are variables that control the performance of the agent during training.

(i) *The learning rate:* is a hyperparameter that controls how many new experiences are counted in learning at each step. A higher learning rate results in faster training, but may reduce the model's quality. (ii) *The discount factor:* determines the level of importance given by the reinforcement learning agent to the rewards that are expected in the far future, as compared to those that can be received immediately.

6.4 Adaptive Q-learning Algorithm

Like most machine learning algorithms, there are two stages in our proposed method; the training and the test stage. The simulation environment includes routes with vehicles and **VRU**. We consider a **VRU** a vehicle with lower velocity where they are able to communicate by sending **VAM**. To simplify matters and since our focus is solely on the essential components of these messages, we assume that **VAM** and **CAM** share the identical sizes due to their matching mandatory fields [2]. With the frequency selection that corresponds to a certain network state, the simulator provides the next state and the reward to the agents. In the training stage, the Q-learning policy used in each action selection is random at the beginning and gradually improved with the updated Q-networks, as described in Algorithm 4.

In the testing stage, the actions of selecting messages' transmission frequencies are chosen with the minimum Q-value given by the trained Q-networks, based on which the evaluation is obtained.

6.5 Performance Analysis

In this section, we present simulation results to demonstrate the performance of our proposed adaptive approach.

6.5.1 Performance metrics

Our Q-learning algorithm for Cooperative Messages Type, Size and Frequency Adaptation was assessed based on several factors including message latency, aggregated throughput (as detailed in section 6.3.2) in terms of number of **CAM** and **CPM**, and the quantity of messages transmitted to the **MEC** server. This evaluation included

Algorithm 4: Q-Learning Training Algorithm**Input:** learning rate α , exploration probability ϵ , simulation environment**Output:** Q-table**Training Algorithm():**

Initialize the model:

 $Q(s,a)=0$ for all $s \in S, a \in A.$;

Start environment simulator and generate vehicles and VRU.

for *each episode* **do**

Initialize S

for *each step* **do**

- Capture the required parameters from the environment to compute the current state.

- Determine the neighboring vehicles/VRU and identify the reporting vehicles.

- Select the periodicity and the neighboring threshold using the ϵ -greedy strategy.

- Capture the next state and the reward generated by the environment based on the selected action.

- Save the (reward, old-state, action, new-state).

- Update the Q-table using:

$$Q_t(s_t, a_t) \leftarrow (1 - \alpha)Q_{t-1}(s_t, a_t) + \alpha [r_t + \gamma \min_{a \in A} Q(s_{t+1}, a)]$$

end**end****return** Q-table;

a comparison between outcomes with and without reinforcement learning using fixed 10 Hz beaconing rate [88].

6.5.2 Simulation Setup

Table 6.1 illustrates the crucial aspects of our advanced simulation to ensure better comprehension. We developed the simulation model with Python and SUMO simulator [12], incorporating a road network from VANET project in San Francisco covering an area of 2500 m x 2500 m inspired by [115] for improved reliability. We do not consider the long-term reward, and just consider the immediate reward. Thus, we set the discount factor to zero. To maintain balance between exploration and exploitation, we employed ϵ -greedy policy while utilizing MEC server for hosting the learning algo-

Table 6.1: SIMULATION PARAMETERS

Parameter	Value
Training time	~2 days
SUMO play ground size in m ²	2500*2500
CAM size (3GPP Model) [113]	190 Byte
CPM fixed part size in Byte [114]	121 Byte
Size per included perceived object in CPM [114]	35 Byte
Learning rate	0.9
Discount Factor	0
epsilon	0.3

Table 6.2: STATE SPACE

State	Velocity Variation (%)	Neighbouring rate (%)	Vehicular density (%)
0	[0, 33[[0, 33[[0, 33[
1	[0, 33[[0, 33[[33, 66[
2	[0, 33[[0, 33[[66, 100]
6	[0, 33[[33, 66[[0, 33[
...
26	[66, 100]	[66, 100]	[66, 100]

rithm linked to an [RSU](#) at the center point of the map. Due to its resource-intensive nature, Grid5000 [15] was utilized to execute the training algorithm, and we allocated computing for the weekend, otherwise the job is killed. In this experiment, we set the maximum number of road users communicating simultaneously supported by one [MEC](#) server to 1000. For each network state, we have five values of periodicity 100, 400, 700 and 1000 *ms* and five values of thresholds 5, 7, 10, 12 and 15 perceived objects. For delay sensitive safety applications, we can choose lower periods to minimize the delay. We have established 3 tiers for each of the 3-part sets to reduce complexity in the state space. These tiers comprise low, medium and high levels as represented by table 6.2.

6.5.3 Simulation Results

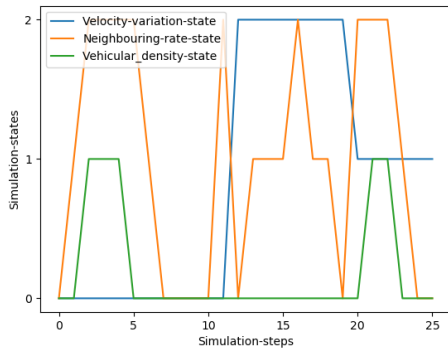


Figure 6.2: The testing scenario states.

Figure 6.2 plots the state variations in each simulation step in a testing scenario when the figure 6.3 shows the selected period by the RL algorithm during the testing scenario example. The algorithm's decision-making process in selecting a periodicity is impacted by the reward function assigned to each state. In order to minimize latency and the aggregated throughput, the algo-

rithm aims to determine an appropriate threshold value that represents the number of perceived objects to include in a CPM.

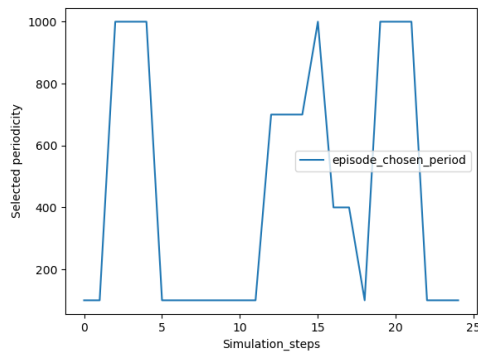


Figure 6.3: Selected periodicity.

This, in turn, affects the overall size of the CPM. By carefully considering these variables, the algorithm is able to make informed decisions regarding periodicity. For instance, in high neighboring rate as we can send more CPM that includes neighboring objects data and as the objective is to decrease the aggregated throughput, the algorithm tends to select longer periods.

As shown in figure 6.4, by decreasing the number of sending vehicles and incorporating neighboring vehicles' data using a 35-byte field per detected object in the CPM message, significant improvements in throughput have been achieved. Furthermore, adjusting message frequency based on network conditions rather than individually sending CAM every 100 ms has resulted in reduced throughput. By utilizing the RL joint Cooperative Messages Type, Size and Frequency Adaptation method, there has been a significant decrease in the amount of messages sent as shown in figure 6.5.

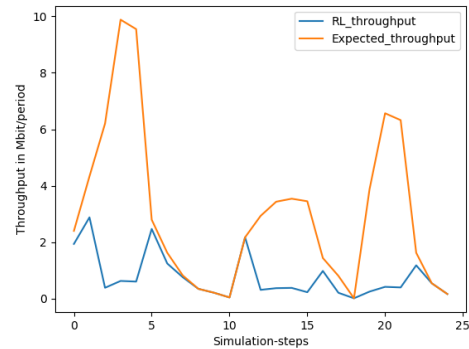


Figure 6.4: RL vs. expected 10 Hz beaconing throughput.

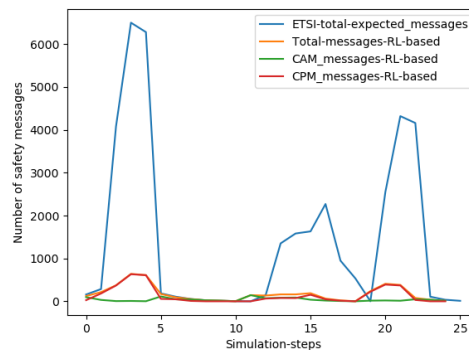


Figure 6.5: The number of messages in CAM and CPM: RL vs. 10 Hz beaconing.

This is achieved by reducing the number of sending road users while relying on neighboring states, as opposed to having all network elements sending CAM messages every 100 ms. The number of CAM in figure 6.5 is very low compared to the number of CPM during the simulation, this reflects that the approach can benefit VRU whose data is reported by nearby vehicles in a CPM.

6.6 The Path Forward: Expanding the Research Landscape

Moving forward, one possible avenue for further exploration is to broaden the scope of the state space to include a more diverse range of scenarios and variables. For instance, in addition to velocity variation, neighboring rate, and vehicular density, we can consider the available network and computing resources, the **CAV** penetration rate (or vehicles' heterogeneity rate), and also the proportion of **VRU** to vehicles as new states. This expansion would allow for a more comprehensive analysis to characterize in depth the environment context. Moreover, we can anticipate improved outcomes by refining the reward function employed in our algorithm. Furthermore, it would be advantageous to conduct comparative assessments between our proposed **RL** algorithm and traditional heuristics to evaluate its effectiveness in selecting the best period and message type for the corresponding state.

6.7 Conclusion

This chapter presents our final contribution regarding the application of networking and communication messages for improving the perception capabilities of **V2X** systems and fostering collective intelligence. We proposed a Q-Learning method for combined Cooperative Messages Type, Size, and Frequency Adaptation. The aim is to determine the suitable message type whether it is a **CPM** or a **CAM** according to network users' distribution, with optimum size by selecting the optimal number of perceived object per **CPM** to minimize the aggregated throughput, and to regulate transmission frequency according to network conditions to reduce network overload. Our technique has potential benefits for **VRU** by reducing their energy consumption

when they are close to reporting **CAV** since their relative data will be communicated in the **CPM** and they don't need to send **VAM**. We conducted tests using an actual vehicular trace dataset to evaluate our approach and found that the algorithm satisfies the optimization function objectives. We believe that resorting to reinforcement learning instead of relying exclusively on heuristics or algorithms presents noteworthy benefits in terms of execution time. When envisioning an algorithm that evaluates network modifications whenever it receives a message, one encounters heightened complexity, resulting in additional latency during execution. Nevertheless, by pre-training our model and leveraging a Q-table that provides the optimal action for each corresponding state, we can reach significant advantages such as low execution time, reduced computational resource requirements, and decreased complexity. In section 6.6, we previously discussed how the environment state was simplified by focusing on three parameters with three levels. However, in order to account for a wider range of possibilities and take advantage of the benefits offered by deep learning, it is possible to further refine this discretization of the state. By doing so, we can enhance the model's ability to capture more intricate nuances within the environment.

Conclusion

7.1 General Conclusion

Connected and autonomous vehicles play a crucial role in intelligent transportation systems by utilizing sensors to analyze the environment based on perceptual features. The primary aim of this thesis was to study the performance of network communication in these systems, where data gathered from sensors and cameras are shared within a network to foster collective knowledge. By employing various [RAT](#) for communication with fellow road users, [MEC](#) servers, and network infrastructure; road users exchange cooperative messages that enhance their ability to build a collective perception of the environment and actively contribute to strengthening the road safety applications. Specifically, in this thesis, we emphasized the vulnerable road users' use case as an illustration of enhancing road safety applications due to the intricate nature of the constraints and complexities involved.

Our first contribution consists in implementing a collision detection system that takes advantage of [SDN](#) to anticipate potential road hazards by collecting and analyzing targeted messages from road users, thereby enabling effective identification

of collision risks. We initially focused on evaluating the system's scalability within a **SDN** network architecture through emulation. A proposed solution suggests adjusting the transmitted message frequency based on risk levels and energy limitations to optimize resource utilization. Moreover, an emphasis is placed on enhancing the system's accuracy and dependability by incorporating prediction techniques to ensure real-time data updates. Simulation results demonstrated how frequency adaptation and trajectory prediction could improve the accuracy of the **VRU** protection system in detecting potential collision risks while reducing network load and energy consumption for **VRU** battery-dependent devices.

Then, after careful evaluation, we raised concerns regarding the efficacy of the suggested centralized **SDN** architecture due to its various limitations. As a result, we transitioned to a hybrid architecture that combines centralized control with decentralized decision-making within individual **MEC** servers assigned to limited geographic areas. Additionally, we have questioned whether there is room for improvement in terms of frequency adaptation.

To address this concern, our second contribution proposes an extension to the adaptive algorithm in an area with one **MEC** server. This extension enhances the current version of the standard and incorporates the kinematics of movements and contextual information obtained from the perceived environment. Simulation results demonstrate that the adaptive scheme surpasses the fixed beaconing and the standard policies limitations. It efficiently mitigates network congestion and minimizes smartphone energy usage while meeting the reliability requirements of safety applications under specific periods.

In our last contribution, we further explored network-based perception and the role of communication messages in enhancing a network's collective understanding. Through an opportunistic **AI**-based approach, we proved that intelligent adaptive

collection leads to reduced network load by leveraging the variety of existent messages and adapting not only the transmission period but also the size of messages.

7.2 Thesis Experiment

This thesis provided an extensive and thorough investigation into the subject of the use of the different types of awareness messages to build a collective network perception, which covered a range of various experiments, including emulation (Mininet-WiFi) to assess scalability, simulation (ns3, SUMO, ms-van3net) of real-world scenarios with vehicular network protocol stack implementation, system modeling, and optimization to simplify the complex representation of the network constraints, and architecture selection by choosing the appropriate architectural frameworks or paradigms to effectively address the research problem holistically with multiple constraints and requirements.

We planned to conduct real-world experiments to replicate our research findings and measure the impact of each variable in the system accuracy and network metrics. Unfortunately, external factors beyond our control hindered us from doing so. Specifically, during the first two years of the thesis project, limited time constraints resulting from the Covid-19 pandemic and insufficiently mature equipment (mainly referring to the available [OBU](#) in the market and [RAT](#)) prevented us from executing these experiments as intended. However, despite this setback, we adapted by conducting a series of alternative methods for investigating and analyzing our proposed system. These included simulations, emulation techniques, system modeling, and optimization approaches. It is important to acknowledge that choosing simulation does not imply an easier task. On the contrary, the utilization of simulation posed numerous challenges, particularly concerning version compatibility and the integration

of different frameworks. These complexities significantly impacted our progress as we left some ideas aside, and we consistently had to consider whether the available simulators could effectively meet the desired objectives. For instance, at the start of this research project, C-V2X technology was not initially implemented. To address the same issues and account for the complexity of integrating VRU in our simulation, we opted to transition from Veins [116] to ns3 coupled with mobility and vehicular networking frameworks. Additionally, we faced several compatibility issues regarding real-time training when attempting to merge the machine learning framework with our existing simulation framework. To address this challenge, we implemented our system model using Python, which allowed us to integrate both the learning frameworks and mobility simulator in our latest contribution.

In the following section, we will outline some ideas of how our research can be validated through practical experiments conducted in real-world settings.

7.3 Thesis extension through real test bed experimentation

Experiment on a limited scale: We envision utilizing a RSU with various RATs. These RATs consist of LTE for smartphone communication and either C-V2X or 802.11bd to facilitate communication between the RSU and vehicles' OBU. A direct connection is established between this RSU and a MEC server. Although our preferred choice of RAT is C-V2X, we aim to evaluate our results using alternative options.

In addition, we need to have at least one vehicle equipped with an OBU connected to GPS receivers and a vehicle application. OpenC2X platform [117] can be utilized for the vehicle application as it employs the ETSI protocol stack and provides a graphical interface with the LDM for storing up-to-date data in the facilities layer.

To facilitate the communication between vehicles and servers using **C-V2X**, an extension of the OpenC2X platform may be required to encapsulate them within User Datagram Protocol (**UDP**) packets. Furthermore, we can implement a web interface module integrated with OpenStreetMap to visualize vehicle and **VRU** positions and risk events.

To facilitate communication between **VRU** and vehicles, a mobile application installed on smartphones is required for the **VRU** to transmit their data to the **MEC** server located near the **RSU**. The **MEC** server processes this data by implementing the collision detection algorithm and trajectory prediction. It also assesses the neighboring rate to optimize the beaconing speed using our **NBS**. An extended transmission period is employed for sending **CAM/VAM** when there is no proximity between **VRU** and vehicles. However, once both entities are in proximity, the standard policy comes into effect which involves monitoring kinematic movements and obtaining accurate real-time information needed for risk computation. In cases where an immediate collision is detected by the algorithm, a **DENM** is generated and transmitted to both **VRU** and Vehicles to warn or take the appropriate action. The same performance metrics can be measured to compare simulation and real-field experiment results.

To validate our latest contribution, we aim to implement the Q-table generated by our model in a real-life scenario involving **CAV** capable of sending **CPM**. The primary objective of this validation process is to assess the accuracy of determining the relative positions of **VRU** and compare the performance of collision avoidance algorithms when each **VRU** transmits its own **CAM**. In the experiment part, the implantation of **CPM** message that contains data from sensors and cameras is the most time-consuming procedure since, to the best of our knowledge, the available **OBU** in the market still lacks all the needed functionalities. Later, larger-scale experiments must be conducted to evaluate our proposed solution's functionality effectively. In

these experiments, we will employ a server application that incorporates an algorithm responsible for computing neighboring rates, identifying equipped **CAV**, and defining reporting vehicles transmitting **CPM**, including data from nearby vehicles. Additionally, this algorithm will determine specific criteria for selecting reporting vehicles while instructing certain **CAV** not to send messages.

7.4 Exploring broader horizons: Expanding perspectives beyond the scope of this thesis

In addition to the limitations and their corresponding solutions discussed at the end of each of our contributions (see sections 5.5,6.6), the proposed real test bed experiment extensions 7.3, and the open issues suggested in our review [2], the work presented in this thesis extends beyond the scope of vehicular networks and safety applications. Its findings and contributions have the potential to be applied across various domains, including IoT and sensor networks. Our first contribution focuses on improving system accuracy and reliability by utilizing prediction techniques to ensure data freshness. This concept can be implemented in real-time data collection algorithms across different applications. In our second contribution, we aimed to enhance the messages' transmission by adapting it opportunistically according to the surrounding environmental information. This context-aware adaptive concept can also benefit industries utilizing sensor networks, allowing for smart beaconing adaptation to handle large scale networks, save sensors energy consumption and computing resources, and enhance the network reliability depending on the use case scenario, such as the number of transmitting devices, the distance between nodes, etc. The most recent contribution focuses on harnessing artificial intelligence methods to strategically utilize various types of communication messages and the data they communicate. This approach

reduces the number of transmitting users by enabling **CAV** equipped with sensors and cameras to report data from non-equipped vehicles and **VRUs**, thereby enhancing the network's collective knowledge. Similarly, in industrial settings, such as sensor data collection, this concept can optimize energy consumption by deducing certain data from correlated information using learning techniques, thereby improving efficiency.

In this research, we directed our attention to enhance network knowledge and understanding by incorporating communication-based perception. For future work, we propose the integration of vision-based perception with communication-driven perception. This fusion method can be achieved through contextual fusion, which takes into account the context of data sources, including their relevance and level of accuracy. Additionally, feature-level fusion can also be employed where features or attributes from different data sources are combined to generate new information such as object recognition. This method shows great potential in the identification of **VRU** by utilizing a combination of visual data captured from cameras and linking them to their corresponding messages.

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