UNIVERSITY OF TARTU
Faculty of Science and Technology
Institute of Computer Science
Data Science Curriculum

Lisanne Siniväli

Edge-Case Handling via Message-Based V2X for Enhanced Vehicle Autonomy

Master's Thesis (15 ECTS)

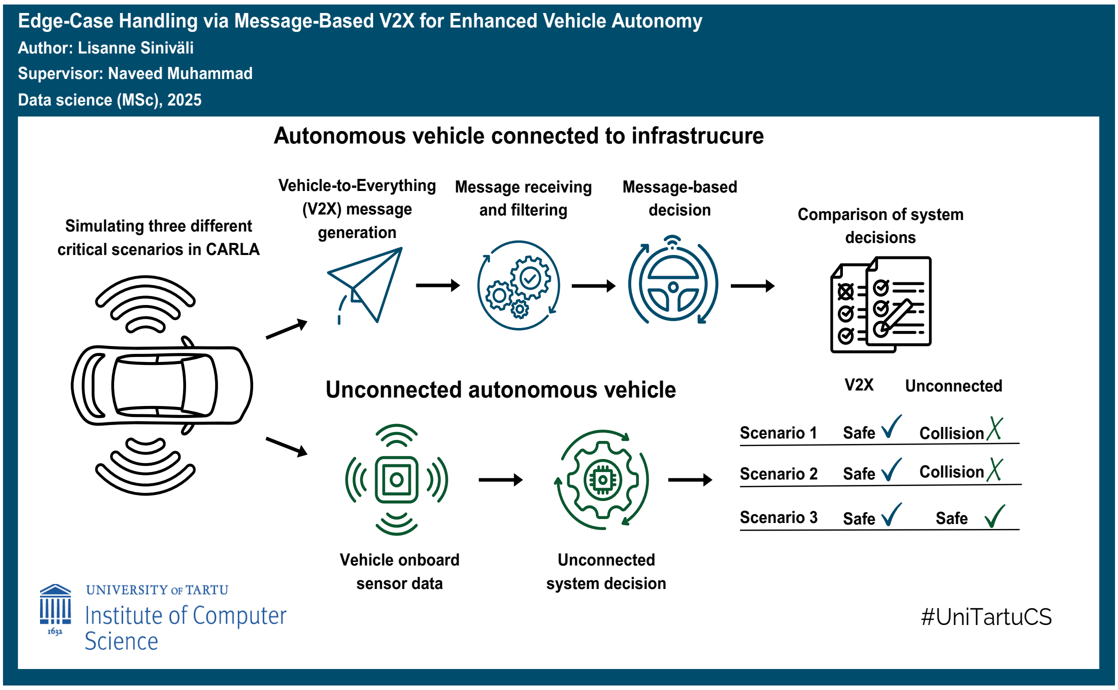
Supervisor(s): Naveed Muhammad, PhD

Tartu 2025

Edge-Case Handling via Message-Based V2X for Enhanced Vehicle Autonomy

Abstract:
Autonomous vehicles (AVs) are becoming more common in public traffic, but they still struggle with rare, unpredictable situations (also known as edge cases) that current onboard perception systems often fail to handle. Existing AV systems mainly rely on cameras, LiDAR, and radar to understand their environment, but these sensors are limited by range, field of view, and environmental conditions. Infrastructure-based Vehicle-to-Everything (V2X) communication has been proposed as a solution to address these issues, but many approaches are complex and inefficient. This thesis investigates how AV safety in edge-case scenarios can be improved using a lightweight, event-driven V2X communication layer. The proposed system is based on simplified Decentralized Environmental Notification Messages (DENMs) that are triggered only by critical events. Compared to the usual onboard-only setups, this approach extends the detection range and gives the vehicle more time to react, especially in situations where perception fails or results in a delayed reaction. And since it only sends messages when needed, it avoids network overload while still increasing safety. The results suggest that you do not need a complicated or high-bandwidth system to make AVs safer in tough situations. With the right infrastructure support, even a small addition like this can act as a reliable safety layer and help AVs handle edge cases more confidently.

Visual abstract:



Keywords:
Autonomous Vehicles, Edge-Case Handling, Vehicle-to-Everything, CARLA simulation, Robot Operating System (ROS)

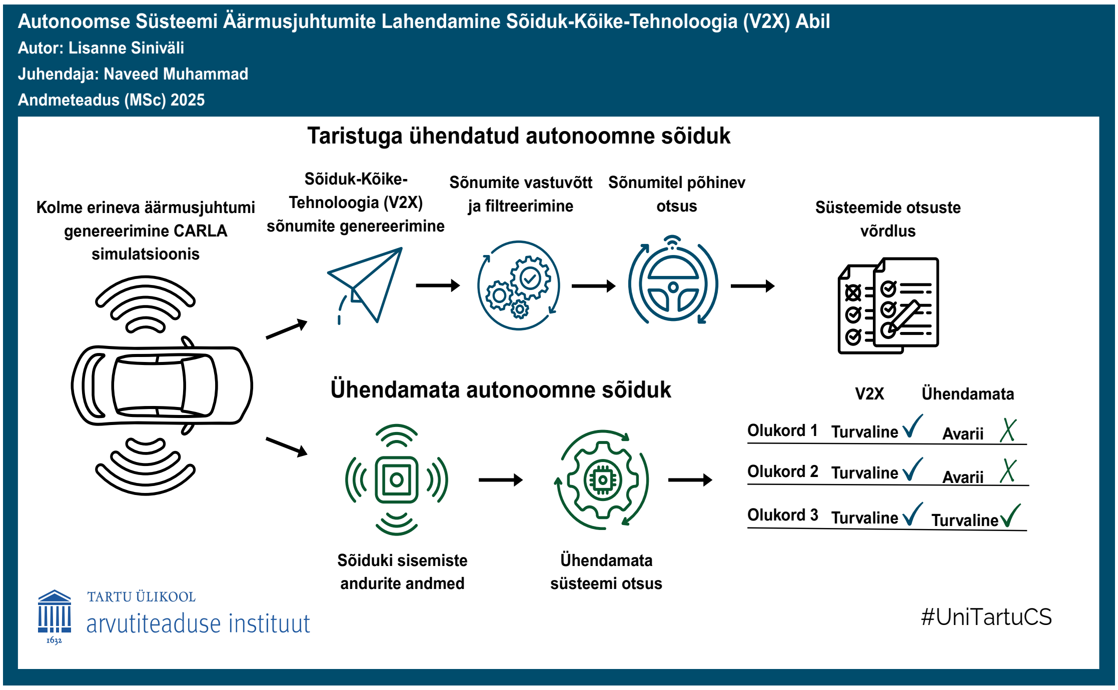
CERCS: P170 Computer science, numerical analysis, systems, control

Autonoomse Süsteemi Äärmusjuhtumite Lahendamine Sõiduk-Kõike-Tehnoloogia (V2X) Abil

Lühikokkuvõte:

Autonoomseid sõidukeid esineb liikluses järjest rohkem, aga siiski on sõidukile paigaldatud sensoorikal endiselt raskusi harvaesinevate või ettearvamatute olukordadega (ehk äärmusjuhtumid). Praegused autonoomsed süsteemid sõltuvad keskkonna tajumisel peamiselt autole paigaldatud anduritest nagu kaamerad, LiDAR ja radar. Eelmainitud andurid on aga piiratud võimekusega nii vaatevälja kui ka tuvastuskauguse poolest ning nende töökindlus sõltub suuresti ilmastikuoludest. Äärmusjuhtumite lahendamiseks on välja töötatud sõiduk-kõike-tehnoloogiat (V2X), kuid paljud nendest lahendustest on keerukad ja ebaefektiivsed. Käesolev uuring käsitleb, kuidas parandada autonoomsete sõidukite ohutust äärmuslikes olukordades, kasutades lihtsustatud V2X tehnoloogiat. Antud lõputöös uuritud süsteem kasutab detsentraliseeritud keskkonnateate (DENM) tüüpi sõnumeid, mis rakenduvad ainult kriitiliste sündmuste korral. Eeltoodud lähenemine parandab sõiduki reageerimisaega võrreldes süsteemidega, mis tuginevad üksnes masinal olevale sensoorikale. Võrgu ülekoormuse vältimiseks saadetakse sõnumeid ainult ohtlikes olukordades. Tulemustest järeldub, et autonoomsete sõidukite ohutuse parandamiseks ei ole vaja keerukaid süsteeme. Õigel taristul põhinev tugi võimaldab ka väikestel lisandustel toimida usaldusväärselt ja turvaliselt ning aidata isejuhtivatel sõidukitel äärmusjuhtumitega kindlamalt toime tulla.

Visuaalne kokkuvõte:



Võtmesõnad:
Autonoomsed sõidukid, Äärmusjuhtumid, Sõiduk-Kõike-Tehnoloogia (V2X), CARLA simulaator, Roboti operatsioonisüsteem (ROS)

CERCS: P170 Arvutiteadus, arvutusmeetodid, süsteemid, juhtimine (automaatjuhtimisteooria)

Contents

1 Introduction

1.1 Background and Motivation

Autonomous vehicles (AVs) have been a talking point for years. When they were first introduced, people were convinced that by 2025, self-driving cars would be a part of everyday life [1]. And in some ways that prediction is not entirely wrong. Autonomous vehicles are already being used in ride-hailing services (Waymo, Cruise), logistics (self-driving trucks) and even airport shuttles [2].

However, full Level 5 autonomy has not yet been achieved. In fact, we are further away from it than many had believed [3]. Although autonomous vehicles are becoming more common in everyday traffic, they still struggle with rare and unpredictable situations. These include extreme weather, hidden pedestrians, or other vehicles that violate rules. The scenarios discussed previously highlight the current limitations of AVs and show that they are not yet capable of reliably handling all real-world driving situations. This thesis looks into how full infrastructure connectivity and a lightweight Vehicle-to-Everything (V2X) communication layer can help make autonomous systems more fail-safe, both in everyday driving and in unexpected situations.

1.2 A brief history

The first step towards autonomous cars was taken in 1926 [4], when Houdina Radio Control demonstrated a radio-controlled car, the "American Wonder", in New York City. However, the vehicle lacked real autonomy and was controlled remotely by radio signals sent from a second car following behind it. The autonomous car as we know it today, with sensors like LiDAR, GNSS, and onboard computers, was first introduced in the 1980s, thanks to advances in computer technology.

One of the most significant efforts was the Eureka PROMETHEUS Project (late 1980s–1990s) [5], it achieved a 1,000 km autonomous drive on Parisian highways, demonstrating hands-free operation, lane changes and convoy driving. At the same time, the Autonomous Land Vehicle program (1984) [5] and Carnegie Mellon's Navlab project (1986) [6] were making breakthroughs in the US. NavLab 1 (1986) was equipped with onboard sensors and processing power, allowing it to drive slowly and navigate the city. By 1989, Carnegie Mellon University had developed a neural network-based steering and navigation system. NavLab 5 (1996) completed a cross-country trip from Pittsburgh to San Diego, driving mostly autonomously while speed and braking were controlled by researchers. Although simplified, the logic behind autonomous vehicles today is based on the foundational work of the 1980s.

From then on, autonomous systems advanced significantly through developments in the automotive industry, research, and competitions. One of the biggest contributors to this was the Defense Advanced Research Projects Agency (DARPA) [7] competition in the 2000s. It was a prize-based challenge that aimed to accelerate the development of autonomous ground vehicle technology.

The first competition in 2004 ended without a single team completing the course or claiming the 1 million dollar cash prize. However, it still brought engineers and developers together to push AV technology forward. At the second event in 2005, five teams successfully completed the challenge. Stanley, Stanford University's entry [7], finished first with a time of 6 hours and 53 minutes, winning the two million dollar award.

In 2007, DARPA took it one step further by introducing a challenge set in a mock urban environment that required autonomous vehicles to navigate traffic, follow road rules, and interact with other vehicles. This competition laid the groundwork for AV systems to evolve beyond off-road driving and become the foundation for modern driver-assistance technologies.

In 2009, Google launched its self-driving car project, which later became Waymo. In 2012, Google revealed that its prototypes had driven autonomously more than 300,000 miles [8] without a single accident. By 2013, many companies including General Motors, Ford, Mercedes-Benz, and BMW had started developing their own semi-autonomous driving systems. Meanwhile, Waymo continued testing fully autonomous taxis, becoming the first company to operate driverless taxi services in Phoenix, Arizona (2018) and the first autonomous ride-hailing service to offer paid, fully driverless, 24/7 rides to and from an airport, starting with Phoenix Sky Harbor International Airport (2022).

1.3 Levels of Autonomy

The field was rapidly developing, and it was predicted that autonomous cars would become as common as human-driven cars on the road. However, in 2018, a fatal accident involving a self-driving Uber in autonomous mode led to the death of a 49-year-old pedestrian, marking what was likely the first pedestrian fatality involving an autonomous vehicle [9]. The car had a safety driver inside, but they failed to react in time. There was also a crash in 2023 in San Francisco, where a Cruise robotaxi hit and then dragged a pedestrian who had previously been struck by a non-autonomous vehicle [10]. In addition to the severity of the accident, it later turned out that Cruise had omitted key details about the incident in its report. These accidents make it clear that AV systems still needed major improvements in fail-safe mechanisms and edge case handling.

Looking ahead, by 2030, Goldman Sachs estimates up to 10 percent of global new car sales could be Level 3 vehicles [11]. However, to reach that point, vehicles must progress through a standardized framework consisting of six levels of driving automation, defined by the SAE [12]. These levels describe how much control and decision-making the system handles and how much is left to the human. At levels 0–2, the driver must continuously monitor the environment and remain fully engaged. These are primarily driver assistance systems such as adaptive cruise control or lane keeping. For other three levels, the driver can be less engaged.

The last three levels are:

- Level 3 (Conditional Automation) – The car can drive itself under specific conditions, such as on highways, and does not need human input while active. But if something happens that the system can not handle, the driver must be there to take over [13].
- Level 4 (High Automation) – The car can drive fully autonomously in specific areas and conditions without a driver, but will not work everywhere. Example: Waymo's fully driverless taxis in different cities.
- Level 5 (Full Automation) – No human driver is needed. These vehicles are expected to operate without conventional driver controls, such as a steering wheel or pedals, requiring only the passenger's input of a destination. This level does not yet exist for public use.

1.4 Vehicle connectivity

For level 5 deployment, AVs must overcome remaining challenges, particularly edge-case scenarios involving unpredictable behavior in traffic and issues related to infrastructure integration. Research continues to focus on making autonomous systems fail-safe in all traffic conditions. It has been observed that handling such unpredictable scenarios using only onboard sensors is not feasible in many cases, primarily due to visibility limitations [14].

One of the most effective ways to ensure full connectivity within infrastructure is to use V2X [15]. V2X relies primarily on wireless communication networks, and an autonomous vehicle typically to this system is often referred to as a Connected Autonomous Vehicle (CAV). The purpose of V2X is to improve safety by enabling data sharing within the infrastructure. V2X improves autonomous vehicle safety by extending perception beyond onboard sensors, enabling faster decision-making in critical scenarios such as emergency braking and obstacle avoidance. Real-world tests confirm its effectiveness in making autonomous driving more reliable [16].

V2X can improve CAV performance in various situations; however, this thesis focuses primarily on edge cases and safety-critical scenarios. The V2X categories used in this thesis are listed in more detail below and illustrated in Figure 1.

- Vehicle-to-Vehicle (V2V): Enables direct communication between vehicles that are close to each other, regardless of whether they are autonomous or not.

- Vehicle-to-Pedestrian (V2P): Facilitates communication between vehicles and nearby pedestrians, including walkers, cyclists, and others in urban environments. The entities mentioned here are also referred to as Vulnerable Road Users (VRU).
- Vehicle-to-Infrastructure (V2I): Allows communication with infrastructure elements such as road signs, traffic lights, and other sensors or components that enhance vehicle safety (e.g., Roadside Units (RSUs) and Onboard Units (OBUs)). RSUs and OBUs differ slightly: RSUs have strict operational requirements and greater computing power compared to OBUs.

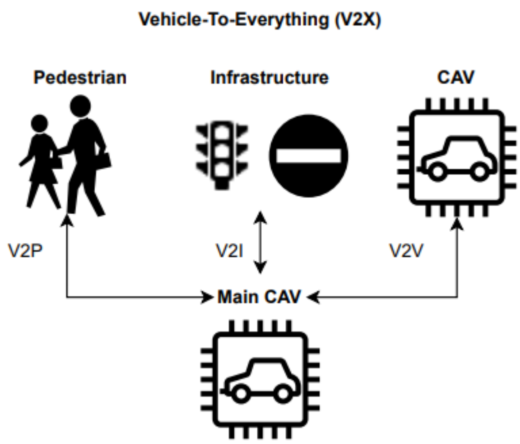


Figure 1. Vehicle-To-Everything Communicaiton

There are two main V2X approaches: Dedicated Short-Range Communications (DSRC) and Cellular V2X (C-V2X). DSRC is a Wi-Fi-based system that allows direct, low-latency communication but has limitations in range and scalability. On the other hand, C-V2X uses existing cellular networks (LTE/5G) to provide greater coverage and better integration, although it can introduce latency variations in high-traffic environments [17].

Both DSRC and C-V2X are components part of the United States' regulatory approaches [18]. In contrast, European regulatory bodies use ITS-G5 as the main V2X technology, which is based on DSRC. Although the United States now strongly favors C-V2X communication and has officially shifted away from DSRC, Europe is taking a more balanced direction. It continues to support ITS-G5 while also encouraging a hybrid approach, exploring C-V2X as a complementary technology rather than a full replacement.

In Europe, safety messages that are published periodically are called Cooperative Awareness Messages (CAMs). The purpose of these messages is to maintain a relevant overview of the environment and infrastructure. The content of CAMs depends on the message publisher type. For example, traffic lights send out the same structured message every second, ensuring vehicles receive real-time updates on their operational state. Non-periodic safety messages are referred to as Decentralized Environmental Notification Messages (DENMs). This message is triggered when an event occurs in the infrastructure. When a collision occurs, a new DENM message is created and continues to circulate for as long as the event is no longer relevant [19].

1.5 Problem Statement

Even with all the recent advances in autonomous driving, full Level 5 autonomy remains unavailable for public use. Both modular and end-to-end approaches struggle to reliably handle edge cases that happen in real-world environments. These are the unusual or unpredictable situations that current sensor-based systems often fail to detect or respond to properly.

However, as infrastructure connectivity becomes more widely available, there is an opportunity to improve autonomous systems by going beyond vehicle-mounted sensors. With access to external data, such as roadside sensors, traffic lights, or other connected agents. These systems can better understand the environment, especially in situations where local sensors are limited.

1.6 Research Objectives

The objective of this thesis is to design a V2X-integrated autonomous driving support system capable of remaining fail-safe in both normal and edge-case situations. The system relies exclusively on DENM-style messages to communicate dangerous events to the vehicle, avoiding the need for complex object-level data sharing.

The approach assumes that existing autonomous systems are already reliable in most standard scenarios and focuses on increasing their performance in critical or unusual cases where onboard perception may fail, such as poor weather, occluded pedestrians, or unpredictable traffic behavior.

To validate the proposed system, a series of edge-case simulations are performed in CARLA, using the Tartu Autonomous Driving Labs Autoware Mini autonomy software. The aim is to evaluate how much V2X-based messages can improve safety and responsiveness when the vehicle faces situations beyond what its onboard sensors can reliably handle.

1.7 Research Contributions

This thesis presents a V2X architecture designed to improve safety in edge cases by providing an additional layer of support when onboard systems might fail. It uses minimal data and the V2X layer relies solely on DENM-like messages to warn the vehicle about nearby dangers. In contrast, many existing works depend on object-level collective perception or high-bandwidth data exchange.

Secondly, this thesis focuses on edge-case performance evaluation compared to existing methods. Most other works focus on a single critical or typical scenario, which limits the scope and usefulness of their testing. This thesis includes multiple edge cases and compares the solution against a tested baseline.

Third, a message filtering pipeline is developed and implemented using the Robot Operating System (ROS). This filtering logic evaluates the incoming alerts based on distance, time-to-collision (TTC) and event priority, ensuring that only the most relevant and urgent information reaches the vehicle decision-making module. The system is tested in a simulation environment using CARLA and is integrated with Autoware Mini.

1.8 Structure of the Manuscript

The remainder of the manuscript is divided into the following chapters:

- **Related Work:** This chapter reviews existing research on autonomous vehicle architecture, V2X communication, cooperative perception, and edge case classification. This thesis also discusses the limitations in current systems that this thesis aims to address.

- **Methodology:** This chapter describes the simulation environment, system architecture, and the structure of the DENM-like messages used. It also explains the filtering logic and how the V2X layer was implemented alongside the AV stack.

- **Results:** This chapter presents the results of simulation-based test scenarios, comparing the baseline AV system with the enhanced version enabled by V2X in multiple edge cases.

- **Discussion:** This chapter reflects on what the results mean, analyzes the strengths and limitations of the proposed system, and considers how the approach fits into real-world deployment.

- **Conclusion and Future Work:** This chapter summarizes the main findings and proposes future research directions, including real-world testing, improved system integration, and message security.

All of the text in this thesis was written by the author. No generative AI tools were used for content creation, except for tools that process existing text and improve formatting, such as Overleaf's built-in features.

2 Related work

Both modular and end-to-end approaches have their own advantages and disadvantages. In a modular design, the system is divided into separate components, such as perception, planning, and control. This separation simplifies debugging and maintenance, but often introduces latency and increases system complexity [20]. End-to-end architecture uses a single AI model that takes raw sensor data as input and outputs driving commands. This can reduce latency and improve adaptability, but at the same time requires large amounts of training data and is difficult to debug [21].

However, both approaches face a common challenge: dealing with edge cases. Modular architectures can suffer from sensor fusion failures and rule-based system constraints, while end-to-end models lack robustness when encountering unseen data and situations.

There is a reason why dealing with edge cases in traffic remains an unresolved issue. Numerous studies have highlighted problems within autonomous systems [22], [23], [24], [25], but they fail to implement solutions to these identified challenges. Edge cases often involve unpredictable or rare traffic situations that autonomous systems do not frequently encounter in training, making them particularly difficult to handle. One proposed solution is to wait for technological advancements, hoping that future vehicles will have enough computational power to solve these issues [26]. The alternative approach is to tackle edge cases directly by developing methods to handle them using existing technologies. Despite the fact the study by [27] provides an in-depth survey of anomaly detection techniques for autonomous vehicles, it focuses solely on onboard intelligence. The present thesis addresses this limitation by proposing a lightweight and infrastructure-supported communication system capable of detecting anomalies that may be out of sight or otherwise undetectable by vehicle onboard sensors.

2.1 Infrastructure Support in Autonomous Driving

Infrastructure plays an important role in enhancing AV performance. Many studies have shown that adding an additional layer to AV environmental awareness has the potential to improve automated driving operations and safety [28], [29]. Even with advanced sensors on the car, the main issue remains: all sensors are mounted on the vehicle itself, limiting their field of view. However, infrastructure offers free space to mount additional sensors, filling in these blind spots. For object detection and sensing based on the infrastructure, roadside sensors are used. These sensors typically include LiDAR, cameras, and radar, strategically placed to improve situational awareness [30]. The authors in [28] show how roadside sensors improve awareness of AV in cities. The study by [29] shows that infrastructure-based road hazard warning systems positively impacts traffic flow, safety, and efficiency by informing vehicles of upcoming dangers, allowing responses to potential threats. A similar study evaluating heterogeneous networks (Het-

Net) incorporating DSRC, LTE, and Wi-Fi shows that seamless connectivity improves real-time hazard warnings and facilitates reliable traffic data exchange [31].

Although the previously mentioned works focus on testing various simulation systems, optimizing them, and showing improvements, they lack testing in critical edge cases where AV systems face the most challenges. This thesis aims to overcome this gap by testing V2X messaging in high-risk edge case simulations.

2.2 V2X Communication

Because of this, it is crucial to select a communication system that performs reliably across different conditions and ensures low-latency message delivery. Various wireless access technologies are used to support V2X communication, including cellular networks, satellites, Bluetooth, and Wi-Fi. Each of these technologies has its own advantages and disadvantages, but to be suitable for real-time, safety-critical V2X applications, they must meet specific latency, reliability, and coverage requirements. Many of the previously mentioned technologies were not originally designed for real-time safety applications and, therefore, have certain limitations. However, the most suitable technologies for V2X are Wi-Fi-based DSRC and cellular-based C-V2X [32].

2.2.1 DSRC

The initial V2X protocol, Dedicated Short-Range Communication (DSRC), was standardized in 2010 and is based on the Institute of Electrical and Electronics Engineers (IEEE) 802.11p standard. This standard allows the use of the 5.9 GHz band and establishes rules for its deployment in the United States (DSRC) and Europe (ITS-G5). Wireless Access in Vehicular Environments (WAVE), which evolved from traditional Wi-Fi technology, was developed to support transportation communication. Since DSRC has been in use for over a decade, it is a well-tested and widely understood solution. However, due to high latency over long distances, increased costs, and frequent channel congestion, DSRC has been now often replaced by Cellular V2X (C-V2X), which offers higher reliability and faster data transmission [33].

2.2.2 C-V2X

Cellular Vehicle-to-Everything (C-V2X) was standardized in 2017 and is defined by 3GPP standards. Like DSRC, C-V2X also operates on the 5.9 GHz band for message transmission. However, it also uses cellular networks, allowing different communication methods to be used depending on the urgency of the message. 3GPP divides C-V2X into two main parts:

- Long-Term Evolution V2X (LTE-V2X): Based on 4G technology, this system uses the existing cellular network to provide wider coverage and enables early warnings about distant hazards.

- New Radio V2X (NR-V2X): A 5G-based system introduced to address LTE-V2X limitations, such as message delays and network congestion [34].

When reviewing research that compares these technologies [35], [36], [37], it is clear that C-V2X is a significant improvement over DSRC. One of the most critical differences is that DSRC has a communication range of approximately 1 km, whereas C-V2X offers a much longer range, which is important for safety and handling edge cases. A study by Anwar et al. compared 802.11p, NR-V2X, and 802.11bd technologies, finding that while DSRC (802.11bd) has a lower packet error rate, NR-V2X outperforms it in all other aspects [38]. Despite this, DSRC remains more tested and, therefore, reliable for short-distance communication. 802.11bd is a successor of 802.11p technology. The simulation results show that IEEE 802.11bd improves data transfer rates, doubling performance compared to IEEE 802.11p, while also cutting transmission latency by more than half [39].

2.3 Cooperative Perception

One of the ways to share information through V2X is by sharing sensor perception data, a method known as Cooperative Perception (CP). With this approach, vehicles can extend their perception range by using sensor data from surrounding infrastructure or other road users. After receiving the data, it is processed using advanced data fusion algorithms to build a unified environmental model.

The study by [40] shows that even with state-of-the-art technology, CP still faces open challenges, including latency, robustness, and real-time performance. Another work, [41], attempts to address data redundancy using a probabilistic data selection method that filters out less informative objects, optimizing bandwidth usage. Their approach claims to reduce communication load by up to 60 percent while maintaining system reliability. However, the system is not tested in high-risk scenarios and still relies on large message volumes.

Similarly, the authors in [42] proposed a CP-based system designed to tackle latency issues. Instead of transmitting raw object detections, their system shares fused object tracks, reducing message size and improving fusion efficiency. While effective in reducing data load, this work focuses more on improving perception quality than on testing in critical safety scenarios, where real-time reliability is essential.

Although the previously mentioned studies [40], [41], [42] show that CP is a step forward in addressing limited perception, they also highlight ongoing issues with latency, robustness, and message size. These solutions depend on complex models and large data payloads, which may not be ideal for safety-critical applications. In such cases, a simpler and more reliable system design is preferred. The system proposed in this thesis deliberately avoids large CPM messages altogether and instead relies on lighter DENM-style alerts. Although this design sacrifices detailed environmental information, it significantly reduces bandwidth usage and enables faster, more scalable spreading of critical hazard information.

2.4 Handling Edge Cases in Autonomous Driving

There are various ways how edge cases are detected and resolved in different studies. The authors in [43] focused on detecting and identifying edge cases that arise from crashes or complex situations where Automated Driving Systems (ADS) encounter difficulties. The main idea is that identifying these edge cases allows system improvements. The authors classify edge cases into different types, including sensor edge cases, which occur under difficult weather conditions like snow or fog, causing sensor errors; content edge cases, where an autonomous vehicle faces unlawful or unusual behaviors from pedestrians; and temporal edge cases, which arise when traffic conditions change rapidly.

A similar concept is presented by [44] in their study, where they focus on generating new and challenging edge cases. Their approach uses real-world data and reinforcement learning to create high-risk scenarios, which are then used to test autonomous systems. The study by [45] aims to identify critical scenarios beyond the edge cases. Their method involves analyzing 86 studies from 2017 to 2020 and highlighting the open issues discussed in those studies. They also emphasize the importance of scenario-based testing, highlighting how vital it is for ADS safety, which aligns with this thesis' approach.

The classifications mentioned in previously discussed studies [43], [44] are useful to understand how different types of edge cases impact AV performance. These insights help inform the design of the simulation experiments conducted in this thesis. Scenario-based testing for ADS is also applied, with test cases developed to align with the critical problems and current challenges identified in the existing literature. This alignment ensures that the evaluation focuses on relevant and realistic conditions where fail-safe behavior is most needed.

However, the approach taken in previous studies [44], [45], only considers edges that have already been detected or occurred. It is not always possible to identify all potential edge cases in advance, as unexpected situations can still occur. Therefore, this thesis argues that AV systems must be able to respond to edge cases dynamically, even without prior knowledge that they could happen.

[46] attempted to solve this problem by training a model using real-world data from a lane-following scenario. The pre-trained model was then tested on critical scenarios. However, the model's actions still depended on the data it was trained on, and there were not always enough data to cover every possible edge case.

From previous research, three main edge cases stand out. Difficult weather conditions, where objects on the road are hard to detect due to heavy rain or snow. Unpredictable pedestrian behavior, where a pedestrian walks unexpectedly on the road. In addition, there are uncommon traffic scenarios, such as a nearby car randomly merging into another lane or an ambulance trying to maneuver through traffic.

One of the main problems that come out in research is weather [47]. Thesis by [48] tries to find ways to improve perception in difficult weather conditions such as fog and rain. It points out how fog, rain, and snow make it harder for onboard sensors like cameras and LiDAR to work properly, especially in blind spots or occluded areas. The review shows that sharing perception data on V2X helps fill in blind spots, especially when weather makes it difficult for a single vehicle to see. But it also highlights issues such as bandwidth limits, delays, and problems with long-distance perception in fog or snow.

The authors in [32] focused on improving road user safety, specifically addressing edge cases such as detecting VRUs. Their approach uses V2X communication while improving the sensors involved in V2X and integrating deep learning methods for data processing. They propose an end-to-end AV motion controller architecture driven by a temporal deep neural network (DNN). The purpose of this system is to detect VRUs and predict their future trajectories, enabling the AV to react more quickly when danger approaches. The idea of including pedestrians in V2X communication through smartphones and smartwatches is receiving significant attention in current research and will also be applied in this study.

Similarly to previous work, the study by [49] also aims to improve the V2X system, but this time by using Roadside Units (RSUs) to enhance intersection control. Their system places V2X-enabled traffic lights and RSUs to make AV behavior in traffic more efficient and safe. They achieved a reduction of approximately 75 percent in fuel consumption and tested their system in both simulation and real-world environments. Their work directly demonstrates how to build a V2X communication system where the infrastructure actively participates in the AV decision-making process. Furthermore, their system provides a foundation for improvement, such as incorporating emergency alerts from distributed infrastructure sensors to enhance AV responsiveness to critical situations.

The study by [50] focuses on improving AV safety and stability in severe driving conditions, such as slippery roads. They propose a risk-informed decision-making strategy that combines Finite-State Machine (FSM) logic for regular driving and Model Predictive Control (MPC) for emergencies. This approach helps the AV react to dynamic road conditions and other vehicles. Their system uses Time-To-Collision (TTC) and Deceleration Rate to Avoid Collision (DRAC) as safety indicators, which allows the vehicle to assess risk and choose a safe zone in real-time, like moving onto a road shoulder to avoid an accident. Although they implemented many safety measures, the system still struggles in severe emergencies.

2.5 Research Gaps

Although several studies discuss how infrastructure connectivity can assist in specific situations, there remains a significant gap in the literature. Most studies address individual types of edge case separately, but there is a lack of research on a single fully connected system capable of handling multiple types of edge case simultaneously. This thesis aims to address this gap by exploring how a fully connected V2X system can handle different types of edge cases together.

One of the most essential aspects when dealing with edge cases is the robustness and effectiveness of the system. Studies in the literature were able to solve the singular edge case in a particular environment, but also pointed out systems complexity and latency issues. That is why this thesis avoids large CMP messages and CAM messages, whose purpose is to just raise awareness. Focusing on event-triggered hazard warning and danger messages, there are fewer messages, and therefore fewer latency issues. This thesis takes inspiration from all the studies reviews earlier to purpose a simplified system, transmitting only high-priority event-driven alerts using DENM. Those earlier studies also highlighted message filtering as one of the most essential ways to improve the safety and effectiveness of the system.

3 Methodology

3.1 Research Approach

The goal of this research is to create and test a lightweight V2X system that helps autonomous cars stay safe in difficult or unexpected situations by using only DENM-like messages. Using simulation data, the system will be tested in a controlled environment where the sensor input mimics real-world conditions. The simulation framework ensures consistent test conditions, allowing accurate and repeatable evaluations of system performance. Using this approach, the research aims to develop an improved autonomous driving system that can handle both expected and unusual challenges - edge cases, through improved connectivity with infrastructure and other road agents.

The first edge case involves unpredictable moving objects, such as pedestrians entering urban traffic areas. While many pedestrians in this proposed system are connected to V2X networks through smartphones or wearable devices, some may not be connected at all. In addition, pedestrian behavior is often unpredictable. Individuals may cross roads suddenly, ignore traffic signals, or emerge from behind buildings or parked vehicles. In such cases, onboard sensors on autonomous vehicles may not detect them in time to respond safely.

To address this, it is essential that infrastructure-based sensors are capable of detecting these unconnected or unexpected objects and broadcasting hazard messages through V2X. Urban environments must be equipped with cameras, LiDAR, or radar units capable of identifying such objects and generating alerts. These infrastructure sensors are typically more powerful and accurate than simple chips embedded in traffic lights or signs and can perform basic object classification and motion prediction.

While traffic lights and fixed signs usually broadcast their current state and location, they should also be capable of transmitting real-time alerts about nearby hazards. For example, if a wild animal or an unidentified object is detected moving into the roadway, the infrastructure network can quickly issue a DENM-style alert to nearby vehicles. This allows autonomous systems to take preemptive safety actions, such as slowing down or changing lanes well before the object becomes visible to onboard sensors.

The second edge case occurs when the sensors cannot identify objects in the infrastructure. In bad weather conditions, when visibility is severely limited or non-existent for autonomous vehicle cameras, traffic signs should be equipped with sensors that transmit their position and purpose. For example, if a stop sign is covered in snow, an autonomous vehicle can still identify it through vehicle-to-infrastructure communication, ensuring that it does not drive to an intersection. A similar issue arises with speed limit signs; if they are misidentified, the resulting speed difference from the correct limit could create serious safety risks. To avoid accidents, all critical road signs should be equipped with small chips that continuously transmit their information [51].

The third edge case involves sudden and unexpected movements by other vehicles. If a vehicle suddenly changes direction, nearby autonomous vehicles should react immediately. To handle such cases, moving objects should constantly share their location and speed. If a vehicle makes an unexpected and significant change in direction, the closest autonomous vehicles should send an alert message so that the surrounding vehicles can adjust accordingly [43].

By addressing these common edge cases, the system demonstrates how full connectivity to infrastructure can effectively solve past challenges while preparing for future edge cases. The ability to integrate sensor data from the infrastructure, communicate in real-time, and proactively manage hazards ensures that autonomous vehicles can operate more safely and reliably, even in unpredictable environments.

3.2 System Architecture

In the proposed system, various sensors are placed on or around infrastructure elements like traffic lights, road signs, pedestrian zones, and intersections. These sensors are used to detect objects or events that might not be visible to an autonomous vehicle due to occlusion or sensor limitations.

The infrastructure and vehicle are equipped with various sensors, including:

- **LiDAR** – Measures distance by targeting objects with laser pulses and calculating the time it takes for the reflected light to return. It helps with detecting the location and shape of objects such as pedestrians. LiDAR is not affected by nighttime conditions, but it is more sensitive to rain, as raindrops can scatter the laser signal.

- **Radar** – Uses radio waves to calculate distance and velocity. Radar performs well in rain and low-visibility conditions, but it is generally less precise than LiDAR when it comes to identifying object shapes or types.

- **Camera** – Captures visual data around the vehicle and is essential for object detection and classification using AI and image-processing algorithms. However, cameras are sensitive to lighting conditions and may perform poorly in darkness or glare.

- **GNSS (Global Navigation Satellite System)** – Provides global positioning, navigation, and timing information using satellite signals. It is used for estimating vehicle location with a known margin of error.

- **Environmental Sensors** – Detect conditions such as temperature, rain, fog, and road surface status. These sensors are often mounted in infrastructure and assist in broadcasting environmental hazards through V2X.

- **RFID Tags** – Used to store static data about infrastructure elements such as traffic signs (e.g., stop signs or speed limits). RFID readers [52] in vehicles or infrastructure can read these tags to confirm location or identify sign types in poor visibility conditions.

As described in the related work, various wireless access technologies, including cellular, satellite, Bluetooth, and Wi-Fi, offer different trade-offs for V2X communication. However, only Wi-Fi-based DSRC and cellular-based C-V2X meet the latency, reliability, and coverage requirements necessary for real-time, safety-critical applications.

While many simulations assume ideal conditions, this thesis builds on previous research and reflects the current state of autonomous and V2X technology. As a result, a hybrid system is proposed and implemented to better address real-world challenges, as shown in Figure 2.

NR-V2X is used for the V2I and V2P messages, as these messages are typically less frequent, slower in speed, and originate from greater distances. 802.11bd is used for V2V communication, as it requires higher message speeds and is more critical to safety.

By combining NR-V2X for long-range, less frequent messages and 802.11bd for high-speed, safety-critical communication, the hybrid system ensures both reliability and efficiency. This approach overcomes DSRC's range limitations and LTE-V2X's congestion issues, leading to a more robust V2X communication framework. Additionally, system messages are going to overlap with each other, ensuring still somewhat working V2X communication, while one of the technologies is not working properly.

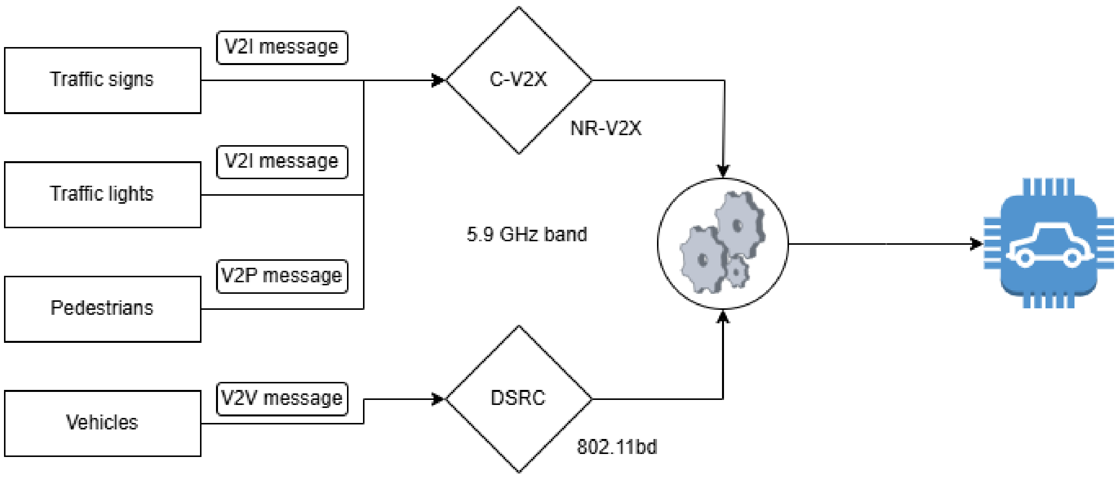


Figure 2. V2X communication flow using DSRC and C-V2X technologies over the 5.9 GHz band. Messages from infrastructure, vehicles, and pedestrians are processed by the autonomous vehicle system.

3.3 V2X message structure

When deciding how to structure a V2X message or choose the right protocol, it is important to consider the goal of the system. In large-scale V2X networks with many vehicles and infrastructure nodes, splitting messages into different types (such as CAM and DENM) is useful. It helps reduce congestion and improve efficiency since DENMs are only sent when something unusual happens.

However, this thesis is based on the idea that modern autonomous systems are already reliable in most standard driving situations. Constantly sending awareness messages (such as CAM) becomes unnecessary if the vehicle's onboard sensors are already capable of detecting the same information. Therefore, the proposed system is intentionally designed to be lightweight, relying solely on DENM-like messages to signal events that local perception might miss, such as hidden pedestrians or unexpected obstacles at intersections.

By taking advantage of the fact that today's autonomous systems can handle most scenarios, external assistance is only provided when an edge case or unusual situation is detected. This approach significantly reduces message volume and minimizes communication delays, making the system more efficient and better suited for fail-safe behavior in critical moments.

Unlike fully ETSI-compliant DENM messages, this thesis uses a custom, simplified DENM-like format tailored for simulation and evaluation. The message structure includes only the essential fields required for hazard communication, such as hazard type, location, and detection time, omitting layers such as cryptographic signing or strict schema enforcement. This design choice prioritizes real-time performance and low communication overhead, which are critical for edge-case handling.

The DENM message used in this thesis is structured into five main parts, as shown in Figure 3. It is inspired by the ETSI EN 302 637-3 standard [53], but simplified for simulation purposes. The Header contains metadata such as the message type (DENM), sender ID, and timestamp. The managementContainer includes the detection time of the event. The situationContainer specifies the nature of the event.

The locationContainer provides spatial information through both eventPosition (in geographic coordinates) and referencePosition (relative or local coordinates). This allows vehicles to assess both the sender's location and the position of the detected hazard. Finally, the alaCarteContainer contains extended information in the form of hazardDetails, which can represent either a moving object (e.g., an unknown vehicle or pedestrian) or an environmental condition (e.g., fog or reduced visibility).

This message structure does not include cryptographic and security-related fields, as the primary goal of this system is to test the fail-safe behavior of autonomous vehicles under edge-case scenarios, rather than secure message exchange.

This proposed system includes four different message providers: traffic signs, traffic lights, vehicles, and pedestrians. The message types involved are V2I, V2V and V2P.

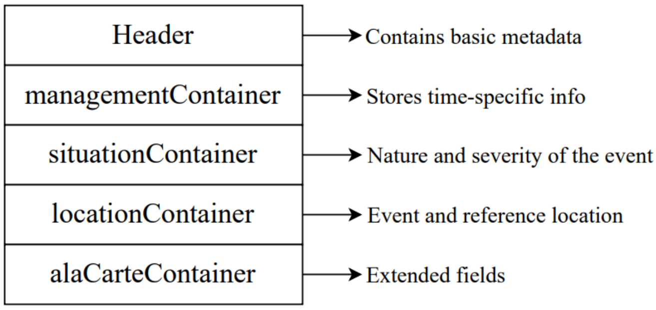


Figure 3. Vehicle-To-Everything Message Structure

It is also important to note that this V2X message is not meant for sharing sensor data or expanding a vehicle's field of view. Although many studies have researched and found that this can add additional safety to autonomous systems, it is not the best solution for edge cases. Processing sensor data locally and sending out only dangerous objects is more efficient because it reduces bandwidth usage. When raw data is shared, the vehicle has to go through processing again, which slows down its reaction time. Research shows that transmitting full sensor data requires high data rates, which can overload the network and introduce delays. By only sharing necessary hazard details, V2X communication becomes faster and more reliable [54].

3.3.1 V2I message structure

V2I message is communication between vehicle and stationary roadside units. To use this communication, the infrastructure must be fully equipped with sensors and chips capable of detecting and publishing relevant information across the map. In this thesis, the V2I communication comes specifically from traffic lights and traffic signs. Although the overall message structure remains the same for both, traffic lights include an additional light state message to indicate their current status. Traffic lights and signs act as RSUs and can process and share information coming from the infrastructure.

This message example, as shown in Figure 4, reports a situation detected by the infrastructure, such as a red traffic light with poor visibility due to fog, or the presence of a moving object near the intersection. The detection section is flexible, allowing for both object-based and weather-based hazard reporting depending on the event type.

```
{
  "Header": {
    "messageType": "DENM",
    "stationID": "traffic_light_01",
    "timestamp": "1711701821.123"
  },
  "managementContainer": {
    "detectionTime": "1711701821.123"
  },
  "situationContainer": {
    "eventType": "trafficLightStatus",
    "eventSeverity": "danger",
    "lightState": "red"
  },
  "locationContainer": {
    "eventPosition": {
      "latitude": 52.52,
      "longitude": 13.405
    },
    "referencePosition": {
      "x": 143.5,
      "y": 78.2
    }
  },
  "alaCarteContainer": {
    "hazardDetails": {
      "hazardType": "movingObject",
      "objectType": "unknownVehicle",
      "weatherCondition": "fog",
      "visibility": "low"
    }
  }
}
```


Figure 4. V2I message structure

3.3.2 V2P message structure

V2P communication is designed to provide the speed and location of vulnerable pedestrians near traffic. With the widespread use of smartphones and smartwatches, pedestrians can actively participate in traffic communication, allowing vehicles to detect and respond to their presence. In addition to the V2I structure, V2P messages include velocity information, enhancing the accuracy of pedestrian movement predictions, and improving overall traffic safety. Adding velocity information improves safety because a fast-approaching pedestrian poses a greater risk than one who is nearby but is moving slowly at a steady pace.

V2X message structure for Vehicle-to-Pedestrian communication is shown in Figure 5. The message is sent by a pedestrian device and contains information about the user's position, movement state, and crossing behavior, allowing nearby vehicles to react accordingly.


```json
{
  "Header": {
    "messageType": "DENM",
    "stationID": "pedestrian_device_07",
    "timestamp": "1711704821.654"
  },
  "managementContainer": {
    "detectionTime": "1711704821.654"
  },
  "situationContainer": {
    "eventType": "vulnerableRoadUser",
    "eventSeverity": "warning",
    "pedestrianState": "crossing"
  },
  "locationContainer": {
    "eventPosition": {
      "latitude": 52.5204,
      "longitude": 13.4049
    },
    "referencePosition": {
      "x": 150,
      "y": 75.2
    }
  },
  "alaCarteContainer": {
    "hazardDetails": {
      "hazardType": "movingObject",
      "objectType": "pedestrian",
      "speed": 1.2
    }
  }
}
```


Figure 5. V2P message structure

3.3.3 V2V message structure

V2V communication is currently the most tested type of V2X communication, as setting it up is significantly less expensive than the previous two types. In addition to the capabilities of V2I and V2P, V2V communication can also include wheel angle data in the message structure. This allows the system to detect sudden and unexpected movements and react in advance, improving overall traffic safety.

V2X message structure for Vehicle-to-Vehicle communication is shown in Figure 6. The message is triggered by a sudden braking event and informs surrounding vehicles of a potential hazard ahead.


```json
{
  "Header": {
    "messageType": "DENM",
    "stationID": "vehicle_203",
    "timestamp": "1711705122.987"
  },
  "managementContainer": {
    "detectionTime": "1711705122.987"
  },
  "situationContainer": {
    "eventType": "vehicleEmergency",
    "eventSeverity": "danger",
    "eventDescription": "suddenBraking"
  },
  "locationContainer": {
    "eventPosition": {
      "latitude": 52.5206,
      "longitude": 13.4052
    },
    "referencePosition": {
      "x": 153.4,
      "y": 79.8
    }
  },
  "alaCarteContainer": {
    "hazardDetails": {
      "hazardType": "movingObject",
      "objectType": "car",
      "speed": 0
    }
  }
}
```


Figure 6. V2V message structure

3.4 Simulation Setup

The simulation environment was built using the CARLA simulator, with integration through ROS (Robot Operating System) to manage sensor input, vehicle control, and V2X message exchange. CARLA is an open source simulation platform designed for developing and testing autonomous driving systems. It allows for custom map creation, configurable traffic behavior, weather conditions, sensor models, and support for multi-agent scenarios.

ROS acts as the middleware between CARLA and the autonomous driving system. It handles data communication between nodes and provides essential visualization and debugging tools such as RViz, which shows sensor output and system behavior in real time.

This research uses autonomous driving software developed by the Autonomous Driving Lab [55] at the University of Tartu. The system, called Autoware Mini [56], is open-source and distributed under the permissive MIT license. Since Autoware Mini is built in Python and based on ROS1, this thesis uses the same toolchain to ensure compatibility. Although Autoware Mini is aligned with the official Autoware framework and uses similar message types, it is intentionally simplified for research and teaching purposes.

The simulated vehicle is modeled after a Lexus RX450h, equipped with virtual sensors including LiDAR, camera, GNSS, and radar. The system enables full autonomous control, including object detection and tracking. This setup is ideal for evaluating different types of edge cases, each of which may require different sensor types for optimal detection and comparison.

To evaluate the effectiveness of the V2X-enhanced system, both the baseline autonomous system and the V2X-integrated version were tested. The baseline system is modular and has been previously validated in real-world scenarios for reliable object detection and navigation. For V2X testing, only the driving module of the system is used, while message reactions are implemented separately in a ROS-based filtering logic module. These reactions are currently designed conceptually and are not yet integrated into motion planning or direct vehicle control.

The V2X receiver logic is implemented using ROS. The infrastructure sensors simulated in CARLA publish V2X messages through ROS topics, and the ego vehicle subscribes to these messages. This allows the system to receive and respond to alerts generated by other road agents or infrastructure elements.

3.5 V2X message filtering

In the algorithm proposed in this thesis for the improved autonomous driving system V2X (Algorithm 1), the data come from two different sources: infrastructure sensors and on-board sensors of the autonomous vehicle. After getting the data, it is important to process it so that the car reacts to the most crucial information. As this thesis uses only messages similar in structure to DENM, there is no need to perform perception or object-level sensor fusion. These types of messages are already event-based and contain processed information, which reduces the need for low-level perception. It is still necessary to process the messages properly to avoid overloading the processing capacity due to receiving too many messages in a short time and to merge the messages from the infrastructure and the vehicle together.

Message filtering is important to reduce latency in urgent messages and also to ensure that the vehicle acts on the most important situations first. The aim of this filtering system is to keep it robust and effective. The first method is distance-based filtering. As messages can come from all over the city, it is necessary to process messages originating within a certain geographic radius of the vehicle. Most edge cases are relevant only when they are close to the vehicle. Depending on the urban or highway environment, the distance is different.

An additional way to prioritize messages is to use the Time-to-Collision (TTC) calculation [57]. TTC is defined as the estimated time before a collision occurs if both the ego vehicle and the object maintain their current speeds and trajectories. The formal definition is given as follows:

$$TTC = \begin{cases} \frac{D_{1-2}}{V_2 - V_1}, & \text{if } V_2 > V_1 \\ \infty, & \text{otherwise} \end{cases} \tag{1}$$

Where:

- D_{1-2} represents the distance between the ego vehicle and the object in front.
- V_1 and V_2 are the speeds of the object and the ego vehicle, respectively.

Adding speed to this formula shows how critical the situation is and, therefore, makes filtering easier. Notably, the same formula can be applied when the object is stationary by setting $V_1 = 0$, simplifying the equation to:

$$TTC = \frac{D_{1-2}}{V_2}$$

Although there are more complex TTC formulations, this simplified approach, based only on vehicle speed and object distance, is sufficient for real-time filtering in safety-critical scenarios.

The last way to filter messages is based on Event Type / Priority-Based Filtering. A slippery road is not as important as a pedestrian in the blind spot. It is essential that these types of messages receive priority handling. In these test cases, messages are filtered into danger or warning category.

Algorithm 1: Filtering and Decision Logic for V2X Safety Messages

```
Input: Incoming DENM message from infrastructure
Output: Trigger reaction or discard message
Extract message fields: event position, event type, severity, timestamp
Get the vehicle's current position and speed
Step 1: Distance Check
Calculate distance between vehicle and event
if distance > maximum allowed then
    Discard message (too far away)
    return
end
Step 2: Time-to-Collision (TTC) Check
Calculate how quickly the vehicle is approaching the event
if vehicle is not moving toward the event then
    Discard message
    return
end
Compute TTC = distance / closing speed
if TTC > threshold then
    Discard message (event is not urgent)
    return
end
Step 3: Severity Check
if message severity is 'danger' then
    Trigger safety reaction
    return
end
if message severity is 'warning' then
    Trigger cautionary reaction
    return
end
Otherwise, discard message (not relevant)
```

3.6 Experiments - Edge cases in simulation

3.6.1 Normal Driving

The system was first tested under normal driving conditions using the standard CARLA map. During this baseline test, no DENM messages were triggered, as no hazardous or unusual events occurred. The only functional difference from a typical autonomous drive is that the vehicle continuously subscribes to and filters incoming V2X messages. However, since DENM messages are generated only when dangerous situations arise, the number of incoming messages was minimal and did not affect system performance. The autonomous system operated as expected, and the inclusion of V2X logic had no measurable effect on driving behavior or latency.

3.6.2 Pedestrian Hidden Behind Infrastructure

The second scenario was designed to test the system's response to a vulnerable road user (pedestrian) partially hidden from the vehicle's field of view. The test was conducted near an intersection where the pedestrian is occluded by a traffic signal post. The vehicle approaches at regular speed, with limited visibility of the pedestrian to simulate a realistic edge case.

Importantly, the pedestrian in this scenario is not part of the V2X network. This simulates a real-world case where not all road users are connected. For comparison, the modular system (non-V2X) relies on LiDAR detection, which is generally effective in detecting the presence of objects without the need to classify them. However, when the pedestrian is fully hidden behind large structures or vehicles, the onboard sensors fail to detect the pedestrian. In contrast, the V2X-enhanced system successfully receives a hazard alert from infrastructure sensors and is able to respond earlier.

3.6.3 Reduced Visibility at Intersection (Fog and Rain)

This test scenario focuses on the vehicle's ability to recognize traffic light states under poor visibility conditions. The same intersection is used, but the simulation includes fog and heavy rain. In the V2X-enhanced system, infrastructure detects the weather condition and transmits a high-priority DENM message, alerting nearby vehicles.

In the modular system, the autonomous vehicle must rely on camera input to detect the traffic light state. Since camera performance significantly degrades in low visibility, the reliability of light color detection is reduced. In contrast, the V2X system provides consistent warning, enabling the vehicle to make informed decisions despite adverse environmental conditions.

3.6.4 Red Light Violation by Another Vehicle

In this scenario, the test is conducted in a different simulated town where a second vehicle intentionally ignores a red light. The V2X infrastructure detects the violation and sends out a critical-priority DENM message. The ego vehicle receives the alert and can prepare for evasive action.

For the modular system, LiDAR is again used to detect the moving vehicle. Although LiDAR may detect the violating vehicle once it enters the intersection, the reaction time is shorter and there is less contextual understanding of the situation. The V2X-enhanced system benefits from early detection and awareness of traffic rule violations not visible to onboard perception alone.

3.7 Evaluation Metrics

In the evaluation, three key performance metrics are used to compare the baseline perception-only system and the V2X-enhanced system. These metrics are commonly used in autonomous driving and V2X research to assess system response and safety performance [58, 59, 33]. First, the reaction time is measured. This refers to the time delay between when a DENM message is received and when the system finishes filtering the message and decides on an action. This metric highlights how quickly the system can process and respond to unexpected dangers.

Secondly, the detection distance is evaluated. This metric reflects how close a traditional (modular) perception-only system must be to an object before it can detect it. When combined with the vehicle's speed, it helps demonstrate whether the vehicle has enough time and distance left to safely react. For the V2X-enhanced system, the detection distance was set to 50 meters. This value is chosen not based on the maximum V2X communication range, but rather because 50 meters provides a realistic minimum distance required for the vehicle to brake safely at urban speeds, while minimizing excessive message traffic.

Finally, the result of the collision is recorded. If the reaction time and detection distance are insufficient, a collision may occur. This metric directly indicates whether the added V2X functionality contributes to successful hazard avoidance in edge-case scenarios.

4 Results

This chapter shows how the baseline system and the V2X-enhanced system performed during testing. The results are based on key safety metrics such as reaction time, detection distance, and whether a collision happened or not.

4.1 Setup and Scenario Description

This section explains the simulation setup and how the test scenarios were built. It covers the tools, message formats, and conditions used to run the experiments.

- Simulator: CARLA (version 09.13)
- Tools: ROS, Python, custom message filters
- Vehicle speed range: 20–50 km/h
- Sensors: LiDAR, camera, V2X receiver
- V2X message type: Simplified DENM (JSON format)
- Scenarios tested:
  - Normal driving without events
  - Pedestrian hidden behind infrastructure
  - Reduced visibility at intersection
  - Traffic violation by another vehicle

4.2 Scenario-Based Results

The following sections presents the results observed during simulation testing. A video showing all test scenarios and system behavior can be accessed online at: `https://youtu.be/AZtWVRIGKkw`

4.2.1 Normal Driving (No Events)

In this baseline test (Figure 7), no DENM messages were triggered, as there were no abnormal situations. The vehicle navigated the environment without issues using only its onboard perception. Both the modular system and the V2X-integrated system successfully completed the scenario with no collisions, false detections, or incorrect reactions (Table 1).

Reaction time	Detection distance	Collision
N/A	N/A	0

Table 1. Normal driving metrics

Figure 7. Normal Driving

4.2.2 Pedestrian Hidden Behind Infrastructure

With V2X: The RSU of the traffic light detected an unidentified pedestrian and published a warning DENM message (Figure 8 and Figure 9). The integrated V2X system detected the pedestrian as soon as the pedestrian was in the dangerous range (Figure 10). The message latency was only 120 ms and the pedestrian was detected more than 30 meters away, ensuring enough time for vehicle to react and avoid collision. (Table 2).

Reaction time	Detection distance	Collision
120 ms	50	0

Table 2. Pedestrian hidden metrics V2X

Without V2X (Figure 11): The autonomous vehicle failed to stop in time, resulting in a collision in the baseline scenario. The pedestrian was partially occluded behind a post and was only detected by the LiDAR sensor when the vehicle was approximately

8 meters away. At the allowed speed of 50 km/h, the detection distance was not far enough for the vehicle to react and stop safely, demonstrating the limitations of onboard perception in occluded environments.

Figure 8. Pedestrian hidden behind post

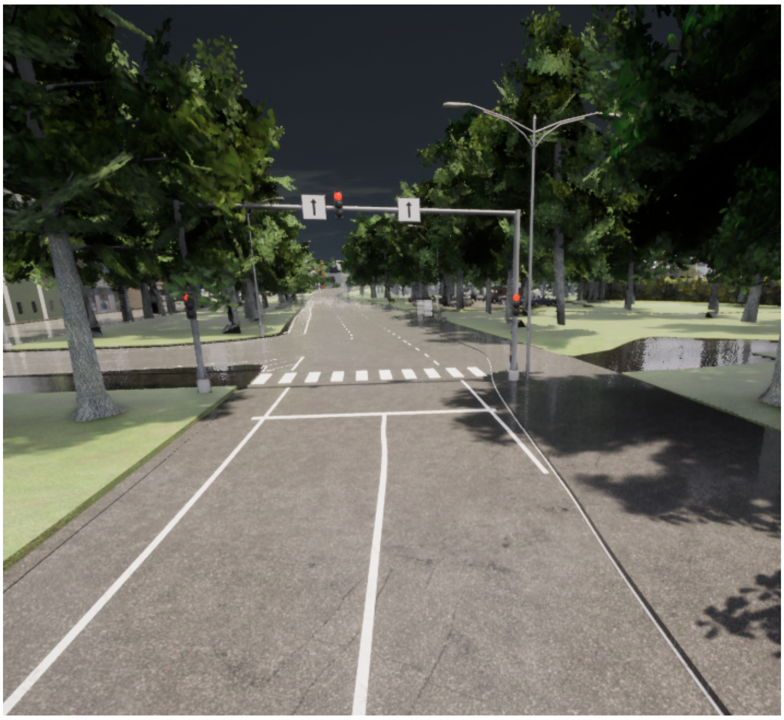


Figure 9. The same scene as in Figure 8 (i.e. pedestrian hidden behind a post), seen from a more distant viewpoint.

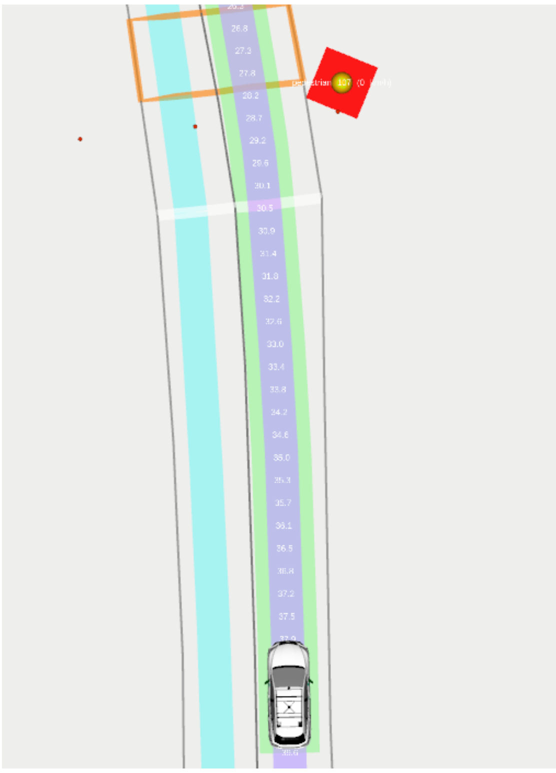


Figure 10. Pedestrian detected early via V2X alert, before line-of-sight is established

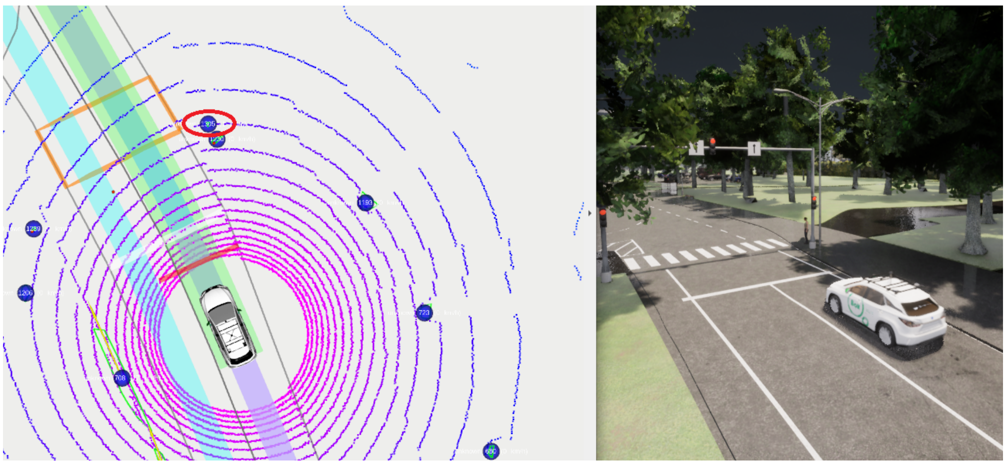


Figure 11. Pedestrian detected early via V2X alert, before line-of-sight is established

4.2.3 Reduced Visibility at Intersection (Fog and Rain)

With V2X (Figure 12): The traffic light RSU detected a bad weather scenario and broadcasted a DENM message indicating a dangerous condition. The vehicle received the message with a latency of 120 ms and was able to respond in time, successfully stopping at the red light, despite reduced visibility caused by rain and fog (Table 3).

Reaction time	Detection distance	Collision
110 ms	50	0

Table 3. Reduced visibility metrics V2X

Without V2X: The modular system relied on onboard cameras to detect the color of traffic lights. Although the system was able to correctly identify the position of the traffic light, the color classification was less reliable under adverse weather conditions (Figure 13). While the traffic light was red, the system first detected it as such at a distance of 9 meters (Figure 14), but with only slightly over 50 percent confidence. The system did not reach near 100 percent confidence in the red light detection until the vehicle was approximately 6 meters away, which was too late to ensure safe stopping at the given speed.

Figure 12. Reduced visibility traffic light detection with V2X

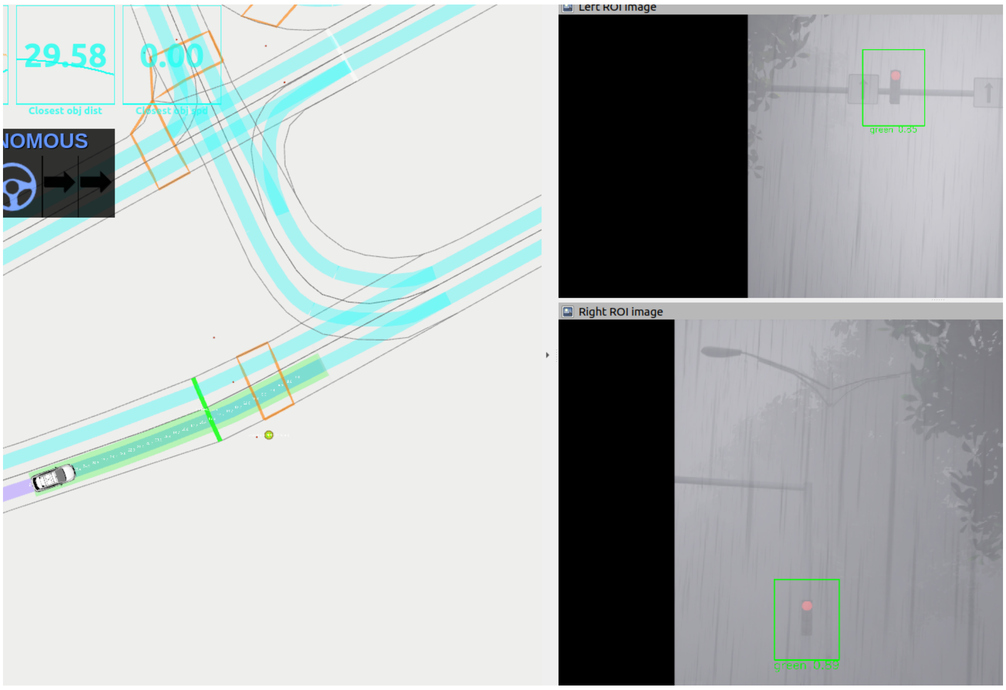


Figure 13. Reduced visibility traffic light detection wrong with camera

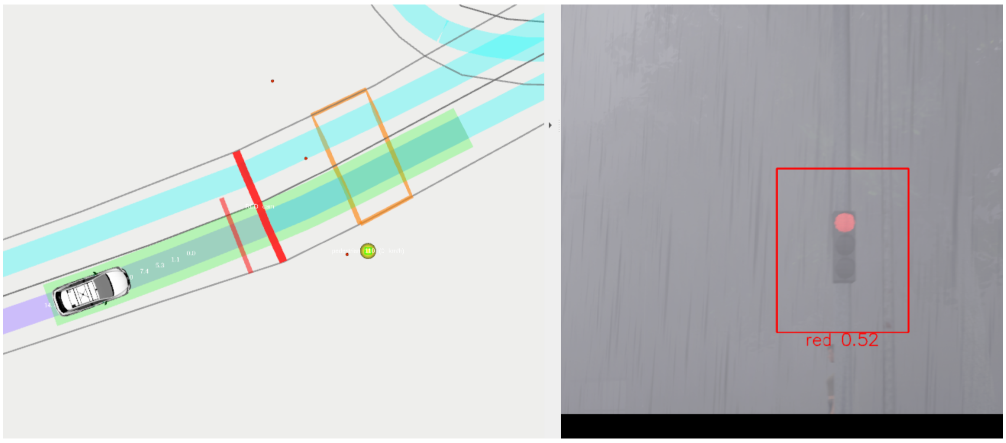


Figure 14. Reduced visibility traffic light detection correct with camera

4.2.4 Red Light Violation by Another Vehicle

With V2X (Figure 15): In this test case, the vehicle detected that a red light was ignored and published a danger-level DENM message to other nearby vehicles. Since the event occurred directly at the intersection, the information was sent relatively late, and the distance between the two vehicles was around 10 meters (Table 4).

However, what makes this case different is the purpose of the message. The autonomous vehicle is aware that there is a dangerous situation ahead, and thanks to the shared V2X information, it reacts by braking and waiting for the hazard to pass. Even though the message arrives late, the V2X system allows nearby vehicles to become aware of the danger and potentially react faster than they would using onboard sensors alone.

Reaction time	Detection distance	Collision
125 ms	10	0

Table 4. Red light violation metrics V2X

Without V2X (Figure 16): The autonomous vehicle used LiDAR to detect the other vehicle and was able to avoid a collision. However, without knowing the context of the situation, the vehicle still drove into the intersection and came dangerously close to the violating vehicle. Since it had no prior information about the red light violation, the AV did not understand the situation and therefore did not know to wait it out. This highlights a key limitation of relying solely on onboard perception — the system can react, but it lacks the situational awareness that V2X communication provides.

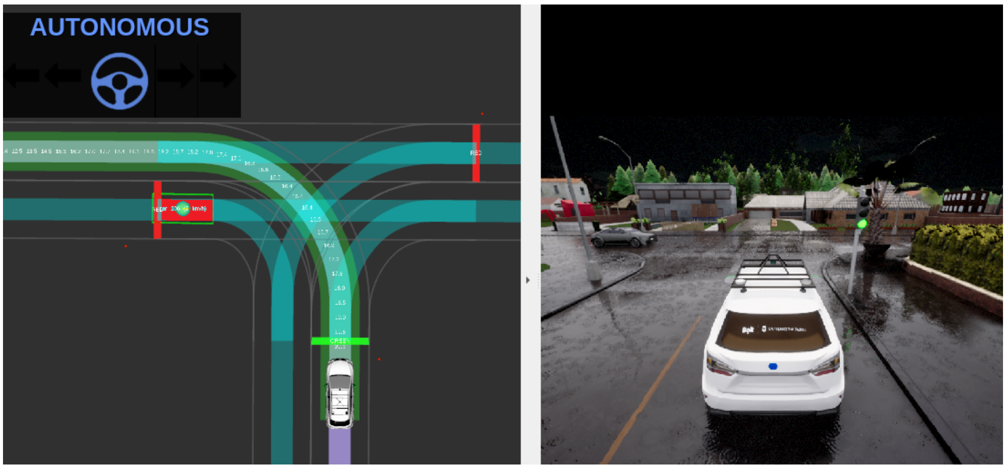


Figure 15. Red light violation detection with V2X

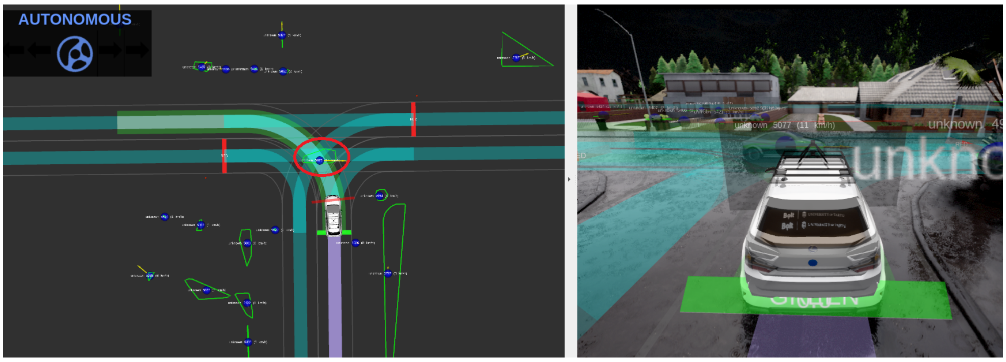


Figure 16. Red light violation detection with LiDAR

4.2.5 Summary table

The test results demonstrate that adding a lightweight V2X layer significantly improves safety. As shown in Table 5, when the system received V2X alerts, the vehicle detected the hazards early enough to allow a safe reaction. In each test case, the detection distance provided enough time to avoid a collision (Figure 17). However, if we take into account the distance at which the system without V2X was able to detect the hazard, it is likely that it did not have enough time to react, which would result in a dangerous situation. When comparing the results, the system without V2X ended up in a dangerous situation 66.7 percentage more often when dealing with edge cases (Figure 18).

Experiment	Reaction time	Detection distance V2X
Baseline (no V2X)	N/A	N/A
Pedestrian Occlusion	110 ms	50
Foggy Intersection	120 ms	50
Red-Light Violation	125 ms	10

Table 5. Summary of Detection and Reaction Metrics for V2X

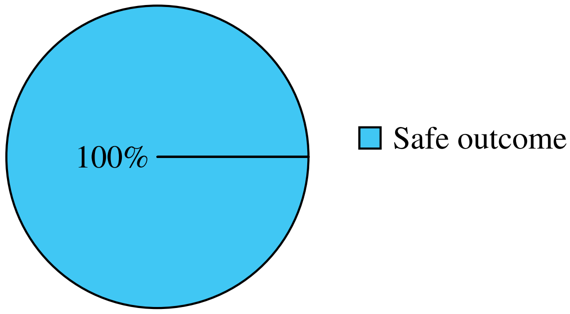


Figure 17. Outcome distribution for test scenario with V2X support

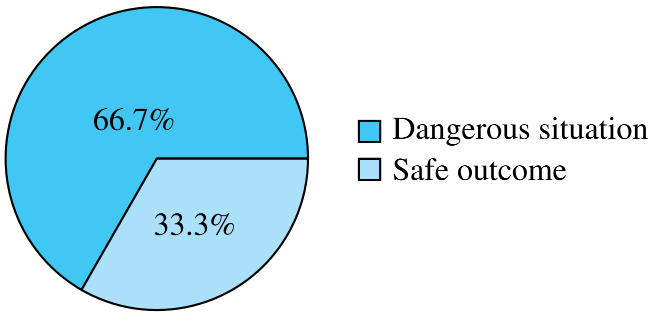


Figure 18. Outcome distribution for test scenario without V2X support

5 Discussion

The purpose of this thesis was to test a lightweight DENM-only V2X communication layer to improve AV safety in edge cases. The simulation results indicate that the V2X layer certainly improves the safety of the autonomous system.

The system was first tested under normal driving conditions (see Section 4.2.1) without abnormal events. During this baseline scenario, the V2X layer remained inactive, as expected, and did not interfere with the core functionality of the autonomous driving stack. Since the V2X system is based on event-triggered messaging, it remains silent under normal conditions. It only activates when something happens, letting the regular system handle everything without interference.

The second scenario simulated a pedestrian hidden behind infrastructure (see Section 4.2.2), making them invisible to the AV's onboard sensors. Without V2X assistance, the pedestrian was detected only at approximately 8 meters. Too late for the vehicle to react safely when driving at 50 km/h. In contrast, the V2X system received a DENM-style alert 50 meters before the vehicle reached the crossing point. This early detection enabled a safe and timely response, confirming the benefit of infrastructure-assisted perception in occluded environments. Moreover, the system's event-triggered design ensured that only essential messages were broadcast, helping to avoid communication channel congestion.

The results of the third test mirrored those of the previous test, proving the V2X system more safe. In bad weather conditions (see Section 4.2.3), the camera was unable to detect the color of the traffic lights. Even more dangerously, the color was detected incorrectly, which meant that the car could drive into the intersection at the same time as other cars or pedestrians. With the V2X system, bad weather was detected, DENM-like messages published information to the vehicle, and the situation stayed safe. Initially, a scenario with fully occluded traffic lights due to snow coverage was considered. However, then the test case would have favored the V2X system due to cameras not being able to detect the color at all. However, this case showed that when RSUs actively publish their data, be it traffic lights or signs, the safety of the autonomous vehicle improves significantly. It is not possible to build an autonomous system that is so robust that it can detect signs through bad weather or when commercial signs include similar pictures. The only way to ensure that the vehicle receives the correct information is through direct communication, which means that signs and signals must be able to broadcast their data digitally. Although this can be implemented in various ways, having signs publish their information on V2X is arguably one of the simplest and most foolproof approaches.

The fourth test showed that even when the V2X system gets the information late, it is still more useful than no information. The regular system was able to detect the red light runner (see Section 4.2.4) pretty much at the same time as the V2X message. In fact, the regular system was able to detect it even earlier because the V2X message was sent out when the other vehicle ran the red light. But with the V2X message, message logs confirmed that the vehicle had run the red light, and therefore the situation was dangerous and it was best to stay away. With the regular system, the autonomous vehicle dealt with the violating vehicle as a regular object, trying to avoid it. By sending out a message about what has happened and what the danger level is, the autonomous vehicle can maintain a safe distance.

5.1 Strengths of the Approach

As proven in previous edge case tests, adding V2X drastically improves system safety. One of the biggest strengths of the system is the scalability. The messages are not constantly published like CAM or CPMs, therefore avoiding overloading the communication channel. One of the biggest bottlenecks of previously mentioned systems is handling delays and message congestion.

Additionally, the proposed system is more cost-efficient compared to CPM-based architectures, due to its simpler implementation and lower data transmission requirements. This makes it a good option for cities in the early stages of V2X infrastructure deployment, where bandwidth and integration complexity may be constrained.

Another strength is that this system assumes that autonomous vehicles are already capable of handling standard driving conditions. It does not try to replace or modify their core logic. Instead, it only steps in when the onboard system might fail, such as during edge cases or unexpected situations. This makes it easier to integrate and test without having to retrain or reconfigure the existing AV stack.

All of the testing was performed using open source tools like CARLA, ROS, and Autoware Mini. These tools are commonly used in research and teaching and allow anyone to reproduce the results or build on top of this work. The system is intentionally kept modular and transparent, so it can be extended in future projects without being locked into specific hardware or platforms.

5.2 Limitations of the Study

While the results show a clear improvement over the base system, there are still limitations that should be addressed. First, the tests were carried out in a simulated environment, meaning that real-world factors such as sensor noise, delays, or hardware malfunctions were not present. All of these are important considerations in real-life deployments and can affect how the system reacts. Secondly, the V2X layer and filtering logic were implemented as a separate ROS node. It was not fully integrated into the autonomous system's motion and path planning modules. While the intended vehicle response was correct, the simulation does not account for the delay introduced by actual planning and control algorithms. In a real vehicle, this could increase the reaction time and affect safety margins.

Additionally, this thesis assumes a "perfect world" around the vehicle and does not address message security. The DENM-like messages used in this system are simplified and not encrypted. In real-world applications, V2X messages should be encrypted and authenticated to prevent spoofing or hacking attempts.

The system also assumes that most traffic signs, vehicles, and pedestrians are connected through processing units or wearable devices such as smartwatches. In reality, this level of connectivity is far from guaranteed. Although the system is designed to detect unconnected road users using infrastructure sensors, full coverage cannot be assumed. In addition, topics such as data privacy, personal information protection, and ethical concerns about message sharing should also be considered in real-world deployments.

Finally, this system relies heavily on the assumption that dangerous situations can be accurately detected and only then are messages published. If initial detection fails, for example, if infrastructure sensors do not recognize a hazard or misclassify it, the system cannot provide any warning to the vehicle. This highlights the importance of well-placed and reliable sensors within the infrastructure. The effectiveness of the V2X layer is entirely dependent on the quality and precision of the initial hazard detection.

6 Conclusion and Future Work

The results of the simulation scenarios showed that the proposed system improved the detection range, the reaction time, and overall safety. Under normal conditions, the V2X system remained passive and did not interfere with the AV base operations. In more complex situations, such as occluded pedestrians, poor visibility, or traffic rule violations, the system provided valuable early warnings and context that allowed the vehicle to make safer decisions.

The main contribution of this work is to demonstrate that even a lightweight DENM-only layer added to an autonomous system can improve overall safety. The lightweight nature of the system ensures that this safety enhancement does not come at the cost of efficiency or require constant high-bandwidth data exchange. Many of the edge cases with which current autonomous systems still struggle can be addressed through infrastructure connectivity.

Although the system showed strong results and outperformed the baseline system in all test cases, there is still future work to be done.

Future work will involve validating the system on real AV-RSU hardware using 802.11p or NR-V2X protocols. This would allow for the evaluation of delay times, malfunctions, and other confounding factors that can affect system performance. In addition, more test cases should be explored, such as roundabouts, highways, and roads with confusing markings. These scenarios would help determine whether the system can handle more complex situations.

The system could also be deployed in some of the most critical areas in a city, such as intersections. When AVs can handle most of the city by themselves, this system can act as a safety net in known problem locations. This approach would also support testing for larger-scale deployments.

For future test cases, it would also be beneficial if the V2X layer was fully integrated with the AV system, meaning that the vehicle not only publishes its intended reaction, but also executes it in real-time as part of the decision-making process.

Finally, future work should address security. It is important to verify that the messages come from trusted sources and to ensure that all communication is encrypted. Before these measures are implemented, the system can be tested in a controlled real-world environment, but it should not be deployed in regular traffic due to potential security risks.

In general, this thesis shows that adding even the simplest V2X layer can improve AV safety. When dealing with edge cases, the safest approach is to directly tell the autonomous vehicle what it is facing, rather than relying on the system to detect it on its own, especially when perception is limited or delayed.

References

[1] Tom Vanderbilt. Let the robot drive: The autonomous car of the future is here. *WIRED*, January 2012.

[2] Graham Gordon and John Kiser. How autonomous ride-hailing can steer us toward the future of cars, December 2023. Ipsos Point of View Report.

[3] Paul Perrone. A comprehensive mathematical and system-level analysis of autonomous vehicle timelines, 2025.

[4] Keshav Bimbraw. Autonomous cars: Past, present and future a review of the developments in the last century, the present scenario and the expected future of autonomous vehicle technology. In *2015 12th International Conference on Informatics in Control, Automation and Robotics (ICINCO)*, volume 01, pages 191–198, 2015.

[5] M. Xie, L. Trassoudaine, J. Alizon, M. Thonnat, and J. Gallice. Active and intelligent sensing of road obstacles: Application to the european eureka-prometheus project. In *1993 (4th) International Conference on Computer Vision*, pages 616–623, 1993.

[6] C. Thorpe, M. Herbert, T. Kanade, and S. Shafer. Toward autonomous driving: the cmu navlab. i. perception. *IEEE Expert*, 6(4):31–42, 1991.

[7] Umit Ozguner, Christoph Stiller, and Keith Redmill. Systems for safety and autonomous behavior in cars: The darpa grand challenge experience. *Proceedings of the IEEE*, 95(2):397–412, 2007.

[8] Chris Urmson. The self-driving car logs more miles on new wheels. `https://googleblog.blogspot.com/2012/08/the-self-driving-car-logs-more-miles-on.html`, August 2012.

[9] Mark Harris. Ntsb investigation into deadly uber self-driving car crash reveals lax attitude toward safety. *IEEE Spectrum*, November 2019.

[10] David Bartz. GM's Cruise Self-Driving Unit to Pay $1.5 Million Fine Over Crash Disclosure. *Reuters*, September 2024.

[11] Goldman Sachs Research. Partially autonomous cars forecast to comprise 10% of new vehicle sales by 2030, 2024.

[12] SAE International. Sae levels of driving automation™ refined for clarity and international application, 2021.

[13] Mercedes-Benz Group AG. Introducing drive pilot: An automated driving system for the highway, March 2023.

[14] Fatih Sezgin, Daniel Vriesman, Dagmar Steinhauser, Robert Lugner, and Thomas Brandmeier. Safe autonomous driving in adverse weather: Sensor evaluation and performance monitoring. In *2023 IEEE Intelligent Vehicles Symposium (IV)*, pages 1–6, 2023.

[15] Automotive Technology. Vehicle-to-everything (v2x) communication: Enhancing road safety and traffic management, n.d.

[16] Chanyoung Jung, Daegyu Lee, Seungwook Lee, and David Hyunchul Shim. V2x-communication-aided autonomous driving: System design and experimental validation. *Sensors*, 2020.

[17] Valerian Mannoni, Vincent Berg, Stefania Sesia, and Eric Perraud. A comparison of the v2x communication systems: Its-g5 and c-v2x. In *2019 IEEE 89th Vehicular Technology Conference (VTC2019-Spring)*, pages 1–5, 2019.

[18] Vasilis Maglogiannis, Dries Naudts, Seilendria Hadiwardoyo, Daniel van den Akker, Johann Marquez-Barja, and Ingrid Moerman. Experimental v2x evaluation for c-v2x and its-g5 technologies in a real-life highway environment. *IEEE Transactions on Network and Service Management*, 19(2):1521–1538, 2022.

[19] Jicheng Yin and Seung-Hoon Hwang. Design of c-v2x cam/denm separate resource pool. In *2022 IEEE VTS Asia Pacific Wireless Communications Symposium (APWCS)*, pages 94–98, 2022.

[20] Jingyuan Zhao, Wenyi Zhao, Bo Deng, Zhenghong Wang, Feng Zhang, Wenxiang Zheng, Wanke Cao, Jinrui Nan, Yubo Lian, and Andrew F. Burke. Autonomous driving system: A comprehensive survey. *Expert Systems with Applications*, 242:122836, 2024.

[21] Ardi Tampuu, Tambet Matiisen, Maksym Semikin, Dmytro Fishman, and Naveed Muhammad. A survey of end-to-end driving: Architectures and training methods. *IEEE Transactions on Neural Networks and Learning Systems*, 33(4):1364–1384, 2022.

[22] Sundas Iftikhar, Zuping Zhang, Muhammad Asim, Ammar Muthanna, Andrey Koucheryavy, and Ahmed A. Abd El-Latif. Deep learning-based pedestrian detection in autonomous vehicles: Substantial issues and challenges. *Electronics*, 11(21), 2022.

[23] Qing Yang, Song Fu, Honggang Wang, and Hua Fang. Machine-learning-enabled cooperative perception for connected autonomous vehicles: Challenges and opportunities. *IEEE Network*, 35(3):96–101, 2021.

[24] Hrag-Harout Jebamikyous and Rasha Kashef. Autonomous vehicles perception (avp) using deep learning: Modeling, assessment, and challenges. *IEEE Access*, 10:10523–10535, 2022.

[25] Darsh Parekh, Nishi Poddar, Aakash Rajpurkar, Manisha Chahal, Neeraj Kumar, Gyanendra Prasad Joshi, and Woong Cho. A review on autonomous vehicles: Progress, methods and challenges. *Electronics*, 11(14), 2022.

[26] Electronics Maker. Driving the future: The role of computing power in autonomous vehicles, n.d.

[27] Daniel Bogdoll, Maximilian Nitsche, and J. Marius Zollner. Anomaly detection in autonomous driving: A survey. In *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, page 4487–4498. IEEE, June 2022.

[28] Roshan Vijay, Jim Cherian, Rachid Riah, Niels De Boer, and Apratim Choudhury. Optimal placement of roadside infrastructure sensors towards safer autonomous vehicle deployments. In *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, pages 2589–2595, 2021.

[29] Kallirroi N. Porfyri, Areti Kotsi, and Evangelos Mitsakis. A microsimulation approach for the impact assessment of a vehicle-to-infrastructure based road hazard warning system. *CoRR*, abs/2010.10262, 2020.

[30] Zhengwei Bai, Guoyuan Wu, Xuewei Qi, Yongkang Liu, Kentaro Oguchi, and Matthew J. Barth. Infrastructure-based object detection and tracking for cooperative driving automation: A survey. In *2022 IEEE Intelligent Vehicles Symposium (IV)*, pages 1366–1373, 2022.

[31] Kakan Chandra Dey, Anjan Rayamajhi, Mashrur Chowdhury, Parth Bhavsar, and James Martin. Vehicle-to-vehicle (v2v) and vehicle-to-infrastructure (v2i) communication in a heterogeneous wireless network – performance evaluation. *Transportation Research Part C: Emerging Technologies*, 68:168–184, 2016.

[32] Syed Adnan Yusuf, Arshad Khan, and Riad Souissi. Vehicle-to-everything (v2x) in the autonomous vehicles domain – a technical review of communication, sensor, and ai technologies for road user safety. *Transportation Research Interdisciplinary Perspectives*, 23:100980, 2024.

[33] Eduard Zadobrischi, Mihai Dimian, and Mihai Negru. The utility of dsrc and v2x in road safety applications and intelligent parking: Similarities, differences, and the future of vehicular communication. *Sensors*, 21(21), 2021.

[34] Jin Cao, Maode Ma, Hui Li, Ruhui Ma, Yunqing Sun, Pu Yu, and Lihui Xiong. A survey on security aspects for 3gpp 5g networks. *IEEE Communications Surveys & Tutorials*, 22(1):170–195, 2020.

[35] Christine Gschwendtner, Simon R. Sinsel, and Annegret Stephan. Vehicle-to-x (v2x) implementation: An overview of predominate trial configurations and technical, social and regulatory challenges. *Renewable and Sustainable Energy Reviews*, 145:110977, 2021.

[36] Rahmat Khezri, David Steen, and Le Anh Tuan. A review on implementation of vehicle to everything (v2x): Benefits, barriers and measures. In *2022 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, pages 1–6, 2022.

[37] Zuobin Ying, Kaichao Wang, Jinbo Xiong, and Maode Ma. A literature review on v2x communications security: Foundation, solutions, status, and future. *IET Communications*, 18(20):1683–1715, 2024.

[38] Waqar Anwar, Norman Franchi, and Gerhard Fettweis. Physical layer evaluation of v2x communications technologies: 5g nr-v2x, lte-v2x, ieee 802.11bd, and ieee 802.11p. In *2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall)*, pages 1–7, 2019.

[39] Shanzheng Xue, Siyuan Gong, and Xinyi Li. A comparative study of ieee 802.11bd and ieee 802.11p on the data dissemination properties in dynamic traffic scenarios. *Applied Sciences*, 14(5), 2024.

[40] Tao Huang, Jianan Liu, Xi Zhou, Dinh C. Nguyen, Mostafa Rahimi Azghadi, Yuxuan Xia, Qing-Long Han, and Sumei Sun. V2x cooperative perception for autonomous driving: Recent advances and challenges, 2024.

[41] Hui Huang, Huiyun Li, Cuiping Shao, Tianfu Sun, Wenqi Fang, and Shaobo Dang. Data redundancy mitigation in v2x based collective perceptions. *IEEE Access*, 8:13405–13418, 2020.

[42] Mao Shan, Karan Narula, Stewart Worrall, Yung Fei Wong, Julie Stephany Berrio Perez, Paul Gray, and Eduardo Nebot. A novel probabilistic v2x data fusion framework for cooperative perception. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*, pages 2013–2020, 2022.

[43] Nastaran Moradloo, Iman Mahdinia, and Asad J. Khattak. Safety in higher level automated vehicles: Investigating edge cases in crashes of vehicles equipped with automated driving systems. *Accident Analysis & Prevention*, 203:107607, 2024.

[44] Dhanoop Karunakaran, Julie Stephany Berrio Perez, and Stewart Worrall. Generating edge cases for testing autonomous vehicles using real-world data. *Sensors*, 24(1), 2024.

[45] Xinhai Zhang, Jianbo Tao, Kaige Tan, Martin Törngren, José Manuel Gaspar Sánchez, Muhammad Rusyadi Ramli, Xin Tao, Magnus Gyllenhammar, Franz Wotawa, Naveen Mohan, Mihai Nica, and Hermann Felbinger. Finding critical scenarios for automated driving systems: A systematic mapping study. *IEEE Transactions on Software Engineering*, 49(3):991–1026, 2023.

[46] Ding Zhao, Xianan Huang, Huei Peng, Henry Lam, and David J. LeBlanc. Accelerated evaluation of automated vehicles in car-following maneuvers. *IEEE Transactions on Intelligent Transportation Systems*, 19(3):733–744, 2018.

[47] Jorge Vargas, Suleiman Alsweiss, Onur Toker, Rahul Razdan, and Joshua Santos. An overview of autonomous vehicles sensors and their vulnerability to weather conditions. *Sensors*, 21(16), 2021.

[48] Jizhao Wang, Zhizhou Wu, Yunyi Liang, Jinjun Tang, and Huimiao Chen. Perception methods for adverse weather based on vehicle infrastructure cooperation system: A review. *Sensors*, 24(2), 2024.

[49] Michael Evans, Marcial Machado, Rickey Johnson, Anna Vadella, Luis Escamilla, Beñat Froemming-Aldanondo, Tatiana Rastoskueva, Milan Jostes, Devson Butani, Ryan Kaddis, Chan-Jin Chung, and Joshua Siegel. Vehicle-to-everything (v2x) communication: A roadside unit for adaptive intersection control of autonomous electric vehicles, 2024.

[50] Hung Duy Nguyen, Mooryong Choi, and Kyoungseok Han. Risk-informed decision-making and control strategies for autonomous vehicles in emergency situations. *Accident Analysis & Prevention*, 193:107305, 2023.

[51] Li Chen, Penghao Wu, Kashyap Chitta, Bernhard Jaeger, Andreas Geiger, and Hongyang Li. End-to-end autonomous driving: Challenges and frontiers. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 46(12):10164–10183, 2024.

[52] AbduladhemAbdulkareem Ali and Hussein Alaa Hussein. Traffic lights system based on rfid for autonomous driving vehicle. In *2017 Annual Conference on New*

Trends in Information & Communications Technology Applications (NTICT), pages 122–127, 2017.

[53] ETSI. Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Part 3: Specifications of Decentralized Environmental Notification Basic Service, 2014.

[54] Ryuichi Fukatsu and Kei Sakaguchi. Automated driving with cooperative perception using millimeter-wave v2v communications for safe overtaking. *Sensors (Basel, Switzerland)*, 21, 2021.

[55] Autonomous Driving Lab, University of Tartu. Autonomous driving lab - software. `https://adl.cs.ut.ee/lab/software`, 2025.

[56] Autonomous Driving Lab, University of Tartu. autoware_mini: A lightweight autonomous driving stack for simulation and teaching. `https://github.com/UT-ADL/autoware_mini`, 2025.

[57] Eric Adomah and Arash Khoda Bakhshi. Safety impact of connected vehicles on driver behavior in rural work zones under foggy weather conditions. *Transportation Research Record: Journal of the Transportation Research Board*, 2676:036119812110491, 10 2021.

[58] Vinayak V Dixit, Sai Chand, and Divya J Nair. Autonomous vehicles: disengagements, accidents and reaction times. *PLoS one*, 11(12):e0168054, 2016.

[59] Di Feng, Ali Harakeh, Steven L. Waslander, and Klaus Dietmayer. A review and comparative study on probabilistic object detection in autonomous driving. *IEEE Transactions on Intelligent Transportation Systems*, 23(8):9961–9980, 2022.

II. Licence

Non-exclusive licence to reproduce thesis and make thesis public

I, **Lisanne Siniväli**,

1. herewith grant the University of Tartu a free permit (non-exclusive licence) to

   reproduce, for the purpose of preservation, including for adding to the DSpace digital archives until the expiry of the term of copyright,

   Edge-Case Handling via Message-Based V2X for Enhanced Vehicle Autonomy,

   supervised by Naveed Muhammad.

2. I grant the University of Tartu a permit to make the work specified in p. 1 available to the public via the web environment of the University of Tartu, including via the DSpace digital archives, under the Creative Commons licence CC BY NC ND 3.0, which allows, by giving appropriate credit to the author, to reproduce, distribute the work and communicate it to the public, and prohibits the creation of derivative works and any commercial use of the work until the expiry of the term of copyright.

3. I am aware of the fact that the author retains the rights specified in p. 1 and 2.

4. I certify that granting the non-exclusive licence does not infringe other persons' intellectual property rights or rights arising from the personal data protection legislation.

Lisanne Siniväli
15/05/2025