A Cloud-Based Road-Traffic Risk Mediator System for IoT-Enabled Vehicles

A Thesis

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School of Applied Computing, Faculty of Applied Science and Technology

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Devon A. Fazekas

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Abstract

For emergency responders, every delay in reaching their destination could be the difference between life and death for those involved in accidents, which is why they must reduce their arrival time as much as possible. ERs are legally permitted to exceed speed limitations, run red lights, and ignore stop signs, all of which put them and nearby civilian drivers at risk of accidents. The traditional methods of using emergency lights and sirens are ineffective at providing civilian drivers with enough warning and context to negotiate traffic in urban areas, resulting in congestion, delays, and increased risk. This thesis describes an innovative cloud-based road-traffic risk mediator system and reports on synthetic test case scenarios. The system, built upon IoT-enabled vehicles and cloud computing, aims to minimize the risk of emergency vehicle-involved accidents by mediating traffic volume along ER paths and offloading the maneuvering computation and decision making for drivers of connected vehicles.

Keywords: IoT, emergency responders, traffic routing, reducing arrival time, reducing traffic volume, improving road safety, cloud computing.

Thesis Supervisor: Dr. Richard Pyne
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I want to thank Professor Richard Pyne for his endless patience and guidance and for my beloved friends and family for all their support throughout the making of this thesis.

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Chapter 1

Introduction

Emergency responders (ERs) are specialized, trained individuals operating emergency vehicles and arriving first at emergency scenes like road accidents or natural disasters. ERs typically include law enforcement officers (LEO), firefighters, and emergency medical service (EMS) technicians [1]. Given the time-sensitive nature of emergencies, ERs need to quickly and safely reach their destinations [2]. They thus are authorized to operate emergency vehicles with the Code Three Running option permitting the use of warning lights, sirens, exceeding speed limits, and crossing against stop signs and red lights to minimize collision risks and arrival times en route to their destination [1, 2, 3].

As the number of registered vehicles continues to grow each year, the increase in urban traffic volume leads to congestion and delays, resulting in increasing arrival times and risk of collisions for ERs when responding to calls [4]. ERs operate under stressful driving conditions, time pressure, and multitasking activities [1]. For instance, the study by [3] found that accidents involving emergency vehicles are four and eight times more likely to result in fatality and severe injury, respectively, compared to civilian drivers. The study also notes that the root cause for 30% of these accidents stems from civilian drivers' wrong behaviour in avoiding the emergency vehicle. The relevant causative factors attributing to these crashes also include:

- Complicated urban intersections [1, 5];

- High traffic volumes [1, 4];
- Lack of recognition by other drivers [1, 4, 6]; and
- Human error [3, 6].

In the United States, emergency vehicle-involved crashes account for thousands of injuries and hundreds of fatalities each year. Between 2004 and 2006, 37,600 LEOs were reported injured [1], 17,000 firefighters in 2015 [1], and 1,500 EMS technicians in 2009 [1]. The average annual fatality count for ERs as a result of these road accidents is approximately 100 for LEOs [1, 7, 8], 45 for EMS technicians [1, 7], and 15 for firefighters [1, 7]. Furthermore, reports from [1] show an average of 60 civilian fatalities each year due to these accidents, which also incur many lawsuits costing the cities millions of dollars due to these injuries, property damage, and life loss [1].

1.1 Statement of the Problem

The Ministry of Transportation (MOT) in Canada is dedicated to moving people safely, efficiently, and sustainably by promoting innovative technology and infrastructure [9]. When it comes to emergency vehicles, they are equipped with sirens and lights, and laws dictate how civilian drivers should respond when nearby an emergency vehicle [9]. For instance, failure to slow down and make room when approaching an emergency vehicle or failure to maintain at least 150-meters behind a travelling emergency vehicle will result in fines between $400 to $2,000 and three demerit points in Ontario based on Section 159(2) and (3) of the Highway Traffic Act [10, 9].

Unfortunately, the traditional methods used by emergency vehicles (i.e., lights and sirens) are human perception-based and have been proven ineffective at attaining the attention of civilian drivers and negotiating traffic in urban areas [3, 11]. A driver must multitask while operating a vehicle, giving attention to the movements of surrounding vehicles, nearby pedestrians, and any other threats that could emerge. By the time civilian drivers acknowledge the warning signals emitted by emergency vehicles, not only do they have difficulty identifying the direction and distance of the source, they may not have sufficient space or time to make the best maneuver, thereby providing minimal aid in reducing arrival times and collision risks for emergency vehicles [12, 3].

Continuing with the reliance on human perception-based warning signals results in additional traffic chaos and accidents [12, 11]. Developing a more sophisticated and assistive system for emergency and civilian drivers could help the MOT increase road safety in urban areas by minimizing the flow rate achieved by strategically distributing traffic flow from primary roads to secondary roads.

A significant number of studies have focused on further developing Intelligent Transporation Systems (ITS), focusing on increasing road safety [13]. One of the common goals among the studies was to reduce the chance of emergency vehicle-involved accidents while also reducing their arrival time. Many papers used approaches to strategically control traffic lights to block traffic from entering an emergency path. Other approaches used telecommunication technologies such as DSRC embedded in the vehicle to provide drivers with a system for earlier warning notifications and maneuvering suggestions [14]. Many papers show that a promising approach is to reduce the number of vehicles on the path of an emergency vehicle by taking alternative routes (e.g., secondary roads or side streets that would typically result in slower commutes but contain less traffic volume) [14]. Research has shown that offloading the driver's avoidance decision-making to a centralized server significantly reduces the traffic volume and delays incurred by the emergency vehicles [14].

1.2 Purpose of the Study

This study will take these ideas of rerouting civilian drivers off the immediate path of emergency vehicles and take them further. The research will simulate various traffic scenarios in urban areas with varying ratios between regular vehicles and IoT-enabled vehicles, referred to as connected vehicles (CVs). The CVs will use cellular data to establish near-real-time two-way communication with our cloud server as it provides traffic data and receives navigation directions to avoid route collisions.

We define a route collision as the event of a travelling civilian vehicle getting closer than the safety threshold of 150-meters, enforced by the MOT [10, 9], to a travelling emergency vehicle. For the system to avoid route collisions, drivers of both types of CVs (i.e., an emergency vehicle and civilian vehicle) need to enter their destinations before driving and follow the paths provided by our system. This study explores the relationship between intelligently regulating traffic flow between primary and secondary roads and the arrival times for emergency vehicles within urban areas such as Toronto, Ontario.

1.3 Outcomes & Contributions

The study by [14] uses a centralized traffic control server to improve road safety and reduce arrival times for emergency vehicles. The server notifies civilian drivers with a message to pull over and halt until the approaching emergence vehicles pass. The server also generates the emergency vehicle's optimal routes using near-real-time traffic information collected from roadside units (RSUs) installed at every intersection. This approach relies too heavily on high penetration rates of RSUs in urban areas' infrastructure, which would be an expensive endeavour to install and maintain, posing scalability, security, and adoption challenges [15]. Additionally, research shows that warning drivers of approaching emergency vehicles without providing maneuver suggestions result in panicking the driver as they are left to evaluate the situation themselves, increasing the risk of further accidents with the emergency vehicle or neighbouring civilian drivers [3, 6].

This research will focus on preemptively assisting civilian drivers in avoiding route collisions and congested road segments. Our Cloud-Based Road-Traffic Risk Mediator System will guide CVs to maintain the safety threshold of 150-meters [10, 9] from all emergency vehicles during their commute. Our system uses predictive analytics and path arrangement algorithms to suggest an optimal detour to the civilian driver of CVs when it predicts that they will collide with an emergency vehicle somewhere along their commute. This cognitive offloading of the decision-making aims to create a stress-free situation by providing ample time for drivers to safely exit the primary path minutes before regular drivers would acknowledge the traditional warning signals of emergency vehicles. As a result, fewer vehicles would be on the emergency path, providing more space for regular drivers to quickly pull over and halt.

This research aims to provide the MOT with a cost-effective improvement to the existing emergency warning system that vehicle manufacturers could mandate on newer models. The system would embed as standard within their IoT-enabled motor vehicles, helping drivers make better decisions that result in safer, smoother, and faster commutes.

1.4 Research Question

This study explores near-real-time route guidance for CVs in regulating traffic volume and flows in urban areas. This study's factors include the headway, V/C ratio, and arrival times. The populations that this study will explore are civilian drivers and emergency responders in regular and CVs in urban areas, such as Toronto, Ontario. This study aims to answer the research question: Does the use of CVs and autonomously mediating urban traffic flow from primary to secondary roads improve road safety and reduce arrival times for emergency vehicles?

1.5 Significance of the Study

By leveraging cloud computing and IoT technologies, civilian drivers will overcome human perception limitations at identifying emergency vehicles, more effectively avoid emergency vehicles, and emergency responders will have fewer vehicles in their path to maneuver around when responding to emergency calls. All of this contributes to minimizing the risk of emergency vehicle-involved accidents, reducing arrival times to emergency sites, and creating safer and smoother commutes for road users.

1.6 Overview of Methodology

Our experiments are simulation-based, consisting of simulation software and a cloud-hosted server. Each experiment tests various realistic traffic situations designed to evaluate the effectiveness of our system against varying penetration rates of CVs. When our server generates a civilian CV's path, it searches for possible route collisions with emergency vehicles within the city. It uses the respective vehicle's current location, speed and traffic data to estimate whether the vehicles could collide (i.e., appear within the 150-meters [10, 9] threshold of each other). If a route collision is likely, we modify the civilian driver's path, optimizing it for the fastest commute while avoiding the collision areas.

1.7 Organization of the Thesis

This chapter introduced our topic and the problem we will be studying. We looked at why we need to study this and how we will benefit from it. In chapter 2, we explore the review of related literature. Chapter 3 incorporates the methodology that we are going to use to conduct our experiments. Chapter 4 reports on our findings. Chapter 5 provides our conclusions and recommendations.

Chapter 2

Literature Review

2.1 Introduction

In 2019, the U.S. Department of Transportation reported more than 36,000 fatalities and 4.4 million critically injured individuals due to accidents involving vehicles [16], making motor accidents the third leading cause of death in the United States [17]. Among these reports, 90% result from human error (i.e., the improper reaction to impending danger) [18]. As urbanization continues to grow, so does the expected number of drivers on the road, ultimately increasing traffic congestion, reducing the space between vehicles, shortening the window of time drivers have to assess a situation, evaluating their options, and reacting safely. These factors increase delays and the risk of ER-involved accidents during an emergence call [19]. Additionally, traffic congestion due to inefficient avoidance of ERs and emergency sites drastically damages our environment from the emissions of each car [20, 21]. Some of the main factors contributing to ER-involved accidents relating to human error include biological limitations, such as perception, communication and processing, as outlined below:

- Perception is the ability to sense and identify emergencies. While humans rely on various biological senses to navigate the world, only a select few provide relevant data while operating a vehicle, such as sound and sight [6]. Drivers generally only use sound to identify honking and sirens; they filter out most other noises. Sight is the most used sense by drivers, but every vehicle has an array of blind spots, and many threats live outside their Line-of-Sight (LoS), usually obstructed by other vehicles, buildings, trees, and poor weather conditions [6];

- Communication is the ability to perceive neighbouring drivers' intentions unambiguously and clearly express your intentions. Standard vehicles are equipped with few external indicators, including a monotone horn, signal lights, and brake lights. But the use of these indicators varies between cultures;

- Processing is the ability to plan strategies for avoiding or preventing dangerous situations by collecting environmental data and assessing the surroundings. Drivers already have potentially high cognitive workloads given many factors such as unfamiliar roads, poor weather conditions, and multitasking, to name a few. Even in optimal conditions, drivers often only have a few seconds to react given the high speeds they travel at, and the decisions they make tend to be ill-informed guesses that often lead to accidents [3].

2.2 Intelligent Transport Systems

Intelligent Transport Systems (ITS) are advanced systems improving efficiency and safety of various transport-related situations, enabling drivers to make better informed, safer, and more coordinated decisions [14, 22, 23, 21]. Vehicles using ITS applications are hereafter referred to as *connected vehicles*.

One medium for *connected vehicles* to communicate is through the Dedicated Short-Range Communication (DSRC) protocol, also known as IEEE 802.11p. DSRC periodically broadcasts messages every 300 milliseconds, where each message contains the vehicle's speed, acceleration, location, and heading [24, 22].

Throughout the last decade, many countries have been investing in standardizing traffic management communication infrastructure, hoping to increase the demand for *connected vehicles* [14]. Nevertheless, despite the promising results in the literature, *connected vehicles* are not yet highly available on the market, and their safety and assistive features are yet to be fully realized [25, 26]. However, with the recent growth of popularity surrounding autonomous vehicles over the last decade, the growing demand for vehicular safety features and stringent government rules for improved traffic management, more comprehensive implementation of *connected vehicles* is inevitable [6, 27, 28].

2.3 ITS in Accident Prevention

Civilian drivers rely too heavily on LoS to perceive their surroundings, often having difficulty seeing or sensing obstacles obstructed by other vehicles, buildings, trees, or weather conditions [6]. Even with the technological advances offered by modern cars such as LIDAR, RADAR, and cameras, these sensors fundamentally rely on LoS, thus performing poorly in terrible weather conditions [6]. This review highlights two problem areas including Non-Line-of-Sight (NLoS) vehicle sensing and guided driving.

2.3.1 NLoS Vehicle Sensing

In 2018, there were more than 12 million reported car-related accidents in the United States [29], with more than 36,000 involving fatalities [29]. The root of many of these accidents stems from the obstructed vision of drivers, either due to blind spots, poor weather conditions, or any number of other causes. NLoS vehicle sensing enables *connected vehicles* to sense each other despite obstacles that would otherwise hide their presence [30].

One study by [3] focused on ER's safety. Many ERs reported driving more than 5 million miles a year and often operated under heavy visual, mental, and cognitive workloads, potentially driving at high speeds through difficult traffic and weather conditions [3]. ERs traditionally rely on sirens and lights to gain nearby civilian drivers' attention but have been proven inefficient at negotiating congested urban traffic. The warning is often recognized too late and conveys only the general location of an ER when outside the LoS of the civilian driver [3]. Without communicating intent and context, civilian drivers will continue making poorly-informed decisions that could lead to further accidents. Multiple studies leveraged V2I communication by installing RSUs near major intersections and using a centralized server to manage traffic data and disseminate information via DSRC [3, 14]. Major drawbacks to this approach are its dependency on the high number of RSUs needed throughout a city to ensure high coverage and the short-range of DSRC which means *connected vehicles* are not communicating in real-time. The results from these studies support that communicating vehicular information to *connected vehicles* will provide civilian drivers with enough context to make safer and better-informed decisions.

2.3.2 Guided Driving

Lane changes are among the most fundamental processes for drivers. However, they account for about 5% of traffic accidents [31] and 10% of traffic congestion [31]. Among these reported accidents, 75% of them were caused by human error [31]. With the advances in *connected vehicles*, more optimized lane changing planning and speed control strategies can be suggested to the driver.

There are many studies on cooperative lane changing algorithms. One study proposes a multi-vehicle cooperative lane change strategy in which the decision-making control is decentralized [31]. This approach creates a more comfortable experience for the involved drivers than unaided lane changes while simultaneously increasing traffic flow and road safety due to offloading the calculation of optimal decisions to an ITS. Unfortunately, the research failed to consider the perceived errors, delays in communication, and systems response times. Additionally, this approach requires a high penetration rate of *connected vehicles*, which is yet to be seen globally.

A DSRC-based freeway merging assistant system was developed [26]. Various lane merging scenarios were tested using a smartphone as a GUI for displaying advisory messages and three *connected vehicles*. Although the tested scenarios were basic, involving only single-hop broadcasting, they were performed in an uncontrollable environment, demonstrating that real-world route guidance systems are feasible and effective even in complex environments.

In the third study, authors [25] focused on improving and maintaining traffic flow during emergency evacuations. The experimenters varied the penetration rate of *connected vehicles* from zero-percent (i.e., base scenario) to 30-percent (i.e., the predicted rate by 2018). The algorithm suggested which lane and speed to maintain based on neighbouring *connected vehicles'* traffic flow data. The study results demonstrated that increasing the percent of *connected vehicles* present in an emergency evacuation led to significant traffic delays early into the situation and that the delay benefits would become positive only after approximately 1/3 of the overall time. It also demonstrated that the amount increased is proportional to the penetration rate of *connected vehicles.* The study's limitations were in the assumptions that drivers of *connected vehicles* would obey every suggestion given by the system.

2.4 ITS in Road Optimization

2.4.1 Route Guidance

We define Route Guidance as the problem of computing an optimal route (by some criteria such as distance or time) between an origin and a destination and adapting to real-time traffic updates guiding the driver on how best to avoid congested traffic. Given the time-sensitive nature of emergencies, ERs need to minimize arrival times by maintaining high speeds and avoiding unnecessary delays. In addition to the high accident risk, civilian drivers' ill-informed decisions also delay ERs. For example, in traffic jams, confused drivers often do not know how and where to form a suitable corridor to let the emergency vehicle through [3].

The study by [13] uses real-time traffic information to avoid congested road sections. The proposed model takes the approach to minimize prerequisite infrastructure by using *connect vehicles* within a VANET as information servers instead of relying on RSUs.

In the second study by [14], the use of a centralized server controls all traffic lights and traffic information. It is also responsible for computing the shortest-time plan and alternative routes, calculated with the *A* algorithm* based on distance and average expected speeds, for ERs. The *A* algorithm* is a best-first graph search algorithm that can find the shortest path. The authors used the relationship between the distance from a given location along the vehicle's route and the its average velocity as the heuristic function used within this algorithm. The first issue addressed is computing the fastest route from the source to the event (destination) for the ERs and adjusting this route based on real-time traffic. The second challenge is to disseminate the warning messages to nearby *connected vehicles* along the ER's route, advising them to move or stay put to avoid route collisions.

2.4.2 Traffic Light Preemption

Many factors contribute to the increasing traffic congestion in urban areas, but intersection traffic lights play a significant role in regulating traffic flow. Traditional approaches use inefficient timer-based decision logic, merely toggling the right-of-way (i.e., green light) signal between the competing directions at a fixed interval. Unfortunately, traffic flow for most of the time is not symmetric, resulting in unnecessary traffic congestion. One study implemented DSRC-actuated traffic lights using off-the-shelf hardware and software to reduce traffic congestion by prioritizing *connected vehicles* [15]. The significant reduction in traffic congestion despite a low *connected vehicle* penetration rate, combined with a cost-effective implementation, makes this approach easily deployable. Another approach makes use of a centralized server to preempt all traffic lights (i.e., displaying a red light to all directions) when an ER is approaching [4]. The intent is to stop all traffic such that no driver will collide with the ER.

Consequently, they cannot control traffic flow without traffic lights and may cause more chaos in nearby roadways. Similarly, another approach entails giving the direction of an approaching ER the right-of-way (i.e., displaying a green light) such that vehicles can move and clear a path [3]. This approach does not warn civilian drivers of the approaching ER, and it also relies heavily on the presence of modified traffic lights to control traffic flow.

2.5 Conclusion

This chapter highlighted the importance of *connected vehicles* and the multitude of advantages they offer over regular vehicle's daily use and emergencies, as well as their respective limitations. We explored existing literature that leverages ITS applications and *connected vehicles* to combat the perception, communication and processing issues civilian drivers face in emergencies.

Chapter 3

Methodology

3.1 Introduction

Given the average driver's biological senses, they only have a few moments to react upon acknowledging the warning signals from ERs. Within these moments, the drivers must identify the ER's location and heading, understand their maneuver options, and safely execute their plan. Unfortunately, it is common for urban roads to approach over-saturated volume-to-capacity ratios resulting in congestion and little space to maneuver [32, 33]. In these situations, ERs are often upon the drivers (i.e., within 150-meters of them) before the traffic can clear a path, causing chaos and significant delays to reach emergency sites which may have fatal ramifications. As risk can be measured as a relation to exposure to nearby traffic [32, 33], these increases in traffic volumes around and ahead of ERs constitute a substantial cause for delays when responding to emergencies and increase the risk of other accidents [1, 3, 4, 6]. By creating an ITS for connected civilian and emergency vehicles, we aim to guide connected vehicles to their destinations along paths that minimize risk, traffic density, traffic delays, and arrival times. This chapter will outline how the data is collected, how we designed the software, and how the experiments will be performed.

3.2 Research Design

To conduct the experiments outlined in this thesis, we developed a software system to simulate urban road traffic behaviour using the open-source SUMO simulator and a cloud server hosted in Google Cloud Platform (GCP) written in the NodeJS language. We use OpenStreetMap extensively as our primary source of road network data. The server will be integrated into the running SUMO simulations through a TCP-based client/server architecture using TraCI available from the product developers.

3.2.1 Road Design & Traffic Attributes

To create realistic urban scenarios, we based the road design of our experiments on popular road segments within Toronto, Ontario, sourced from OpenStreetMap, and the default traffic attributes on historic data sourced from Toronto OpenData, such as the number of vehicles on the road, traffic flow, average speeds, and many more. The city of Toronto was chosen for the models as it is the closest city to the author with significantly high levels of daily traffic flow.

An example of an ideal road segment, as shown in Figure 3-1, would include a network of high-volume intersections with multiple interlaced side roads that could potentially alleviate the pressures from the primary traffic flow.

3.2.2 Vehicle Models

We designed four vehicular models, including (1) ordinary civilian vehicles, (2) connected civilian vehicles, (3) ordinary ER vehicles, and (4) connected ER vehicles. The models vary in behavioural properties, physical properties, and technological capabilities. For instance, connected vehicles can communicate with our cloud server and between each other using V2V technology. ER models can exceed speed limits, run through red lights, and yield nearby traffic.

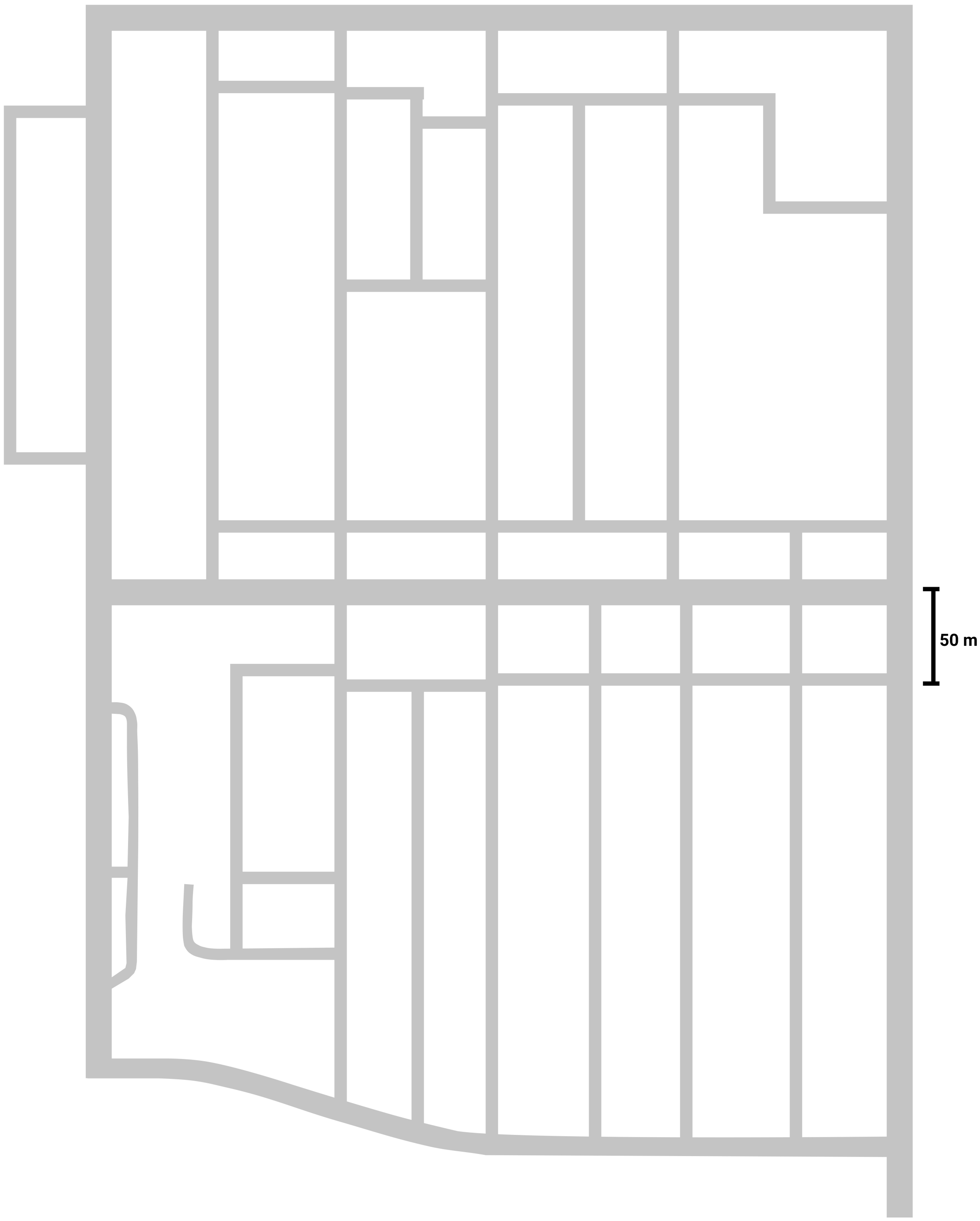


Figure 3-1: An example of a simulated road segment.

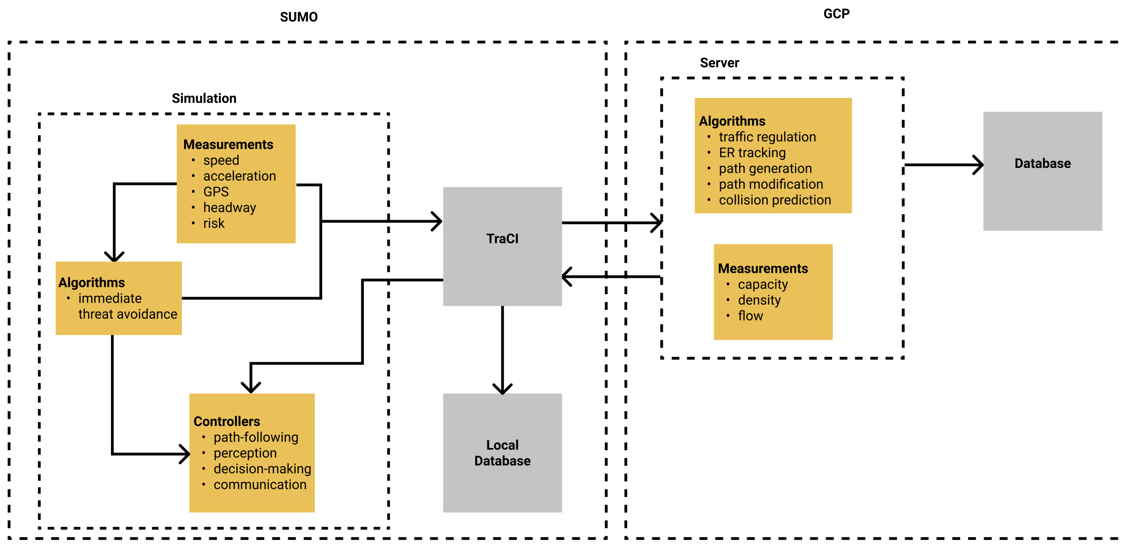


Figure 3-2: Software System Design Diagram.

3.3 Data Collection Methods

The experimental data recorded by the SUMO simulator is exported to a local database for later aggregation and analysis with the exported data from the cloud database. The data is broken into two parts:

1. Road-centric measurements for all vehicles passing through this segment include average speed, traffic flow, capacity, density, average headway, total risk score, and events such as near collisions, congestion, and traffic signals.

2. Vehicular-centric measurements for each vehicle include speed, acceleration, path, delays, frequency of path modification, and frequency of detected ERs.

This list is not exhaustive and will be modified as the author grows familiar with the simulation software.

3.4 Software & Technology Related Design

As illustrated in Figure 3-2, the system is comprised of two major components:

1. the simulator component (on the left);

2. the cloud component (on the right).

The SUMO simulator software manages the simulation component and offers various tools for importing data, designing models, designing networks, and tracking data. A running simulation will continuously measure and compute a wide range of road and vehicular-centric data. The data feeds into the algorithms and controllers sub-components for localized risk assessment and decision-making such as slowing down, turning, and lane changing, as shown in the flowchart of Figure 3-3. The simulator records the data in a local database for later analysis. The data and controllers within a running simulation can be read and manipulated in real-time through SUMO's TraCI middleware, empowering cloud computing.

The cloud server facilitates safer, smoother, and faster traffic for connected vehicles. The flowchart shown in Figure 3-4 describes the relationship between the array of processes that this server is responsible for, including:

1. Path Generation

2. Prediction of ER Path Collision

3. Path Modification

3.4.1 Path Generation

This process is the first to be executed for every new client initiating their commute. It considers the client's current location, desired destination, and current traffic data to generate a path optimized for the lowest arrival time (i.e., fastest commute) using the A* algorithm. Figure 3-5 depicts a minimalistic road segment with a path generated for an ER between two points.

3.4.2 Prediction of ER Path Collision

This process predicts when and where a connected civilian vehicle might collide with an active ER. The pseudocode in Figure 3-6 elaborates on detecting all possible

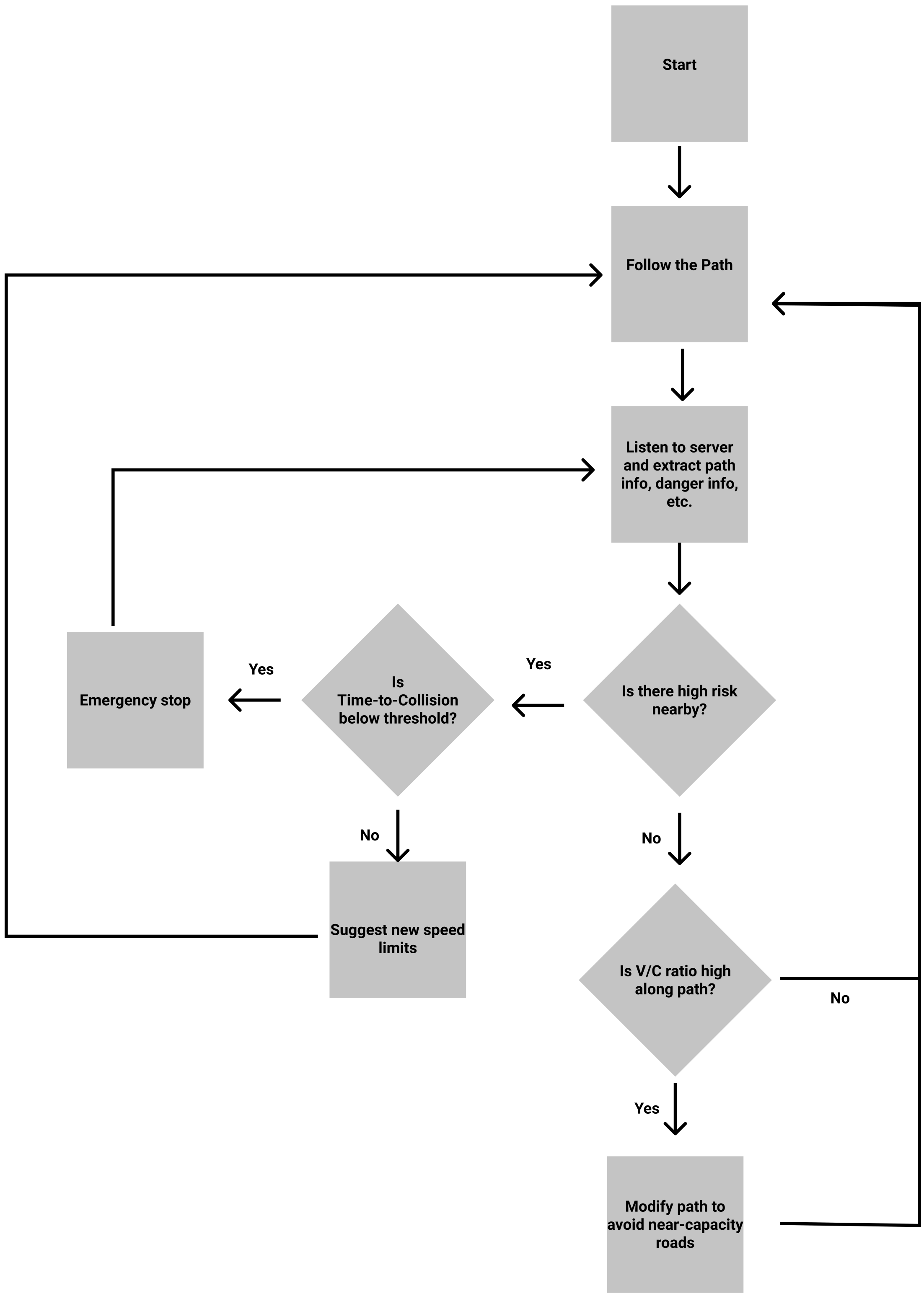
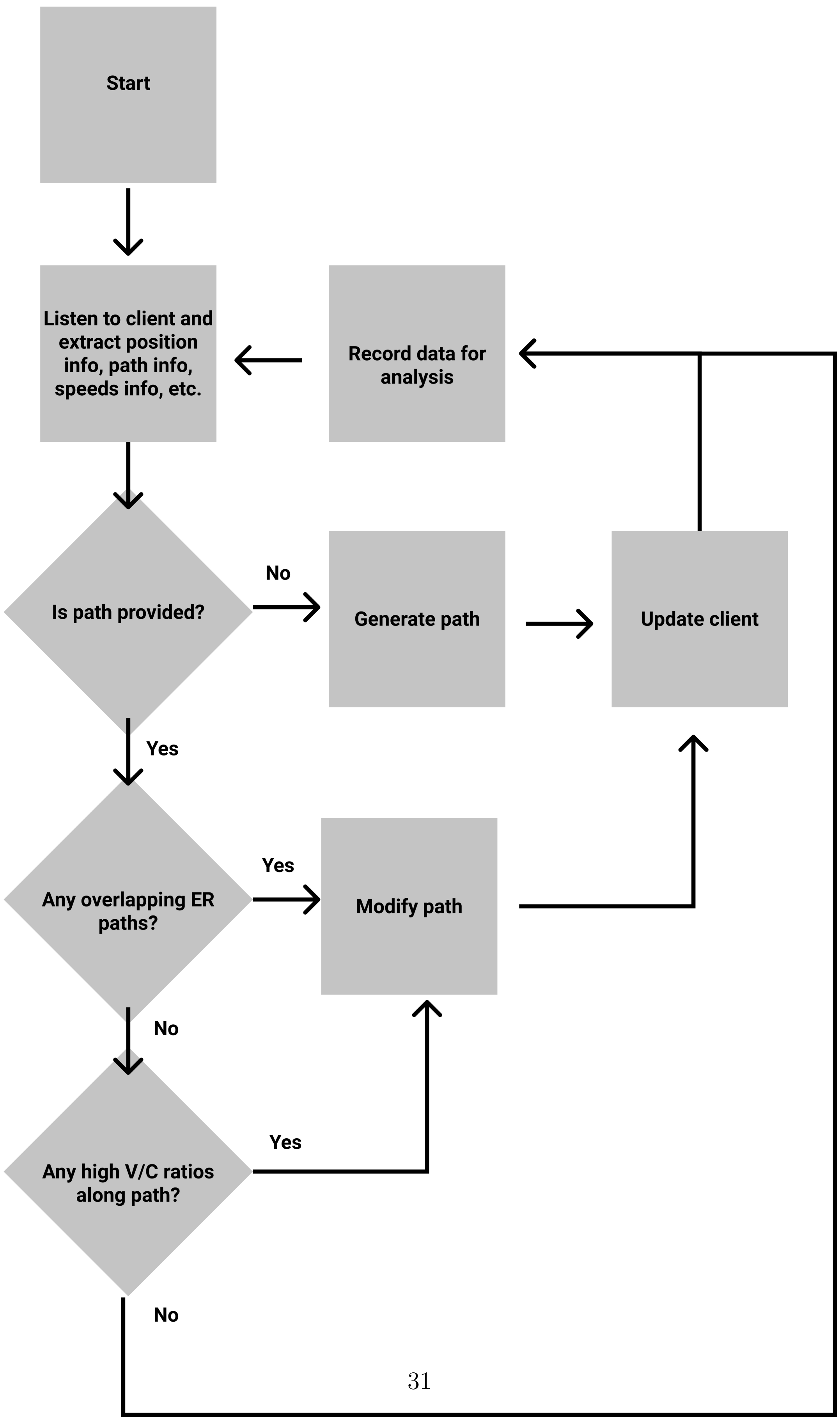


Figure 3-3: Flowchart of onboard vehicle processing.


Start
Listen to client and extract position info, path info, speeds info, etc.
Record data for analysis
Is path provided?
No
Generate path
Update client
Yes
Any overlapping ER paths?
Yes
Modify path
No
Any high V/C ratios along path?
Yes
No

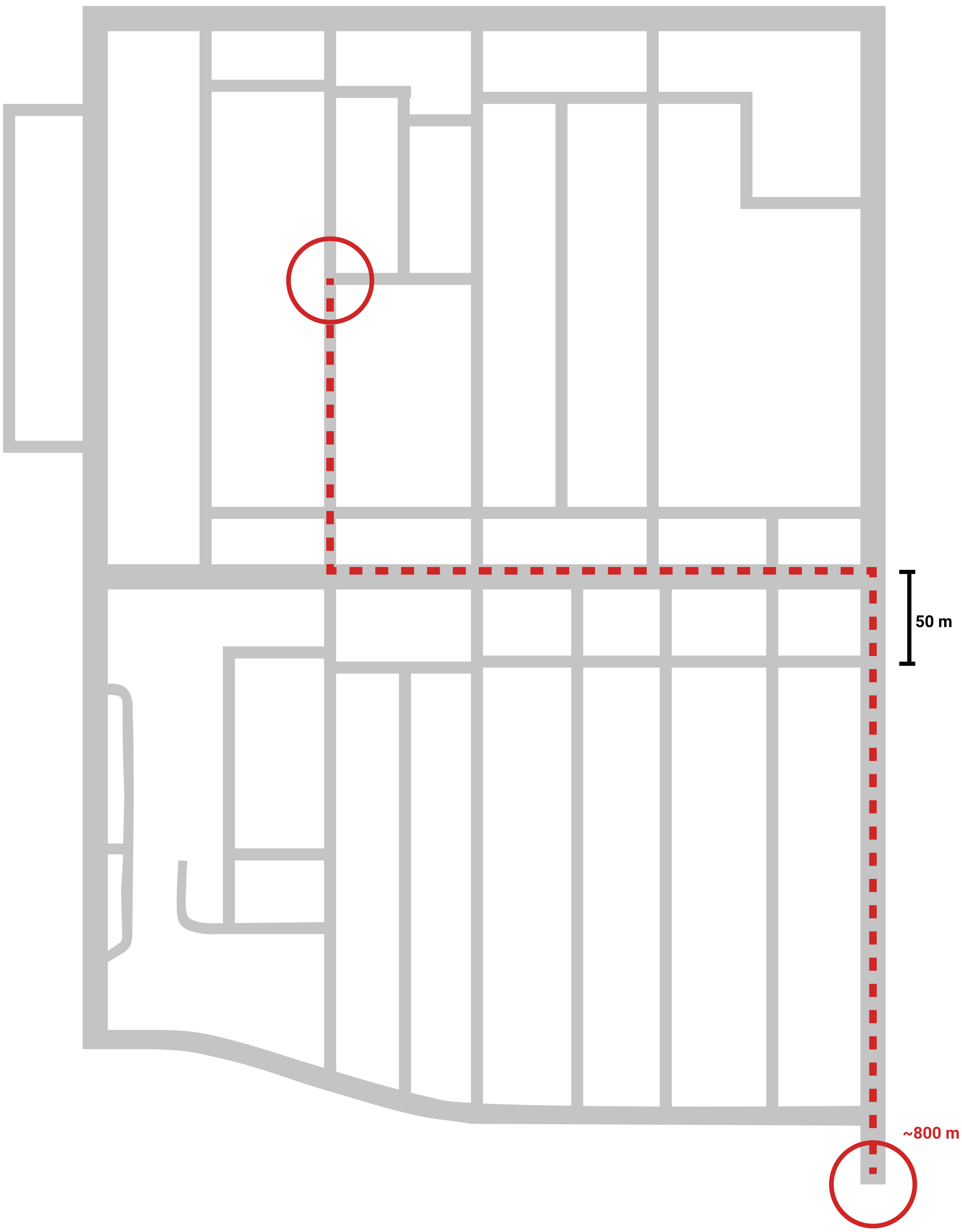


Figure 3-5: Generated Path for an ER.

```
function FindCollisionPath(er_polyline, cv_polyline, er_steps, cv_steps)
    overlaps = []
    overlaps.append(findPathOverlaps(er_polyline, cv_steps))
    overlaps.append(findPathOverlaps(cv_polyline, er_steps))
    overlapPolyline = generatePolyline(overlaps)
    return {overlapPolyline, overlaps}
end function

function FindPathOverlaps(polyline, steps)
    result = []
    for step in steps do
        overlapPosition = locationIndexOnEdgeOrPath(step, polyline)
        if overlapPosition > -1 then
            result.append({step, overlapPosition})
        end if
    end for
    return result
end function
```

Figure 3-6: Pseudocode for path collision detection between the routes of an ER and civilian vehicle.

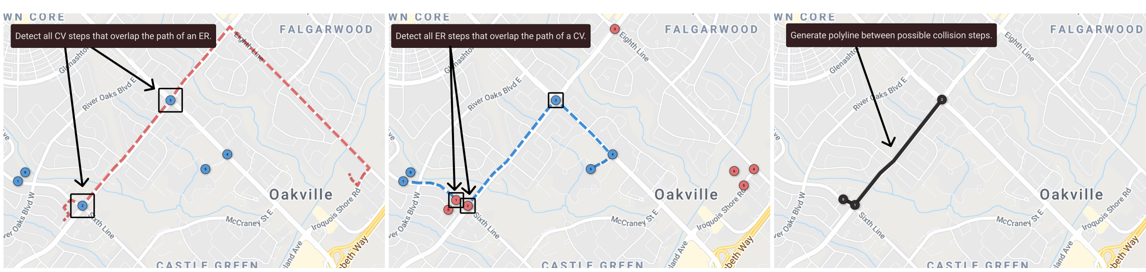


Figure 3-7: Illustration of the path collision detection algorithm between the routes of an ER and civilian vehicle.

```
function ComputeDetour(collisionPath, cv, er)
    stepsToAvoid = []
    waypoints = GenerateWaypoints(collisionPath.polyline)
    for step in waypoints do
        cv_arrivalInMinutes = CalculateArrivalTime(step, vc.currentSpeed, vc.currentLocation, "minutes")
        er_arrivalInMinutes = CalculateArrivalTime(step, er.currentSpeed, er.currentLocation, "minutes", SAFETY_THRESHOLD)
        absArrivalDifferenceInMinutes = |ar_arrival - cv_arrival|
        if absArrivalDifferenceInMinutes <= 2.0 then
            stepsToAvoid.append({step, absArrivalDifferenceInMinutes})
        end if
    end for
    cv.route = Detour(cv.route, stepsToAvoid)
    return cv
end function
```

Figure 3-8: Pseudocode for collision avoidance algorithm.

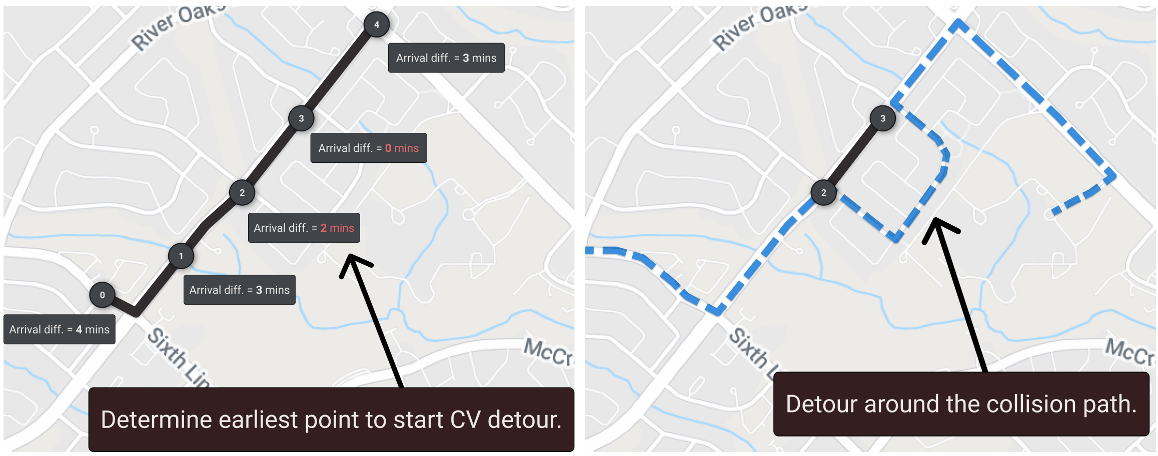


Figure 3-9: Illustration of the collision avoidance algorithm.

collision points along the paths of these two vehicles, and Figure 3-7 provides a visual demonstration.

3.4.3 Path Modification

In the event that the above process predicts a likely collision, this process is responsible for modifying the connected civilian vehicle's path to avoid roads where the collision is predicted to occur. Figure 3-8 and Figure 3-9 describes using the time-to-collision equation as a benchmark for comparing arrival times for both vehicles and deciding where the optimal path modification should occur. Figure 3-10 depicts an example situation where a connected ER's path overlays high traffic volume roads (section b) and how this process evenly displaces localized traffic along side-roads (section a). You should notice the roads overlaying the ER's path (denoted with a

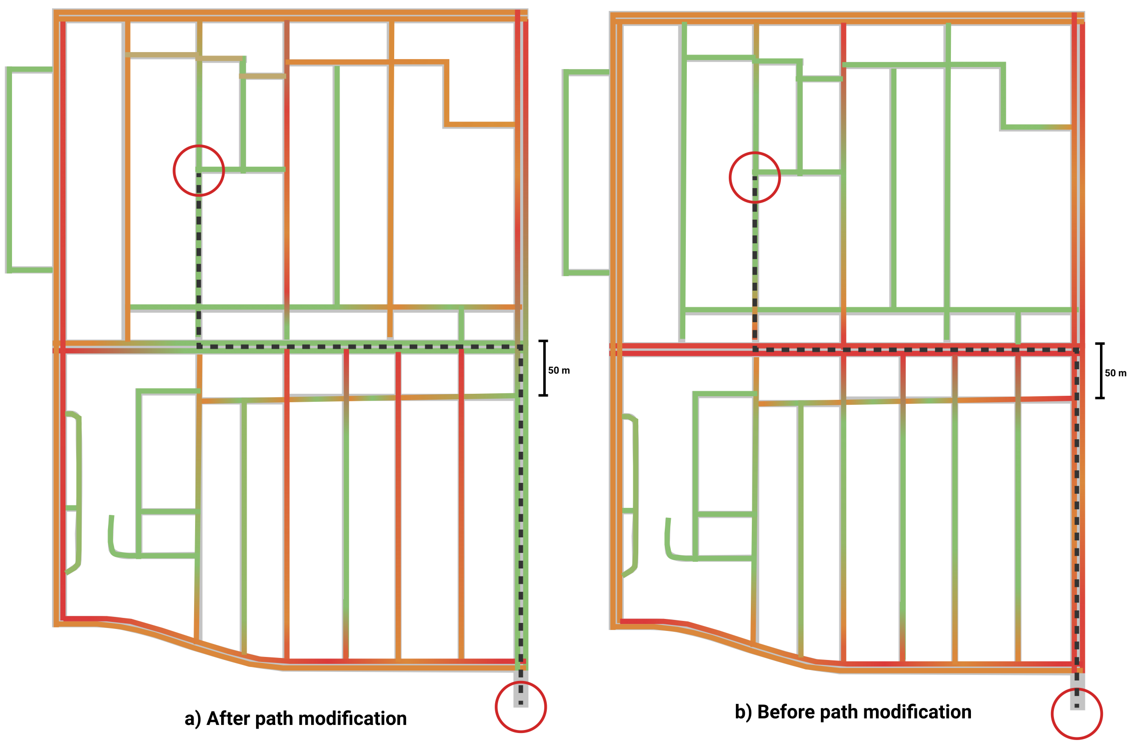


Figure 3-10: A visual representation of the difference in traffic volume before (b) and after (b) the path modification process was applied.

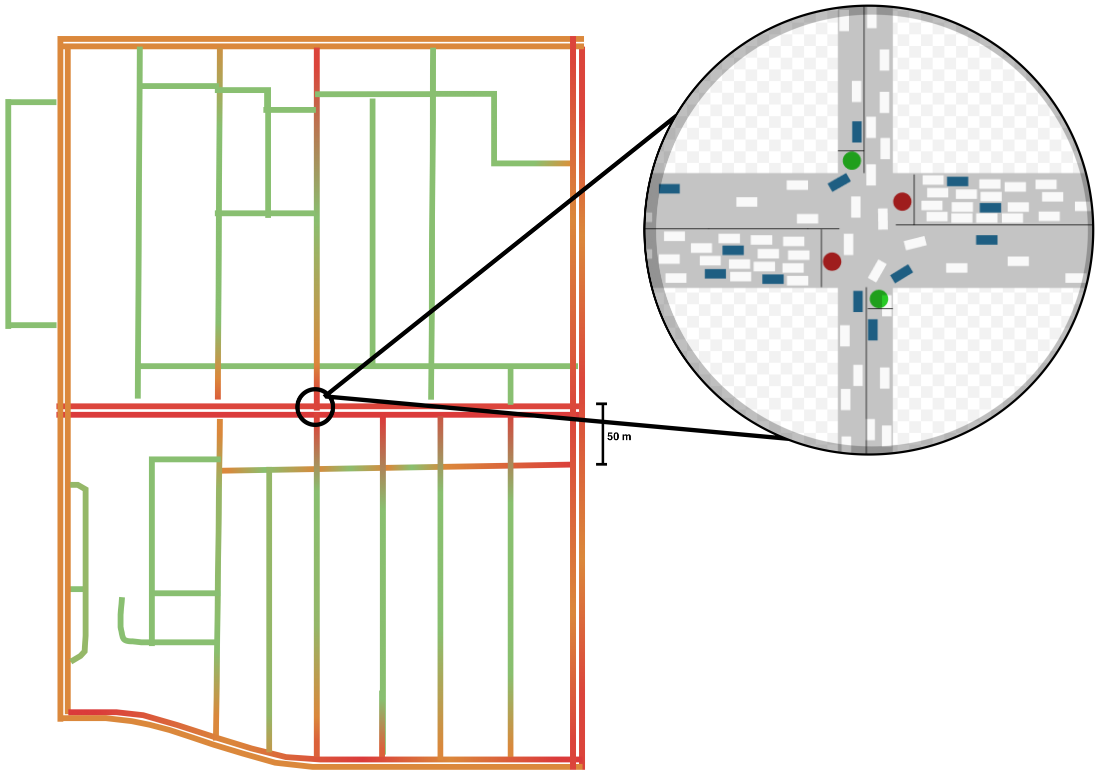


Figure 3-11: Stabilized traffic flow and volume of a road segment.

dotted black line) change from a red color (high traffic volume) to a green color (low traffic volume).

3.5 Comprehensive Experiment Framework

It is the law that all civilian drivers must adhere to proper protocol when nearby an *active ER*, such as slowing down, moving over, and halting until the ER is a safe distance away (i.e., 150 meters away) [10, 9]. Our system helps connected civilian vehicles identify active ERs sooner, with greater context, and helps avoid route collisions with them. At the start of every experiment, as also done in [13, 25], we allow the simulation to run for a consistent but arbitrary amount of time (e.g., 2 minutes), allowing the default background traffic to distribute evenly throughout the road segment. As illustrated in Figure 3-11, the primary roads are expected to have significantly higher traffic volume (shown in red) than secondary roads (shown in green), as per the status quo of ordinary vehicles. After the calibration period, the average speeds, accelerations, and flow should level out should be constant, at which time we can apply any event or variable changes for this experiment, and its effects will be observed.

Each experiment tests how road safety and arrival times are affected by variables such as, but not limited to, the penetration rates of connected vehicles, the number of active connected and ordinary ERs, the number of total vehicles, and origin and destination of ERs. Figure 3-12 does not accurately depict an actual road segment or how location points are placed. It serves to simplify the demonstration of the underlying representation of each experiment.

Experiment 1: Have the ER start in point A and travel to point C. This route represents a firetruck commuting from outside and through an urban road segment.

Experiment 2: Have the ER start in point A and travel to point E, and after 2-minutes, return to corner A. This route represents an ambulance commuting outside and stopping within an urban road segment to retrieve a patient and return to the hospital outside the road segment.

Experiment 3: Have the ER start at point E and travel to point A. This route represents a police vehicle parked within a road segment responding to a call outside.

Experiment 4: Have the ER start at point E, travel to point F, point A, and point C. This situation represents a police vehicle car chase, starting within the road segment.

3.6 Data Analysis Methods

Calculating traffic safety risk is a complex and ambiguous task. The authors of the [34] developed a road safety risk index (RSRI), enabling a quantitative approach for measuring road safety. The RSRI is based on three isolated fundamental elements such as exposure, probability, and consequence.

RSRI = Exposure $\times$ Probability $\times$ Consequence

Where:

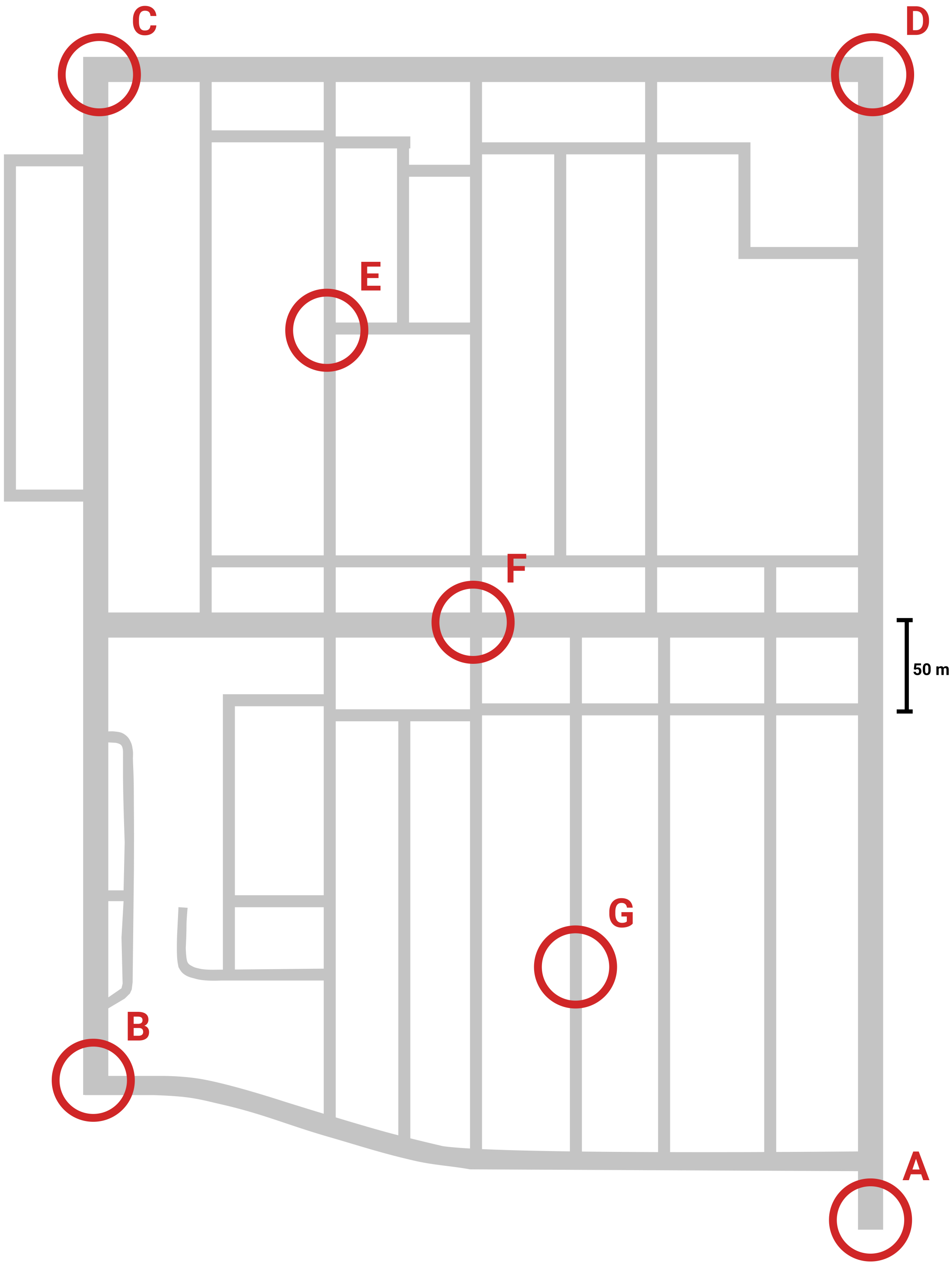


Figure 3-12: Example location of a road segment.

- Exposure = measure to quantify the exposure of road users to potential roadway hazards.
- Probability = measure to quantify the chance of a vehicle being involved in a collision.
- Consequence = measure to quantify the severity level resulting from potential collisions.

Alongside the RSRI parameters, we also consider several traffic parameters and processes known to influence traffic safety measured by proximal indicators. These include speed and speed variance, gap-acceptance in yielding situations, headway between vehicles in traffic streams, and traffic flow rates (including derived measures such as saturation and density). By tracking these various parameters over multiple road segments in different driving situations, we can analyze which parameters significantly impact road safety with varying connected vehicle penetration rates.

3.6.1 Exposure

Exposure is the measure to quantify the exposure of drivers to potential roadway hazards, such as nearby vehicles. It provides a score ranging from zero to a maximum of 3.0, with a high score representing high exposure.

$\text{Exposure}_{\text{urban}} = (\frac{V_{i(\text{major})} \times V_{i(\text{minor})}}{V_{\max(\text{major})} \times V_{\max(\text{minor})}}) \times 3.0$

Where:

- $V_{\max(major)}$ = maximum volume on the major road.
- $V_{\max(minor)}$ = maximum volume on the minor road.
- V_i = volume at the location of a specific roadway.

3.6.2 Consequence

Consequence is the amount of danger the driver can incur if an accident were to happen. It is a ratio between the posted speed and maximum posted speed of a roadway segment. Maximum posted speed can equal the posted speed, or it can be based on a larger area. It provides a score ranging from zero to a maximum of 3.0, with a high score representing high consequence.

Consequence = $(\frac{\text{Posted Speed}_i}{\text{Posted Speed}_{\text{max}}}) \times 3.0$

Where:

- PS_i = posted speed at the location of a specific roadway.
- PS_{max} = maximum posted speed.

3.6.3 Volume-to-Capacity Ratio

Volume-to-Capacity (V/C) is the ratio of current or projected demand flow rate to the capacity of a segment. It is an indicator of how close a roadway is operating to its capacity. An increase in the V/C ratio indicates longer vehicle delays and queuing.

V/C Ratio = $\frac{\text{Demand flow rate}}{\text{Capacity}}$

Where:

- Demand flow rate = volume of vehicles on a transportation facility (vehicles per hour per lane) for a given segment length.
- Capacity = the maximum number of vehicles a transportation facility can handle (veh/hr/ln) for a given segment length.

3.6.4 Headway

Headway is the time difference between successive vehicles as they pass a point or segment, measured from the same point on each vehicle, expressed in seconds per vehicle.

Headway = $\frac{\text{Spacing (ft/veh)}}{\text{Speed (ft/sec)}}$

3.6.5 Traffic Speed

The average speed of all vehicles passing through a point or segment. Variations in the speed of vehicles within and across lanes are important traffic safety indicators.

$v_t = \frac{1}{n} \sum_{i=1}^{n} v_i$

Where:

- v_t is the time mean speed.
- v_i is the spot speed of i^{th} vehicle.
- $n$is the number of vehicles observed.

3.7 Research Validation

To combat any uncertainty that the observed results are the result of our system, the following steps were taken:

- The simulations are generated using time seeds. This enables reproducible situations where causative factors for the results can be validated.
- Every experiment is run with varying levels of connected vehicle penetration rates. This is done to verify whether the obtained results in the situation were a result of the connected vehicles; increasing the number of connected vehicles should amplify the results.

3.8 Assumptions & Limitations of the Study

Human drivers are prone to make mistakes in following a provided path due to distracted drivings or unforeseeable circumstances in the real world. To reduce the complexity of our simulations, we assume that our connected vehicle drivers follow the paths provided 100% of the time. We also do not consider any weather conditions, pedestrians, or non-car road users. We limit the size variations of our vehicle models to one average sedan for civilian drivers and an average firetruck, ambulance, and police car.

3.9 Summary

In this chapter, we described the design and rationale of the experiments' setup, defined the system architecture design and data collection processes, explained the various experiment scenarios, explaining how the results will be used to validate our research, and highlighted any assumptions and limitations.

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Appendix A

Tables