Distributed Intersection Management Algorithms for Autonomous Vehicles

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Abstract

Since a couple of decades, the technological driving aids have gone growing at a dizzying pace with the intention of making these systems more efficient and safe. These driving aids have been covering failures that the researchers name “erratic driving” or “unsafe driving behaviors” and are arbitrary decisions taken by a human driver which endanger all road users.

These bad decisions in addition to the increasing number of driving commutes in a city nowadays (post pandemic), show the need to continue doing technological proposals focused on where there are more complex interactions between vehicles when density increases; for instance, an intersection in rush hour.

The developments in driving aids have been orientated in two topics: the first driving automation (Advanced Driver Assistance Systems - ADAS and Automated Vehicles - AV) and the second road traffic management (centralized or distributed algorithms to traffic control). Although there are currently several automotive companies and research centers working in the two topics, and in special in some cases removing the equation the human behavior, there are still lacks in the configurations for an vehicle autonomous be able to make optimal decisions front to all possible conditions available in a road traffic.

Now, and take into account the two topics aforementioned about driving aids developments, researchers broadly envisage that in order to reach autonomous driving levels higher (first topic) in the next decade, is necessary to study how to do autonomous vehicle interactions (second topic) more efficient. Therefore, road intersections are an instance where it is possible to analyse cases of highly complexity interactions between vehicles, because it is a part of road infrastructure where the vehicles sharing lanes, paths, crossings or lane changes at will and it could generate collisions on conflict points and time delay in the commutes if there is not an appropriate cooperation.

Hence, this thesis proposes a series of distributed algorithms to traffic control on intersections, based on interchange of communications between autonomous vehicles (local interactions) near to the intersections that show emergent behaviors to crossing cooperative, safe way and efficiency with high densities the traffic system on intersections. This research is developed us-

ing simulators with Manhattan-style streets; first implementing scenarios less complex with one-lane city streets and then increase the complexity with multiple-lanes.

Resumen

Desde hace aproximadamente dos décadas, las ayudas tecnológicas a la conducción han ido creciendo a un ritmo vertiginoso con la intención de hacer estos sistemas más eficientes y seguros. Estas ayudas a la conducción han ido cubriendo fallos que los investigadores denominan “conducción errática” ó “comportamientos inseguros al volante” y que son decisiones arbitrarias tomadas por un conductor humano, que ponen en peligro a todos los usuarios de la carretera.

Estas malas decisiones, sumadas al creciente número de viajes en coche en una ciudad hoy en día (post pandemia), muestran la necesidad de seguir haciendo propuestas tecnológicas, enfocadas a donde se producen interacciones más complejas entre vehículos; por ejemplo, una intersección en hora punta.

Los desarrollos en ayudas a la conducción se han orientado en dos temas: el primero sobre la automatización de la conducción (Sistemas Avanzados de Asistencia al Conductor - ADAS y Vehículos Automatizados - AV) y el segundo sobre la gestión del tráfico vial (algoritmos centralizados o distribuidos para el control del tráfico). Aunque en la actualidad hay varias empresas automotrices y centros de investigación trabajando en los dos temas, y en especial en algunos casos eliminando de la ecuación el comportamiento humano, todavía hay carencias en las configuraciones, para que un vehículo autónomo sea capaz de tomar decisiones óptimas, frente a todas las posibles condiciones disponibles en un tráfico vial.

Ahora bien, y teniendo en cuenta los dos temas antes mencionados sobre los desarrollos en ayudas a la conducción, los investigadores prevén a grandes rasgos, que para alcanzar mayores niveles de conducción autónoma en la próxima década, es necesario estudiar cómo hacer más eficientes las interacciones autónomas entre vehículos. Por ello, las intersecciones viales son un ejemplo clave, donde es posible analizar casos de interacciones de alta complejidad entre vehículos, ya que se trata de una parte de la infraestructura vial, donde los vehículos comparten carriles, vías, cruces o cambios de carril a voluntad, y que podría generar colisiones en puntos de conflicto y retrasos en los desplazamientos si no existe una cooperación adecuada.

De esta forma, en esta tesis se propone una serie de algoritmos distribuidos

para el control del tráfico en intersecciones, basados en el intercambio de comunicaciones entre vehículos autónomos (interacciones locales) cercano a las intersecciones y donde se muestran comportamientos emergentes en el tráfico, resultando en cruces de forma cooperativa, segura y eficiente, desde bajas a altas densidades de tráfico vehicular en las intersecciones. Esta investigación se desarrolla utilizando simuladores de tráfico vial, con calles estilo Manhattan; primero implementando escenarios menos complejos con calles urbanas de un carril, y luego incrementando la complejidad con múltiples carriles.

Resum

Des de fa aproximadament dues dècades, les ajudes tecnològiques a la conducció han anat creixent a un ritme vertiginós amb la intenció de fer aquests sistemes més eficients i segurs. Aquestes ajudes a la conducció han anat cobrint fallades que els investigadors denominen "conducció erràtica" o "comportaments insegurs al volant" i que són decisions arbitràries preses per un conductor humà, que posen en perill a tots els usuaris de la carretera.

Aquestes males decisions, sumades al creixent nombre de viatges en cotxe en una ciutat avui dia (post pandèmia), mostren la necessitat de seguir fent propostes tecnològiques, enfocades a on es produeixen interaccions més complexes entre vehicles; per exemple, una intersecció en hora punta.

Els desenvolupaments en ajudes a la conducció s'han orientat en dos temes: el primer sobre l'automatització de la conducció (Sistemes Avançats d'Assistència al Conductor - ADAS i Vehicles Automatitzats - AV) i el segon sobre la gestió del trànsit vial (algoritmes centralitzats o distribuïts per al control del trànsit). Encara que actualment hi ha diverses empreses automobilístiques i centres de recerca treballant en els dos temes, i en especial en alguns casos eliminant de l'equació el comportament humà, encara hi ha mancances en les configuracions, perquè un vehicle autònom siga capaç de prendre decisions òptimes, davant totes les possibles condicions disponibles en un trànsit vial.

Ara bé, i tenint en compte els dos temes abans esmentats sobre els desenvolupaments en ajudes a la conducció, els investigadors preveuen a grans trets, que per assolir majors nivells de conducció autònoma en la propera dècada, és necessari estudiar com fer més eficients les interaccions autònomes entre vehicles. Per això, les interseccions vials són un exemple clau, on és possible analitzar casos d'interaccions d'alta complexitat entre vehicles, ja que es tracta d'una part de la infraestructura vial, on els vehicles comparteixen carrils, vies, creus o canvis de carril a voluntat, i que podria generar col·lisions en punts de conflicte i retards en els desplaçaments si no existeix una cooperació adequada.

D'aquesta manera, en aquesta tesi es proposa una sèrie d'algoritmes distribuïts per al control del trànsit en interseccions, basats en l'intercanvi de comunicacions entre vehicles autònoms (interaccions locals) properes a les in-

terseccions i on es mostren comportaments emergents en el trànsit, resultant en creus de forma cooperativa, segura i eficient, des de baixes a altes densitats de trànsit vehicular en les interseccions. Aquesta investigació es desenvolupa utilitzant simuladors de trànsit vial, amb carrers estil Manhattan; primer implementant escenaris menys complexos amb carrers urbans d'un carril, i després incrementant la complexitat amb múltiples carrils.

I extend my sincere gratitude to all those who have contributed to the completion of this thesis. This academic journey has been enriched by the unwavering support, guidance, and encouragement of numerous individuals who generously shared their expertise and insights.

I am deeply appreciative of the invaluable assistance provided by my advisors, PhD Vicente Julian and PhD Juan Alberola, who played pivotal roles in shaping the outcome of this work. Special thanks to PhD Luis Niño for his significant support in my professional development and to PhD Jorge Zapotecatl for his friendship and guidance in my research. Additionally, I extend my gratitude to PhD Carlos Gershenson for his guidance and collaboration in my research.

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Part I

Introduction

Chapter 1

Introduction

"The greatest satisfaction I can experience is the realization that I have worked in something forward-looking and have brought it to success." – Nikola Tesla.

Abstract

This chapter provides an introduction to the work performed in this thesis giving a brief summary of the area of knowledge on which it is based as well as the challenges that motivate the work together with the objectives that allow its achievement. At the end of the section a summary of the chapters that conform this thesis as well as a list of the publications and projects realized can be found.

Recent research in land transportation systems has focused on achieving improvements in flow and safety. These studies aim to enhance land transportation by understanding the characteristics and complexities of on-road vehicular interactions. Although advances in this field are not new [13, 123, 21], ongoing technological enhancements have deepened our understanding of the challenges in achieving efficient and safer driving.

Technological implementations, such as Advanced Driver Assistance Systems (ADAS), Automated Vehicles (AV), and Connected Vehicles (CV), have addressed some of the issues related to human behavior [156, 56, 57, 8]. These technologies enable vehicles to sense their environment, communicate with it, and make decisions potentially better than human drivers regarding vehicular flow, journey time, collision avoidance, and traffic management by consensus.

European universities like Chalmers University and the University of Naples have collaborated with partners like Ericsson[1] and AstaZero[2]. They demonstrated a proposed system for consensus-based intersection crossing, where an autonomous vehicle successfully interacted with human-driven vehicles to cross an intersection without collisions [44].

These cases suggest that research should focus on autonomous transportation systems and aspects of road infrastructure, such as intersections, where the complexity of vehicle interactions with each other and the infrastructure is significant [2]. This research posits that autonomous transportation systems must integrate communication capabilities to enhance road safety. For example, if a vehicle does not meet these safety conditions, the control of the implemented system must act to avoid a potential collision. This problem is particularly relevant in intersections, which are common in urban areas. Numerous issues remain open, and as a result, this research proposes solutions based on algorithms to explore how to improve the decision-making process of vehicles at city intersections with single and multiple lanes.

[1]Ericsson is a Swedish multinational networking and telecommunications company headquartered in Stockholm. - www.ericsson.com

[2]AstaZero is the world's first full-scale independent test environment for the automated transport system of the future. - www.astazero.com

1.1 Motivation

Currently, the developments in autonomous vehicles and their traffic control at intersections have garnered significant interest among researchers and the automotive industry due to the complex interactions involved. At these intersections, a myriad of complex scenarios can unfold, involving diverse and intricate situations. A wrong decision by an autonomous vehicle during its crossing could lead to a lateral collision, especially if there's a conflict point with another autonomous vehicle or a human-driven vehicle that has already entered the intersection.

At present, traffic control at urban intersections in developed countries is predominantly managed by traffic lights with automatic or flexible sequences [26, 91]. However, several research studies have focused on improving traffic control at intersections using centralized or distributed approaches. In centralized or semi-centralized traffic light control, part of the intelligent transportation system research field, various strategies have been developed to make vehicular flow more efficient and collision-free at intersections. These strategies involve introducing algorithms that change traffic light sequences, with or without a set pattern, based on factors like density, interactions, commutes, velocity, conflicting points, etc [66, 172, 144, 130, 146, 70, 117].

Within the centralized approach, some proposals have eschewed traditional traffic light control (TLC) systems in favor of a "supervisory system" that structures vehicle crossing priorities at intersections to avoid collisions at conflict points [12, 47, 131, 3, 4, 5, 39, 6, 136, 119].

In the centralized control approach, several authors depict their proposals as an effective solution for managing vehicular requests at intersections, preventing arbitrary decisions by vehicles [78, 128, 9]. A typical example is a vehicle, whether autonomous or human-driven, running a red light.

It's important to note that in a centralized control with a "supervisory system", the algorithm validates each vehicle's request. The "supervisory system" also organizes request attention using criteria like "first come, first served", ensuring no request or decision to enter the intersection is left unchecked.

For the decentralized approach, proposals have primarily been based on consensus and interactions, where heuristic algorithms validate priorities for vehicle entry at intersections to essentially avoid collisions [41, 40, 85, 32, 86, 179, 183, 155, 157]. In distributed or decentralized approaches, there is an added level of robustness compared to centralized approaches. The decentralized approach remains robust against failures, whereas in centralized systems, failure of the "supervisory system" or traffic lights can lead to complete control breakdown at the intersection. While centralized proposals often achieve global optimal outcomes, distributed strategies present potential advantages in terms of energy efficiency, computational resources, and robustness to failures. Despite the challenges associated with distributed approaches, they can yield comparable results to global optimization but with reduced energy consumption and computational requirements. These considerations underscore the ongoing relevance and potential benefits of exploring distributed strategies in intersection management systems.

Consequently, this thesis proposes contributing to the future challenges of autonomous driving by developing cooperative interaction algorithms. These algorithms aim to improve vehicular flows and commuting time, avoid collisions at conflict points, provide special emergency attention, and maintain operational integrity in the face of potential decision-making failures with a distributed approach. Evaluating different scenarios, like in cities where we can implement various cases to measure improvements compared to centralized approaches, is necessary. Additionally, our proposal aims to address events where autonomous vehicles may exhibit "uncontrollable" behavior.

1.2 Goals

Considering the motivations described in Section 1.1, the main objective of the research process conducted in this thesis is to develop a coordination system with a distributed approach for the suitable management of entry and crossing at intersections for autonomous vehicles, including emergency autonomous vehicles. This system is designed to tolerate failures due to vehicles with interaction (communication) issues and has been validated against centralized systems for managing traffic at intersections, such as traffic lights or green waves.

To achieve the general goal, it was necessary to implement the following sub-goals:

1. Study the state of the art related to Advanced Driver Assistance Systems (ADAS) and Automated Vehicles (AV). With the analysis of the automated systems currently implemented in vehicles, we aim to understand how it will be possible to achieve suitable levels of interaction between autonomous vehicles.

2. Study the state of the art related to strategies implemented for vehicle crossing at intersections, including centralized or distributed algorithms for traffic control. The main idea is to explore different proposals generated and to identify the current shortcomings and existing limitations.

3. Design and implement algorithms for different types of autonomous vehicles to execute and coordinate to cross an intersection safely and efficiently, without the need for a central server.

   3.1 Develop roles for vehicle behaviors, so that vehicles can negotiate the right-of-way at intersections.

   3.2 Generate rules for messaging exchange between autonomous vehicles near intersections (interactions).

   3.3 Develop roles for vehicle behaviors in the face of physical failures for appropriate decision making. This will generate a system-wide trade-off that keeps it robust from a crossing safety perspective.

   3.4 Develop an extended scenario to add emergency vehicles.

   3.5 Execute extensive experiments on the vehicular traffic simulator to evaluate the performance of our distributed system approach compared to centralized systems.

4. Implement a simulation environment to validate the proposed algorithms. With the studied proposals, it will be necessary to find a simulation environment to conduct various tests, handling primarily microscopic models of vehicular traffic, as well as integrating macroscopic

models to observe the overall effectiveness of our model in large cities (with several intersections).

5. Develop simulated crossing scenarios, progressively increasing complexity with more lanes, failures and emergency management.

    5.1 Execute extensive experiments on the vehicular traffic simulator to evaluate the performance of our proposed distributed system compared to centralized systems.

1.3 Thesis structure

In order to achieve the main goal and sub-goals defined in the previous Section 1.2, the rest of this document is structured as follows:

In Chapter 2, an overview of Automation and driving aids will be presented, along with context on autonomous driving levels. as well as an analysis related to the choice of the vehicle traffic simulator. Finally, different centralized and distributed approaches to intersection management will be discussed.

In Chapter 3, the design of the first algorithm that includes a distributed approach will be presented. This approach involves generating a set of behaviors and communications exchanges to enable autonomous vehicles to coordinate safely and efficiently the entrance and crossing of intersections without the need for a central server. This chapter will also include the simulated implementation of the first algorithm, compared with two proposals with a centralized approach, in a single-lane roads environment.

In Chapter 4, an extension of the first algorithm shown in Chapter 3 will be presented. This extension includes a new set of behaviors and communications exchanges (adding a perception system) to assist autonomous vehicles with communication failures. Similar to the previous chapter, the algorithm will be tested against two centralized approach proposals in cities with single-lane road environments.

In Chapter 5, a set of new behaviors and communication exchanges will be introduced in our algorithm to address emergency autonomous vehicles. For this case, the algorithm will be tested against a centralized system controlled by a traffic light system with green wave phase programming in cities with single-lane roads.

In Chapter 6, a set of new behaviors and communications exchanges will be presented to include in our algorithm for cities with multiple lanes. This complex scenario will be divided to show a first case with normal autonomous vehicles and a second case to include emergency autonomous vehicles. In both cases, three types of probability distributions will be used for the entry of the vehicles in the simulation, to observe emerging behaviors on the global parameters of our proposal. The algorithm will be tested against a centralized system controlled by a traffic light system with green wave phase programming.

Finally, in Chapter 7, the contributions of our distributed approach and the results achieved in comparison with centralized proposals will be presented, along with future research lines related to this work.

1.4 Publication List

- González, C. L., Zapotecatl, J. L., Alberola, J. M., Julian, V., and Gershenson, C. (2019). *Distributed management of traffic intersections.* In Ambient Intelligence–Software and Applications–, 9th International Symposium on Ambient Intelligence (pp. 56-64). Springer International Publishing.

- González, C. L., Zapotecatl, J. L., Gershenson, C., Alberola, J. M., and Julian, V. (2020). *A robustness approach to the distributed management of traffic intersections.* Journal of Ambient Intelligence and Humanized Computing, 11, 4501-4512.

- González, C. L., Pulido, J. J., Alberola, J. M., Julian, V., and Niño, L. F. (2021). *Autonomous Distributed Intersection Management for Emergency Vehicles at Intersections.* In Highlights in Practical Applications of Agents, Multi-Agent Systems, and Social Good. The PAAMS Collection: International Workshops of PAAMS 2021, Salamanca, Spain, October 6–9, 2021, Proceedings 19 (pp. 261-269). Springer International Publishing.

- González, C. L., Delgado, S. L., Alberola, J. M., Niño, L. F., and Julián, V. (2022). *Toward Autonomous and Distributed Intersection Management with Emergency Vehicles*. Electronics, 11(7), 1089.

1.5 Research Projects

The research work presented in this PhD Thesis was carried out in the context of the following research projects:

- **Servicios Inteligentes Coordinados para Áreas Inteligentes Adaptativas**
  Reference: PID2021-123673OB-C31
  PI: Julian, Vicente and Carrascosa, Carlos
  Funded by: AGENCIA ESTATAL DE INVESTIGACION (From 01-SEP-22 to 31-AUG-25).

- **Hacia una Movilidad Inteligente y Sostenible Soportada por Sistemas Multi-Agentes y Edge Computing**
  Reference: RTI2018-095390-B-C31-AR
  PI: Julian, Vicente and Giret, Adriana
  Funded by: AGENCIA ESTATAL DE INVESTIGACION (From 01-JAN-19 to 30-SEP-22).

- **Arquitectura Persuasiva para el Uso Sostenible e Inteligente de Vehículos en Flotas Urbanas**
  Reference: TIN2015-65515-C4-1-R
  PI: Giret, Adriana and Julian, Vicente
  Funded by: MINISTERIO DE ASUNTOS ECONOMICOS Y TRANSFORMACION DIGITAL (From 01-JAN-16 to 30-JUN-19).

Part II

State of the Art

Chapter 2

Autonomous Driving and Its Context

"Autonomous vehicles will not only change the way we move but also the way we live." – Unknown Author.

Abstract

This chapter offers an overview of the research and development in the field of automated vehicles, emphasizing the ongoing evolution of technology to emulate human behavior and achieve error-free autonomous driving. It explores the use of the road traffic simulator, SUMO (Simulation of Urban MObility), and discusses the reasons behind its selection. Additionally, the chapter highlights the significance of traffic intersections, representing scenarios where autonomous driving encounters complex interactions. These intersections have captured the interest of researchers aiming to develop proposals to attain optimal levels of autonomous driving and apply them in real-world situations.

The term Intelligent Transportation System (ITS), has been used to delimit the different technologies to improve safety in daily commuting, as well as with driving efficiency [13]. Although these technologies have been developed for decades, they have become more relevant nowadays due to advances in research about how a vehicle (driverless) could recognise its own surroundings and it could take decisions for the benefit of itself and other vehicles (consensus) on the road. Therefore, the following sections will show the state of the art of the development of autonomous vehicles and the levels of coordination of interactions that they must have in very complex environments such as intersections.

2.1 Automated Vehicles

The National Highway Traffic Safety Administration (NHTSA)[1] is entity of USA government whose main objective is to reduce vehicle accidents. The NHTSA therefore monitors everything related to driving aids and their levels of automation to ensure that these technological developments maintain safe driving, even more so as we begin to move towards fully autonomous driving systems.

The NHTSA describes "five eras of the security" showing the evolution in assistive technologies for driving safety [121]. In the "first era", from 1950 to the year 2000, they list technologies that they classify as "safety-convenient", in where the most representative feature was the incorporation of seat belts [83], whose main purpose was to reduce mortality in road accidents [137, 59, 46]. Moreover, as part of that "era" complementary systems like "Cruise Control" [153], "Anti-lock Brakes" [69] and "Airbags" [120] (although is not named for the NHTSA) were implemented thanks to the revolution in the electronics field.

The following two "periods" are more shorts. The first of 10 years (2000 to 2010), in where the technological advances showed an improvement on control systems and recognition of the surroundings (Electronic Stability Control, Blind Spot Detection, Forward Collision Warning and Lane Departure Warn-

[1] https://www.nhtsa.gov

ing) with driver warnings [121]. For the second of 6 years (2010 to 2016), the technology feature was focus on ‘Àdvanced Driver Assistantce Systems” or ADAS [184], where driving aids began to implement automation to prevent humans errors due to bad or arbitrary decisions.

Finally the NHTSA talks about two following “eras” (2016 to 2025), (from 2025 onward) in where the automation and intelligent control (algorithms, AI, etc.), will be essential to the vehicle safety in the future and will concatenate into error-free autonomous driving.

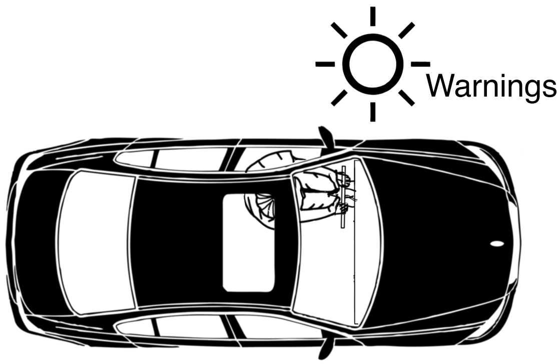
In this point both the NHTSA and the Society of Automotive Engineers (SAE) [125] have defined a classification about automation levels in vehicles. For the case of SAE[2], It developed a document called “SAE J3016 Recommended Practice: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles”, this document was designed in collaborate with the International Organization for Standarization (ISO). In this document is related 5 levels (see figure 2.1) in where the is not automation in SAE level 0 (as displayed in figure 2.1a), in other words the driver has full responsibility for the actions of the vehicle, although the ADAS provide alerts a warnings.

For the SAE level 1 (see figure 2.1b) and 2 (as showed in figure 2.1c) only change the ADAS assistance, due It provides continuous support on acceleration/braking or steering systems, and acceleration/ braking and steering systems respectively.

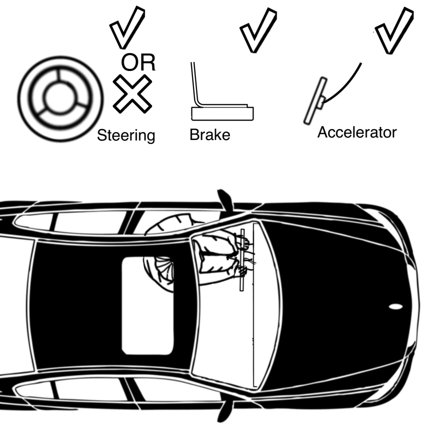
For the SAE level 3, (see figure 2.1d) Automatic vehicle systems take over driving control but the human driver is still available if the control systems fail.

Finally the SAE level 4 (as displayed in figure 2.1e) and level 5 (as showed in figure 2.1f) are fully automated, the difference are the limits areas in the level 4, while at level 5 the control system can drive the vehicle in any scenario (different weather, changes in lighting, with changes in traffic density, etc.) and on any type of road.

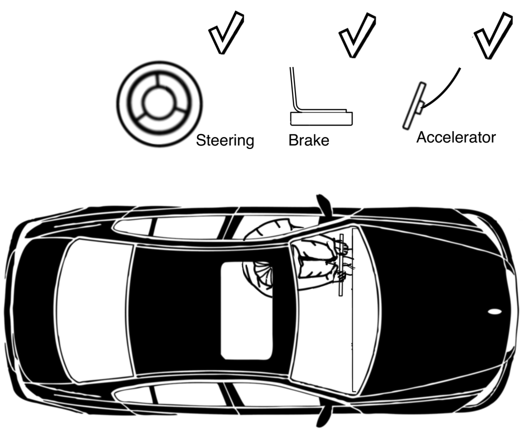
[2]https://www.sae.org



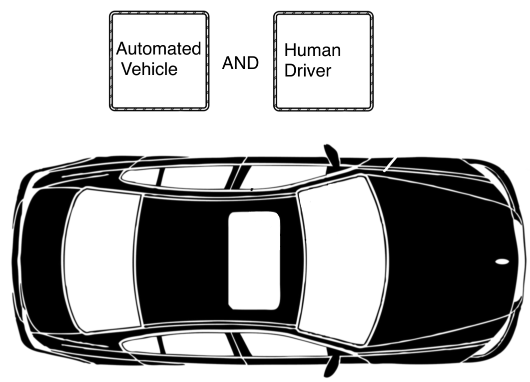
(a) Level 0 -Only Warnings.



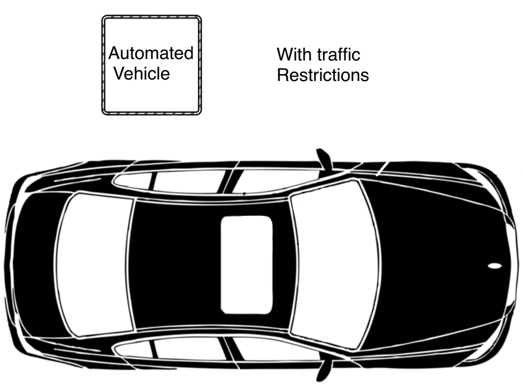
(b) Level 1 -Assistance.



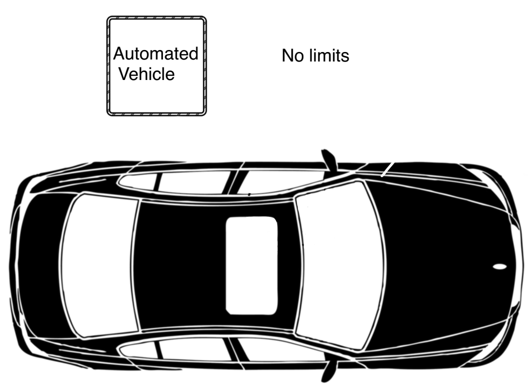
(c) Level 2 -Additional Assistance.



(d) Level 3 -Conditional Automation Driving.



(e) Level 4 -Conditional Automation Driving.



(f) Level 5 -Conditional Automation Driving.

Figure 2.1: Automated driving levels. Created by the author

According to the above and as indicated by NHTSA in the "eras", initiatives in the field of research, began to consolidate the path towards vehicle automation. Such is the case of the Defense Advanced Research Projects Agency[3] (DARPA) who in the year 2005 together with several research centers showed a competition called "DARPA Grand Challenge", where a group of real vehicles adapted to drive by themselves without the help of a human driver (mobile robots) [152, 159, 20], these should cover a distance of more than 200 kilometres in less than 100 hours on the desert (no traditional roads). It challenge exhibited at that year an advance to SAE level 4 of automation driving, which nowadays was standardized by SAE.

In [113], Stanford researchers who were the winners of competition (DARPA Grand Challenge), depict their achievements to reach a autonomous driving level close to SAE level 4, and they agree that the autonomous vehicle must make quick decisions (processing power), after it had recognised its surroundings through multiple perception systems and therefore it could control its actuators for its benefit. They used a modular design to work the software processing, in where all modules (30 modules were used) worked in parallel. In the [113], the researchers show that the software modules are divided in "six functional layers": *sensor interface, perception, control, vehicle interface, user interface and global service.* Finally the researchers discuss the scope of their proposal towards autonomous driving, they describe there are limitations because in the real environments is necessary that a vehicle can take decisions without any delays to control the vehicle actuators and avoid sudden movements when the action processing is late.

2.1.1 ADAS and surroundings perception

In order to efficiently achieve autonomous driving levels, the development of ADAS systems is becoming increasingly important [126, 71]. From simple warnings, where the driver should process this information in fractions of seconds to make informed decisions, to scenarios in which the ADAS system receives various input information and takes control of decision-making [184],

[3] https://www.darpa.mil

thereby enhancing the response to potential critical situations, albeit with certain limitations [126].

Therefore, to ensure reliable outputs when the system takes over control (without human intervention), it is essential to continue refining the ADAS system's ability to enhance its recognition of the surroundings. Nowadays, sensor technology faces various challenges, such as the trade-off between accuracy and cost, along with limitations in information sampling capacity [109]. These challenges may result in the potential need for extensive information storage and highly efficient computing systems [109].

According to the literature, sensors, in general, are divided into two groups: those that measure the internal state of the system and those that measure the external state of the same system. In the case of ADAS technology, it is necessary to utilize both types to understand the vehicle's state at a given moment and what is happening around it. The sensors that measure the external state are termed "exteroceptive" [89, 31], and they are further classified into two types: passive, such as cameras, and active, such as radars and LiDAR (Light Detection and Ranging) technology. In the case of cameras, these systems receive information about the environment through energy inputs at the sensor [89]. On the other hand, LiDAR technology and radars emit energy across electromagnetic fields and receive information about that emitted energy [31].

Advancements in sensors used in ADAS systems will continue to improve, but there will also be a need to implement more robust computer systems to process, in real time, the large amounts of information collected from the surroundings.

2.1.2 Computing systems

Currently, control systems in autonomous vehicles are crucial for managing the influx of information from their surroundings and making decisions based on the traffic situation. Advances in sensors [185], and algorithms, including machine learning and deep learning [177], have significantly improved the capacity of autonomous vehicles [61], to accurately perceive their commuting environments and interactions [118], with other elements such as vehicles, traffic signals, pedestrians, and more.

However, it is imperative to recognize that the processing time required for decision-making in autonomous vehicles is critical, especially during interactions with their environment and at certain speeds. Insufficient hardware can lead to prolonged processing times, potentially resulting in collisions or harm to individuals nearby. Beyond the substantial amount of data, in gigabytes, that sensors like LiDAR can capture to construct the environment, the idea is to train algorithms for classifying and tagging objects, enabling the autonomous vehicle to make timely, informed decisions in real-time.

Certainly, the volume of data collected by sensors, such as LiDAR, is significant, and training algorithms for object classification and tagging is a crucial aspect that empowers autonomous vehicles to make well-informed decisions in real-time. The process involves the following steps:

- **Data Collection**: Sensors like LiDAR generate large volumes of data by capturing detailed information about the vehicle's surroundings. This includes information about other vehicles, pedestrians, road signs, and the overall environment.

- **Data Labeling**: Each piece of collected data needs to be labeled, indicating the presence of objects in the environment. For example, labeling might involve marking specific points as pedestrians, other vehicles, obstacles, etc.

- **Training the Algorithm:** A machine learning algorithm, often a neural network, is trained using this labeled data. The algorithm learns patterns and features from the labeled data, enabling it to recognize and classify objects when exposed to similar patterns in new, unseen data.

- **Real-Time Inference**: Once the algorithm is trained, it can be deployed on the autonomous vehicle's system. In real-time, the vehicle's sensors capture data, which is then processed by the trained algorithm to make decisions on actions such as steering, braking, and accelerating.

- **Continuous Learning**: To adapt to new scenarios and improve over time, autonomous vehicle systems often include mechanisms for continuous learning. This involves updating the algorithm based on additional labeled data collected during real-world driving experiences.

The effectiveness of the autonomous vehicle system depends heavily on the quality and diversity of the training data. Continuous improvements in algorithms and hardware are essential to enhance the capabilities of autonomous vehicles [185, 16], and ensure their safe and reliable operation.

Furthermore, to ensure the safety, accuracy, and reliability of autonomous vehicles, it is imperative to have a computing system capable of processing the interactions among data collection, analysis, decision-making, and control actions over the vehicle's dynamic mechanisms. This processing must occur before the response deadline [109], for interactions with objects or individuals. Avoiding latency [107], which is a bottleneck and a primary challenge in these systems, is crucial.

2.1.3 Communications

The communication, involving the exchange of messages and perception of the environment, plays a key role in the implementation of autonomous vehicles. It is essential for making informed decisions following interactions with one or multiple road stakeholders.

The implementation of these communication systems envisions autonomous vehicles as dynamic nodes in motion. Within a certain range of distance, these vehicles should establish a messaging exchange system that remains active as long as they are within that communication range. In other words, when vehicles move away from each other, there should be a disconnection of the messaging system. As for the perception system, it should be constantly recognizing instances when interactions between vehicles or other elements of a traffic system do not involve message exchange. In such cases, the system needs to collect information from the environment to enhance its understanding.

This type of communication system is known as VANET [37, 38], or Vehicular Ad-hoc Network. It is a wireless network that does not rely on a fixed network infrastructure, unlike cellular communication networks. VANETs can maintain communication links for longer durations [92, 142], between nodes compared to cellular communications, where the node's link may switch to a different antenna depending on its location.

In this sense, a type of VANET communication termed Dedicated Short-Range Communication (DSRC) [96, 170], plays a key role in wireless vehicular communications, offering a dedicated and standardized communication spectrum for vehicles to exchange information efficiently. DSRC facilitates direct communication between vehicles and roadside infrastructure, enabling the seamless exchange of critical safety information, traffic updates, and cooperative driving data. This technology is integral for enabling Vehicle-to-Everything (V2X) communication [53, 106], encompassing Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I) [122], Vehicle-to-Pedestrian (V2P), and Vehicle-to-Network (V2N) interactions. The importance of DSRC lies in enhancing road safety, reducing traffic congestion, and laying the foundation for advanced driver assistance systems (ADAS) and autonomous driving capabilities. As the automotive industry continues to advance towards connected and automated vehicles, DSRC stands as a key enabler, fostering a safer and more efficient future for vehicular communication systems.

2.2 Simulation for traffic management

In the field of vehicular mobility and traffic management, simulation plays a key role in understanding, testing, and optimizing various aspects of transportation systems. Traffic simulators [58, 110, 174, 52], provide a virtual environment to replicate real-world scenarios, allowing researchers, urban planners, and engineers to analyze, evaluate, and improve the efficiency and safety of road networks [145]. This chapter explores the significance, types, and applications of traffic simulators in the context of vehicular mobility.

2.2.1 Introduction to Traffic Simulation

Traffic simulation [161] involves the use of computational models to replicate the behavior of vehicles, pedestrians, and infrastructure in a controlled virtual environment [110]. These simulations aim to capture the dynamics of traffic flow, congestion, and interactions among various elements within a transportation system [111, 29].

2.2.2 Types of Traffic Simulators

- **Microscopic Simulators**: These simulate individual vehicle movements, considering factors such as speed, acceleration, and lane changes. Microscopic simulators offer detailed insights into the behavior of each vehicle [158].

- **Mesoscopic Simulators**: Operating at an intermediate level, mesoscopic simulators focus on traffic flow and interactions between groups of vehicles. They provide a balance between detail and computational efficiency [28, 43, 30].

- **Macroscopic Simulators**: These simulate large-scale traffic patterns and flow, often used for high-level planning and analysis of road networks [133, 124].

2.2.3 Applications of Traffic Simulation

Traffic simulation [161] finds diverse applications in various domains, contributing to a better understanding and optimization of transportation systems. Here are some key applications:

- **Urban Planning**: Simulators assist urban planners in evaluating the impact of new infrastructure, road layouts, and zoning regulations on traffic patterns and congestion [129, 102].

- **Traffic Management**: By testing different traffic signal timings, lane configurations, and control strategies, simulators help optimize traffic management systems for improved efficiency [161, 15].

- **Safety Analysis**: Simulations allow for the study of potential safety hazards, accident scenarios, and the effectiveness of safety measures in reducing risks [11].

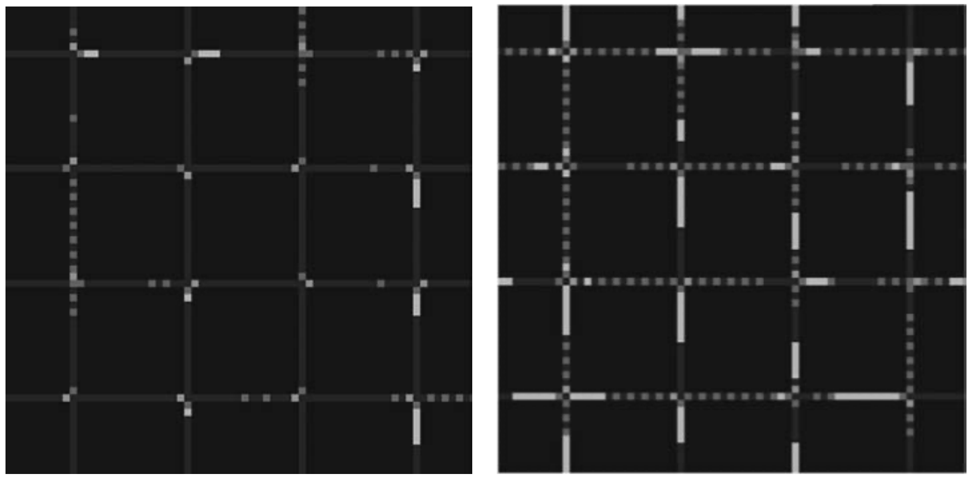
With the rise of autonomous vehicles, simulators become essential for testing and validating the behavior of self-driving cars in various traffic scenarios. These simulations aid in understanding the interaction between autonomous and traditional vehicles. In the following subsections we describe in detail the two traffic simulators employed in this work.

2.2.4 Traffic-Light Simulator

This simulator, developed by Zapotecatl [180], is built on the C++ language and serves as a platform to implement Gershenson's algorithm [63] for self-organized traffic lights. Operating on cellular automata (CA) principles, the simulator models vehicle flow by representing vehicles as moving in a specific direction within cells, where 0 indicates no occupancy and 1 indicates occupancy.

As density increases, all cells become occupied. Notably, the streets in this simulation have only one lane. The flow dynamics between vehicles adhere to the rules of the LAI (Larraga-Alvarez-Icaza) model [103], ensuring that vehicles maintain a safe distance from one another to prevent collisions.

In this simulator (see figure 2.2), each vehicle is modeled using Rule 184 of an elementary cellular automaton (ECA). Rule 184 is an array of cells where the state of each cell depends on its previous state and its closest neighbors. Simply put, if a cell is empty and its left neighbor is occupied, the cell will become occupied in the next step.



(a) City with low density. (b) City with high density.

Figure 2.2: Example of the "Traffic-Light" Simulator Developed by Zapotecatl (Adapted from [65])

This allows for the reproduction of vehicle movement in the simulation. The streets in the simulator are designed in a Manhattan style. Additionally, Rule 252 is used to control traffic flow (stop), while Rule 136 is implemented to prevent turns.

In Gershenson's algorithm, traffic lights are used to control traffic at intersections. Therefore, in this simulator, cycles were generated to keep one street green while the adjacent street is red, and then the phase is changed.

While this simulator is robust and efficient for simulating large cities due to its low-level language and also because the CA can be parallelized. It was specifically designed to implement a particular algorithm. As a result, its capabilities are limited when it comes to incorporating additional features beyond its original scope.

2.2.5 Simulation of Urban MObility-SUMO

The Simulation of Urban MObility[4] (SUMO) [110], stands as a prominent microscopic traffic simulator, revolutionizing the field of vehicular mobility

[4]https://www.eclipse.org/sumo/

research. This chapter delves into the significance, features, and applications of SUMO, emphasizing its role in providing a detailed and realistic microscopic simulation of traffic scenarios.

SUMO is an open-source microscopic traffic simulator designed for simulating road traffic in urban environments. Unlike macroscopic or mesoscopic simulators, SUMO excels in providing a microscopic view, simulating individual vehicles and their interactions. SUMO captures intricate details of each vehicle, including speed, acceleration, deceleration, lane changes, and route choices. Additionally, the simulator models various traffic control elements such as traffic lights, stop signs, and priority rules, allowing for a comprehensive understanding of traffic dynamics. Finally, SUMO enables the simulation of multi-lane roads, considering lane changes, merges, and diverges, crucial for replicating real-world traffic scenarios [110].

SUMO facilitates a deep understanding of individual vehicle behaviors, helping us to analyze the impact of different factors on traffic flow. Moreover, SUMO allows for microscopic simulations, enabling the detailed study of intersections and evaluating the efficiency of traffic with our DIM algorithm and other models, such as traffic lights. Finally, SUMO [110], served as a valuable tool for testing and validating algorithms for autonomous vehicles in diverse and dynamic traffic environments, as demonstrated in complex scenarios in Part III.

2.3 Traffic Intersections: Strategies and Challenges

After exploring in this chapter how both the industry and researchers have investigated scenarios in which autonomous vehicles engage in complex interactions, mimicking and enhancing human driving behavior, various proposals have emerged. These proposals suggest leveraging roadway intersections as a fundamental element for achieving full vehicular automation.

In this section, we will examine several proposals for managing traffic intersections, with a primary focus on two types of classification. Subsequently, we will delve into three specific cases of vehicular complexity commonly encountered in the reality of traffic intersections.

The increasing number of vehicles on global roads has intricately woven the fabric of urban traffic management into a complex tapestry. This surge has accentuated the demand for seamless interactions and communication channels, not only between vehicles and road infrastructure but also among individual vehicles.

The automotive industry has witnessed significant strides in recent years, fueled by technological innovations ranging from autonomous vehicles to communication systems like V2V, V2X, and DSRC [114, 88, 112], intelligent algorithms, image and video recognition, and network processing. These advancements promise substantial benefits [150], including improved energy efficiency, reduced traffic accidents [35, 143, 162], lower emissions, and alleviation of traffic congestion [14].

The current landscape is marked by a proliferation of autonomous vehicle prototypes developed by companies such as Google (Waymo) [84], Tesla Motors [45], Aptiv (Delphi Technologies), Zenuity (Autoliv and Volvo Cars) [82], Baidu, BMW-Intel-Mobileye [134], Daimler-Bosch [19], CISCO-Hyundai, Ford-ARGO, GM-Lyft, Nvidia-Paccar, Honda, Uber, Nissan-Renault, Toyota-University of Michigan [27], Volkswagen, and Waymo-FCA (Fiat Chrysler Automobiles). This surge reflects a collective industry push to unveil the first generation of autonomous vehicles within the next six years (by 2030) [98, 95]. The envisioned outcome is a transportation landscape where autonomous vehicles promise safer journeys and a reduced likelihood of collisions. A notable approach to navigating the challenges posed by autonomous systems involves emulating natural behaviors, particularly cooperative systems that foster interaction among autonomous vehicles [90].

Intersections, serving as critical junctures for traffic management, require meticulous control to avert collisions [135, 149], and streamline the flow of vehicles. The advent of autonomous vehicles further amplifies this complexity, as it introduces a substantial increase in interactions with human drivers. Additionally, varying weather conditions can hinder their ability to act appropriately, making it challenging for them to recognize traffic signals or respond to other drivers on shared roadways. This complexity extends beyond vehicular interactions, encompassing pedestrians, bicycles, motorbikes, and other transportation systems [132, 140, 178]. Autonomous vehicles, equipped with the ability to discern and respond to various elements sharing an intersection, play a key role in managing these diverse interactions.

While technologies such as intelligent traffic lights, sensors, and wireless communications (V2V, V2I) have seen significant advancements, persistent challenges necessitate a deeper understanding of interactions among autonomous vehicles in highly complex scenarios. This underscores the crucial need to generate effective proposals for efficiently managing intersections, especially as we aim for complete automation levels in vehicles, ensuring minimal human intervention even in adverse weather conditions. Addressing these challenges becomes imperative to achieve overarching goals such as reducing wait times, optimizing vehicle flow [175], and promoting sustainability in urban environments [72].

As we explore the complex domain of autonomous driving, intersections emerge as crucial points requiring advanced strategies. The complex and dynamic nature of intersection scenarios has spurred intense research within intelligent transportation systems. This section aims to encapsulate the forefront of this research, elucidating state-of-the-art autonomous driving strategies at intersections [67, 168].

To continue, proposals for managing intersections will be presented and classified into two major categories in this section: Centralized Control of Intersections and Distributed Control of Intersections.

2.3.1 Centralized Control of Intersections

The heart of the centralized driving strategy lies in its pursuit of constructing and executing a globally optimal sequence for vehicles at intersections. This approach depends on the utilization of Vehicle-to-Infrastructure (V2I) technology, facilitating two-way communication between vehicles and the road infrastructure.

The purpose of using V2I technology is primarily to enable communication between all vehicles and a centralized control system [168]. This centralized system assigns priorities to individual vehicles based on specific rules, granting higher priority to certain vehicles, allowing them to proceed first, while others follow suit. To ensure safety, adjustments are made to the longitudinal speeds of vehicles if their time of arrival at the conflict point is within a defined threshold.

While the centralized driving strategy offers a path to global optimization, a notable challenge arises with the increase in computational demands as the number of vehicles grows [168]. This poses a significant hurdle in terms of solution calculation and calls for innovative approaches to address the scalability of this strategy in real-world, high-traffic scenarios.

Numerous centralized approaches have been proposed to effectively manage traffic intersections, as outlined in the literature [18, 169, 50, 74, 182, 34]. In these models, a single control system takes charge of communication with all entities at the intersection, including vehicles, signals, and traffic lights. This centralized coordination offers notable advantages in optimizing traffic flow and ensuring a synchronized and efficient intersection operation.

However, despite their effectiveness, these centralized systems may encounter difficulties adapting to dynamic and changing environments, and in instances of high traffic volume, they can become potential bottlenecks. Therefore, the need for continuous optimization and scalability remains a critical consideration when implementing centralized strategies in real-world, dynamic traffic scenarios [18]. It becomes imperative to strike a balance between the centralized control's advantages and the limitations of centrilized systems to devise robust solutions that can cater to the varying demands of complex urban traffic.

Centralized control systems play a key role in determining the sequencing of vehicle movements at intersections. They are responsible for making decisions regarding which vehicles have the priority to cross first and which must wait. In the presence of at least two vehicles approaching a conflict point within the intersection, the centralized control system allocates the right of way to one of them. Consequently, it becomes essential to assign an appropriate amount of space and time to each vehicle, mitigating the potential for conflicts along its trajectory [50].

Numerous research efforts in the domain of traffic control have centered on the coordination of vehicles at intersections [17]. Among the most used centralized methodologies, we can find the application of the green wave technique. In this approach, a central coordinator oversees the synchronization of traffic lights, orchestrating periodic changes to facilitate the uninterrupted movement of vehicles through the intersection. The green wave technique aims to enhance traffic flow by systematically allowing each vehicle lane its turn to traverse the intersection without encountering collisions.

Despite the widespread adoption of the green wave technique, certain limitations become apparent, particularly in scenarios marked by dynamic environmental changes. For instance, when one lane experiences a traffic jam, the opposite crossing lane may remain empty, showcasing a deficiency in adaptability within decision-making processes [17]. Addressing these challenges necessitates a more specific approach, one that seamlessly adjusts to real-time fluctuations in traffic conditions to optimize overall intersection efficiency and responsiveness.

To address this challenge, more adaptive strategies considering the integration of autonomous and semi-autonomous vehicles have emerged. As an example, in the works [47, 49, 50] the authors propose a centralized solution known as Autonomous Intersection Management (AIM). This innovative approach involves a control system responsible for determining the priority of passage for autonomous vehicles at conflict intersections.

In the AIM framework, autonomous vehicles approaching an intersection send requests to the control system. These requests are carefully evaluated, and the control system decides to accept or deny them based on potential collision risks. If there is any possibility of a collision, the request is denied; otherwise, it is accepted. Upon acceptance, AIM executes a reservation of both space and time within the intersection, adhering to a First-In-First-Out (FIFO) policy. This policy minimizes waiting times, preventing excessively long delays.

However, it's important to note that fault tolerance in such systems is somewhat limited. The centralized manager may face challenges in handling a high volume of requests, potentially leading to overload or even system failure [50, 182]. As the field advances, addressing these challenges will be crucial to enhance the robustness and reliability of such intersection management techniques.

Another centralized proposal can be found in [3] and [7]. In this, a less restrictive supervisory system is employed to orchestrate the crossing of vehicles at the intersection. This supervisor manages crossing requests as scheduled jobs, intervening only when two or more job entries overlap. The model establishes the anticipated arrival time of each vehicle at the intersection, the time required for crossing, and the time needed to vacate the intersection.

The main feature of this model is that autonomous vehicles operate autonomously until the supervisor identifies a potential collision. This autonomous operation enhances efficiency in terms of response time compared to the previous approach. However, it's crucial to acknowledge that the scalability of this model remains somewhat restricted. While it has been successfully tested in a single intersection, its application in a large city with numerous intersections to manage is yet to be explored. Addressing scalability concerns will be key for its potential widespread implementation in complex urban traffic scenarios.

Various approaches within the field of automation and control offer centralized models for the management of intersections, are extensively discussed in [18]. Some contributions, introduce control systems with multiple hierarchical levels. In these models, the centralized manager consistently assigns crossing priority whenever there is a request from vehicles approaching the intersection [3, 7, 74, 165].

While these centralized models offer an efficient mechanism for intersection management, their scalability and adaptability to dynamic traffic scenarios need further exploration. Addressing these aspects will be crucial as cities evolve, introducing more intersections and diverse traffic conditions that demand sophisticated centralized control strategies for optimal performance and safety.

As evident, the adoption of centralized intersection management systems has gained widespread popularity. Authors of centralized proposals argue that consolidating all information within a single system ensures a systematic arrangement for safe crossings without collisions. However, as mentioned earlier, challenges related to efficiency, fault tolerance, and scalability can emerge as critical considerations in the implementation of such systems [18].

In addition to centralized approaches, multiagent systems and other artificial intelligence techniques, such as fuzzy inference, have emerged as viable strategies for intersection management. An illustrative example is found in [99], where the authors use a multiagent system to dynamically alter the state of traffic lights. In this innovative approach, a negotiation process is carried out among an agent manager and neighboring agents to determine crossing priorities. This negotiation incorporates crucial parameters, including traffic density, behavioral patterns, and flow dynamics [99].

The use of multiagent systems introduces a decentralized paradigm, where agents collaborate and negotiate autonomously to optimize traffic flow at intersections. This distributed intelligence allows for adaptability to changing conditions and fosters a more resilient approach to intersection management. Furthermore, the integration of fuzzy inference techniques adds a layer of flexibility, enabling the system to make nuanced decisions based on imprecise or uncertain information.

While these approaches show promising capabilities, their effectiveness in real-world scenarios and their scalability across diverse urban environments need further exploration. The complexity of negotiation and intelligent decision-making within multiagent systems opens research lines for addressing challenges giving dynamic traffic conditions and varying intersection scenarios.

2.3.2 Distributed Control of Intersections

Contrasting with centralized approaches, the distributed driving strategy provides Vehicle-to-Vehicle (V2V) communication for decentralized decision-making. Offering economic advantages and improved real-time responsiveness, this strategy models strategic interactions among vehicles. While it shows some advantages, it typically provides suboptimal solutions compared to centralized approaches.

In essence, the distributed driving strategy eliminates the necessity for a central coordination unit. In this decentralized approach, vehicles approaching intersections, usually follow the first-come-first-served principle. Each vehicle independently communicates with others, fostering a dynamic and cooperative environment. Minor adjustments are made in real-time, guided by specific control methods that enhance the overall efficiency and safety of intersection crossing. This distributed model not only reduces the economic requirements associated with central infrastructures but also promotes a more scalable and responsive system, where vehicles collaboratively negotiate their crossing through intersections.

Within the field of the Distributed Driving Strategy, cooperative game theory and distributed control strategies play key roles. Researchers have explored multi-vehicle interaction strategies, fuzzy logic-based reasoning models, and cooperative decision-making methods grounded in game theory. These approaches contribute to enhancing the collaborative nature of autonomous driving at intersections.

In contrast, distributed approaches provide efficient solutions for managing traffic involving autonomous vehicles at intersections. These models establish behaviour rules that facilitate negotiations of priority between vehicles when crossing intersections. The feasibility of these approaches has been demonstrated under various traffic conditions, showing favorable comparisons with centralized solutions [182]

Distributed approaches that emphasize the need for decentralized control systems can be found in the literature [127, 51, 44, 166, 155, 41, 23]. In studies such as [169] and [73], authors remark the need for a distributed control paradigm that gives the responsibility of negotiating intersections to autonomous vehicles. While this approach empowers vehicles to collaboratively reach agreements, there exists a potential drawback wherein an autonomous vehicle may unilaterally decide to cross, leading to the risk of collisions or the blockage of the intersection. This inherent challenge underscores the critical need for robust and sophisticated communication and coordination mechanisms within distributed frameworks.

The application of multiagent systems was also used in distributed approaches. In [100], authors use a multiagent system to guide intersections by leveraging sophisticated algorithms that forecast the traffic flow of vehicles. This forward-thinking system utilizes the collective intelligence of agents to anticipate and respond to dynamic traffic scenarios effectively. Similarly, in [139], a comprehensive multiagent system is proposed, consisting of several agents dedicated to specific roles such as a road agent, a control agent, and an intersection agent. This system aims to holistically manage intersection crossings, distributing responsibilities among specialized agents to enhance overall efficiency and coordination. These multiagent-based approaches show the potential of distributed intelligence in addressing the complexities of intersection management.

In the vast field of intersection management strategies, literature also explore the field of swarm intelligence and self-organization, presenting innovative perspectives rooted in cooperative intelligence. In [42], a swarm intelligence paradigm is explored, where agents interact autonomously without centralized control. This approach fosters emergent behavior within the swarm, showcasing significant performance gains. However, it's important to note that such benefits may come at the cost of longer computational times, potentially presenting challenges in scenarios demanding real-time responses within complex and dynamic environments.

Another proposal is explored in [64], focusing on self-organization mechanisms. Here, the traffic lights themselves have the capability to self-organize, providing autonomous vehicles with opportunities for smoother and minimally interrupted crossings. This innovative proposal integrates rules that prioritize convoys over individual vehicles during intersections, optimizing traffic flow. The emphasis on self-organization in traffic signal coordination reflects a promising approach to enhance intersection efficiency and adjusting to the needs of autonomous vehicles in diverse and evolving traffic scenarios.

In [127], the authors introduce a pioneering solution called the Hierarchical Robust Control Strategy (HRCS) that provides connection for the autonomous vehicles at intersections. In this proposal, the optimal sequencing of crossings and velocity trajectories is determined through a sequential application of optimal control methods and a robust model predictive control (RMPC) framework. Particularly remarkable is the RMPC's ability to handle additive disturbances and uncertainties in the vehicle's dynamic model and sensor measurements, ensuring safety in real-world scenarios. The optimization challenges are addressed using second-order cone programs, ensuring efficient and unique solutions. Through numerical examples, the study shows the efficacy and robustness of HRCS, demonstrating its superiority over other MPC-based strategies. Exploring the energy-time trade-off under various conditions, the research proves substantial reduction in energy consumption with a moderate increase in travel time. The proposed HRCS not only proves effective but also exhibits practical computational efficiency, making it a promising strategy for real-world implementation.

Additionally, in [166] is presented a hierarchical cooperative intersection control strategy, incorporating layers specifically designed for priority negotiation, strategy bargaining, and strategy optimization. Their main contributions are focused on enhancing efficiency and ensuring safety through priority negotiation and strategy bargaining. Through a comparative analysis with existing Nash-game-based and greedy-based methods, the proposal shows significant improvements within the proposed Strategy Bargaining Layer (SBL). Unlike traditional fixed-order assignment rules, this proposal introduces a dynamic Priority Negotiation Layer (PNL) that negotiates and assigns priorities to the most efficient group of vehicles in a distributed manner. The execution of optimal strategies is facilitated by the Strategy Optimization Layer (SOL), leveraging Model Predictive Control (MPC) in a Hardware-in-the-Loop (HiL) experiment.

With the previous classification, we will now go in depth into three common scenarios representing varying levels of vehicular complexity often encountered in the real-world context of traffic intersections. The first scenario involves "failures in the traffic control system", where disruptions or malfunctions in the standard traffic control mechanisms may occur. The second scenario deals with "emergency handling", addressing situations that demand immediate and adaptive responses due to unexpected events or crises. Lastly, the third scenario involves "multi-lanes", focusing on the needs associated with the coordination and management of traffic across multiple lanes. Understanding and effectively addressing these complexities is crucial for the development of robust autonomous driving strategies at intersections.

2.3.3 Traffic Control Failures

One critical aspect to consider in the traffic control systems at intersections is the system's ability to maintain operational efficiency for the majority of the time. Typically, when a traffic control system at intersections do not function effectively, it fails to provide proper assignments for vehicles crossing the intersection while following predefined rules to prevent collisions or blockages. The breakdown in these operations leads to a loss of the system's reporting and informational capabilities, ultimately having difficulties to maintain its overall functionality. This issue remarks the importance of addressing potential failures and ensuring continuous, reliable performance of intersection traffic control systems.

Hence, the fundamental essence of a fully operative traffic control system depends on the prevention of information loss. This imperative objective determines the need for strategies and mechanisms that safeguard the continuous flow and exchange of critical data within the traffic management framework [60, 47]. In the next discussion, we will explore different findings and methodologies drawn from the literature, offering valuable insights into how the challenge of information loss has been tackled. By understanding and addressing this key complexity parameter, researchers aim to enhance traffic control systems, ensuring their resilience and effectiveness even in the face of potential disruptions or failures.

As commented above, a critical and inherent aspect that requires specific consideration is the potential occurrence of failures within traffic control systems. These failures can manifest due to several factors, ranging from dynamic shifts in environmental conditions to unforeseen malfunctions in the network of devices managing traffic flow. Therefore, mitigating the impact of these faults and ensuring robust fault tolerance becomes paramount to sustain operational continuity and avert potential breakdowns in the efficient management of traffic systems [63]. Proactive strategies must be implemented to promptly identify, address, and rectify faults, in order to enhance the resilience of the traffic control infrastructure. This emphasis on fault tolerance not only safeguards against disruptions but also contributes to the overall reliability and efficacy of the traffic management ecosystem.

In a traffic control system with a centralized strategy, the unit of control plays a key role in broadcasting information to both autonomous vehicles and human drivers. If this control unit loses its ability to transmit information, the entire system becomes inoperative and fails to perform. In contrast, in a distributed strategy, the advantage lies in the capacity to transfer the management of information dissemination among the vehicles themselves. This results in a redundant control strategy, where the failure of one vehicle to broadcast information does not compromise the entire system's functionality.

The literature explores strategies that consider potential communication failures [79, 138, 148, 173, 163], and also strategies with communication failures during execution. In this study, the researchers advocate for a distributed control strategy incorporating rules of interaction within the algorithm, enabling vehicles to make decisions autonomously when faced with communication failures. A notable aspect of their approach is the absence of external devices like traffic lights or infrastructure sensors. This distinguishes it from semi-centralized approaches, such as that proposed by Gershenson et al. (2004) [63], where priority is determined by traffic lights.

While centralized approaches excel in overcoming the efficiency and scalability challenges faced by distributed methods, a notable gap remains in their fault-tolerance capabilities. In this context, the seamless functioning of autonomous vehicles is crucial for effective coordination in a distributed environment. The key strength of distributed systems in intersection management lies in their robustness when faced with failures. Unlike centralized approaches, they can easily manage bottlenecks, ensuring the system responds adeptly without compromising operational efficiency or risking a collapse.

2.3.4 Emergency Handling at Intersections

Emergency handling at intersections is a critical aspect of road safety and traffic management. Efficiently managing the passage of emergency vehicles through intersections is crucial for ensuring good response times and potentially saving lives. Recent research has explored the development of strategies to address emergency situations, incorporating specialized behavior rules to facilitate the seamless movement of emergency vehicles.

In recent years, researchers have been dedicated to developing advanced traffic control strategies specifically tailored for intersections. The inherent complexity of dynamically changing environments, where diverse vehicles traverse in various directions and encounter multiple conflict points, poses a significant challenge for traffic optimization, particularly in urban settings.

Various approaches have been explored, ranging from intelligent traffic lights to sophisticated centralized protocols designed to dictate the rules to be followed by vehicles at intersections.

Traditional traffic control systems often operate by allowing the green light for one lane while keeping all other lanes on red. However, this simplistic approach becomes inadequate when dealing with scenarios involving multiple levels of vehicle priority or the presence of emergency vehicles. In such cases, a specialized protocol is essential due to the elevated risk of collisions among vehicles and the potential enhancement in response times for emergency vehicles [94, 104].

In the contemporary landscape, the research challenges within transportation systems have embraced the integration of advanced technologies capable of managing the complexity inherent in vehicle-to-vehicle and vehicle-to-infrastructure communication [2]. These technologies are designed to ensure that vehicles consistently adhere to safety protocols on the road. When a vehicle deviates from these safety conditions, the implemented technology's control mechanisms intervene to prevent potential collisions, particularly at intersections. While there remain several challenges to be addressed in such systems, the utilization of intelligent algorithms signifies a promising avenue for exploring novel and improved solutions to these complex issues.

Effective communication among vehicles [1, 77], is instrumental in achieving the outlined objectives. Over recent years, numerous studies have dedicated their focus to establishing a certain level of coordination among autonomous vehicles, particularly during critical moments such as intersections, where collaboration among vehicles on different roads is imperative. Examples of such studies can be found in [72, 95, 116, 55, 22, 115] and [151]. These investigations contribute valuable insights into methodologies, trust mechanisms, and planning strategies that enhance the communication and coordination capabilities of autonomous vehicles in challenging traffic scenarios.

Managing emergency vehicles amidst the daily traffic of a city poses a complex challenge, particularly as the density of vehicles on the streets significantly increases. Without proper control, this process may lead to delayed travel times when an emergency vehicle needs to cross an intersection with one or more conflicting roads. Moreover, there is an increased risk of collisions during the crossing. In response to this concern, various papers have emerged to explore the integration of emergency vehicle management within autonomous vehicle traffic control. The fundamental concept of these proposals is to prioritize emergency vehicles over other vehicles.

The majority of proposed solutions emphasize centralized approaches utilizing various forms of infrastructure. However, decentralized solutions have also been explored, where vehicles approaching an intersection establish a network and collectively determine actions to enhance the flow through the intersection.

In scenarios involving conflicts at vehicle intersections, effective management of vehicles with designated priorities, such as emergency vehicles, becomes crucial. In this context, prior research has been conducted to expedite the passage of emergency vehicles through intersections in comparison to non-priority vehicles.

In [25], the authors demonstrated the feasibility of integrating specific attention features for emergency vehicles into a vehicular flow simulator. Additionally, [48] introduced a strategy focusing on emergency vehicles, where lanes with emergency vehicles are given higher priority, resulting in reduced delays for these vehicles compared to regular ones. Another approach, as seen in [76], aims to minimize delays for emergency vehicles by prioritizing their crossing without causing significant delays to other lanes. Similarly, [94] proposes a centralized solution considering the distance of the emergency vehicle to the intersection and its arrival probability, leading to adjustments in traffic lights, including those for pedestrians.

An essential aspect of these systems is the ability to prioritize specific vehicles at intersections, particularly emergency vehicles such as ambulances, fire trucks, or police cars. Several previous works have focused on optimizing the routes of these vehicles within cities, as seen in references [87] and [141]. Furthermore, certain approaches aim to enhance the flow of emergency vehicles at intersections, especially when compared to other types of vehicles. The subsequent section delves into an analysis of these works. It's worth noting that the majority of these proposals are grounded in centralized solutions.

In the literature, various studies, including [54, 75, 176] and [62], have been dedicated to reviewing approaches addressing the intersection traffic signal control problem. Additionally, specific reviews on the problem of vehicle prioritization at intersections, such as [108], have been conducted. In the majority of cases, these proposals lean towards the adoption of centralized solutions.

Proposals also exist that specifically focus on prioritizing public transport vehicles to optimize their flow within cities. In [24], the authors suggest integrating a bus signal priority strategy and pre-signal methods at intersections to enhance bus performance. Another noteworthy example is presented in [81], where bus priority is achieved by incorporating a dedicated bus lane alongside an adaptive pre-signal control algorithm that dynamically adjusts to the demands of both private and public transport in real-time. For ambulances, [147] introduces an innovative approach that utilizes a dedicated app connecting ambulances and traffic signal stations through a cloud network. This system ensures that when an ambulance approaches an intersection, the traffic signal remains green to facilitate the ambulance's smooth passage.

In the work presented by [154], the authors introduced an RFID communication protocol to enhance the efficiency of emergency vehicle management. A notable distinction from previous proposals lies in the approach to leadership. Unlike the initial proposal, in this case, the leader not only coordinates the intersections but also retains information about the queues at traffic lights. This enables the leader to evaluate the presence of additional emergency vehicles within those queues, thereby contributing to an improved and more responsive system.

In the centralized intersection control system proposed by [49], the authors employ a multi-agent system comprising two distinct types of agents: the driver agent, installed in each vehicle, and the intersection manager agent. The driver agent is responsible for transmitting a request message to secure space at the intersection, while the intersection manager agent processes and either accepts or rejects these crossing requests.

The underlying algorithm is built upon slot reservations at intersections. In scenarios with multiple requests, the attention mode operates as a queue, adhering to a first-come-first-served basis. After successfully crossing an intersection, all driver agents notify the intersection manager to indicate that the intersection is now available for others.

Crucially, the proposed algorithm accommodates emergency vehicles by treating their requests as special, prioritizing them over regular requests. However, it's worth noting that this approach doesn't address scenarios where multiple emergency vehicles approach the intersection simultaneously.

Alternatively, semi-centralized approaches have been explored, as seen in the work [101], where low-cost infrastructure is integrated into lanes to enhance the traffic light system. Communication between different control systems of the proposed infrastructure allows for adjustments in traffic lights when emergency vehicles are present. Self-organized approaches are also introduced, such as in [164], where a protocol called VTL-PIC transforms normal traffic lights into a virtual traffic light. This protocol involves electing a leader among vehicles at the intersection when a potential conflict is detected, and the leader manages the traffic. Moreover, [97] presents an IoT-based approach for emergency vehicle priority and self-organized traffic control at intersections. The intersection controller receives data on emergency vehicle positions (through GPS devices) and vehicle density at each approaching lane, allowing it to dynamically adjust traffic lights based on the detected traffic conditions.

2.3.5 Intersections with Multiple Lanes

In this section will be presented a complex scenario, in where the demand for superior computational capabilities becomes pronounced, especially in distributed control systems. The intricacy arises due to the potential divergence of one or more vehicles from the collective consensus in distributed strategies, where vehicles may make autonomous decisions arbitrarily, deviating from the agreed-upon coordination. This divergence poses a significant challenge, underscoring the imperative for robust computational performance. The distributed strategy must operate with precision to foster seamless coordination, thwarting any inclination of individual vehicles to autonomously dictate their passage through the intersection. In such a context, the ability to maintain a harmonious flow while accommodating the diverse decisions of autonomous entities becomes paramount, necessitating advanced computational frameworks for effective control and management.

Therefore, intersections with multiple lanes present additional challenges due to the complexity of vehicle trajectories and the different conflicting points between the different lanes of surrounding streets. Research has examined specific approaches to manage these intersections, considering effective coordination between vehicles and the mitigation of potential conflicts [17]. The subsequent discussion encapsulates an overview of the current state of multiple-lane intersection control. This exploration delves into various methodologies, challenges, and advancements in the field, offering a comprehensive perspective on the existing landscape of research and implementations related to the management of intersections with multiple lanes.

In [171], the research presents a decentralized optimal control method for guiding Connected and Autonomous Vehicles (CAVs) through multi-lane intersections, focusing on minimizing travel time and energy consumption. CAVs initially determine a reference trajectory using optimal control and employ a search algorithm to identify conflicting vehicles, establishing safety constraints. An Optimal Control Barrier Function (OCBF) controller ensures optimal trajectory tracking while considering safety and vehicle limitations. Simulation results demonstrate the approach's effectiveness in diverse scenarios. Ongoing work aims to extend decentralized CAV control to traffic networks and address challenges in complex environments, including improvements in lateral dynamics for curved trajectories.

The researchers in [80], proposed a centralized control strategy to address urban traffic congestion using the Autonomous Intersection Manager (AIM). The study employed simulations to explore optimization strategies at both micro and macro levels within networks of autonomous intersections. At the micro level, the investigation involved analyzing diverse navigation strategies for individual vehicles, while at the macro level, Braess' Paradox was revisited, and the study explored dynamic traffic flow reversal in specific lanes. Unlike previous methods, AIMs showcased the capability to swiftly reverse individual lanes, demonstrating significant improvements over existing control mechanisms. The findings underscored the potential advantages of incorporating autonomous vehicles for advanced traffic management, with anticipated efficiency gains in addressing congestion in larger road networks.

In [167], introduces the MI-phase-time network, a novel traffic coordination control mechanism that enhances flexibility in representing traffic control constraints across multiple intersections. It can emulate traditional methods or offer improved options for phasing sequence and durations. The model is categorized into four levels of traffic control modeling, demonstrating through experiments that effective coordination benefits from flexible phase durations and sequences. The optimization framework, based on vehicle space-time trajectories, anticipates a future where such data is widely available, allowing for novel and robust traffic control strategies.

In [33], researchers introduced a decentralized coordination framework tailored for Connected and Autonomous Vehicles (CAVs) navigating multiple adjacent intersections without traffic signals. The framework operates on two levels: upper-level planning involves CAVs computing energy-optimal arrival times, ensuring safety and exploring lane changes, while lower-level planning tackles real-time optimal control problems. The proposed approach exhibited significant improvements in fuel consumption, traffic delays, and travel time across various traffic volumes. Ongoing research delves into uncertainties related to vehicle-level control and explores the impact of communication errors. Additionally, the study emphasizes the need for addressing coordination challenges in mixed-traffic scenarios involving both human-driven and autonomous vehicles.

In [93], the study focused on addressing autonomous driving scenarios at multi-lane intersections with mixed traffic flow. The authors introduced an integrated decision and control framework, incorporating static path planning and optimal path tracking. The static path planning involved defining expected velocity curves, while the optimal path tracking enhanced the constrained Optimal Control Problem (OCP) for each static path, considering interactions with pedestrians, bicycles, and traffic signals. The approach utilized model-based Reinforcement Learning (RL) with offline training and online application, showcasing efficient and safe decision-making in simulations. The framework demonstrated a significant reduction in computational time compared to Model Predictive Control (MPC). Future work aims to extend capabilities for dynamic variations in surrounding participants and train a unified policy network for diverse tasks.

2.4 Conclusions

As seen, we have reviewed the literature on the path toward autonomous driving, focusing on technological advancements that enable automated vehicles to interact with their surroundings, gather information, make decisions, and take real-time actions. However, achieving suitable levels of autonomous driving in real-world scenarios requires studying complex environments where automated vehicles may encounter execution deficiencies. Hence, research proposals on traffic control at intersections have been instrumental.

Through the evaluation of proposals outlined in the literature on traffic control at intersections, we can provide a brief summary highlighting the identified deficiencies. Centralized approaches lose effectiveness entirely if their control systems fail. Moreover, as complexity increases (e.g., multi-lane setups, turns), there is a need to increase computational resources. Other proposals, closer to real-world scenarios, demonstrate challenges in handling emergency vehicles, resulting in imbalanced queues at high densities. Prioritizing emergency vehicles throughout their commute leads to increased vehicle halting and waiting times. Additionally, many proposals fail to scale their experiments to environments with multiple intersections or large cities.

In this context, we present an algorithm aimed at addressing shortcomings identified in the state of the art. Our proposal introduces a distributed model for managing intersections, leveraging interactions through a perception and messaging system. This system induces diverse behaviors to enhance global performance, akin to centralized intersection control models. Additionally, our algorithm includes extensions to handle vehicles with communication failures and mitigate the impact of emergencies on waiting times for other vehicles. While similar to other analyzed works in prioritizing roads for emergency vehicles, our proposal stands out for its distributed solution, ensuring scalability and eliminating the need for traffic lights by coordinating priorities to prevent blockages at intersections. Finally, we aim to scale our proposal to environments with multi-lanes and large cities to evaluate global variables in comparison with centralized strategies.

In summary, efficient management of intersections is essential for the successful implementation of automated vehicles in urban environments. While centralized approaches have proven useful, distributed models offer advantages in terms of scalability and fault tolerance. The consideration of failures, emergency handling, and the management of intersections with multiple lanes are critical aspects that require attention to ensure the safety and efficiency of traffic in the future of autonomous driving.

Part III

Development

Chapter 3

Distributed Intersection Management Approach

"Swarm intelligence is the ability of decentralized systems to solve complex problems by coordinating local behavior among autonomous agents." – Marco Dorigo.

Abstract

This chapter presents our proposed algorithm for interactions among autonomous vehicles at intersections, employing a distributed approach. We have developed a set of behaviors that emerge from interactions, ultimately providing solutions for safely crossing intersections, avoiding collisions, and preventing blockages between vehicles at conflicting points. This is particularly relevant as the simulated city streets in our scenario are single-lane. The chapter concludes with a series of experiments designed to compare the performance of our distributed model with two centralized approaches.

This chapter begins by detailing our proposed distributed approach to managing the interactions between autonomous vehicles at traffic intersections. It further explores this concept using a simulator based on cellular automata, aimed at validating the approach in comparison to centralized methods. The coordination of autonomous vehicles becomes increasingly challenging in scenarios with high traffic densities, mixed traffic, or during directional changes in commutes that require lane sharing. Such complexities, especially at traffic intersections, have drawn significant attention from researchers.

Most existing research favors a centralized approach for traffic intersections, a setting fraught with intricate conditions for autonomous vehicles. However, it has been demonstrated that centralized systems for traffic coordination are not robust against faults and can only be considered optimal under the assumption that they never fail.

In response to the growing interest in developing advanced levels of automation in driving, particularly in complex scenarios, this research advocates a shift to a distributed approach. This approach is based on the communication systems among autonomous vehicles situated near traffic intersections. As a result of these interactions, vehicles take on specific roles or behaviors, enabling efficient navigation through intersections, which is crucial for minimizing the risks of collisions and delays. The chapter will elaborate on these interactions and present experimental evidence to validate the effectiveness of the distributed approach over centralized systems.

3.1 Distributed Intersection Management (DIM)

In this section, we present the Distributed Intersection Management Approach (DIM) system to provide autonomous vehicles with the capacity to negotiate and manage crossings at intersections. This system is aimed at being scalable and flexible as well as achieving similar levels of efficiency than a centralized system. The DIM model is composed by four parts: the traffic flow model, the autonomous vehicle model, communications model, and behavioral roles.

3.1.1 Traffic flow

The traffic flow model of DIM is based on the LAI (Larraga-Alvarez-Icaza) [103] model for large traffic networks simulation. LAI is a model for traffic flow that captures the drivers reactions in a real environment. We use this model to understand the behavior of the traffic while preserving safety on the road.

LAI model allows us to represent the interactions of the vehicles on a shared lane and direction. This model defines the following three main rules in order to represent the behavior of a vehicle:

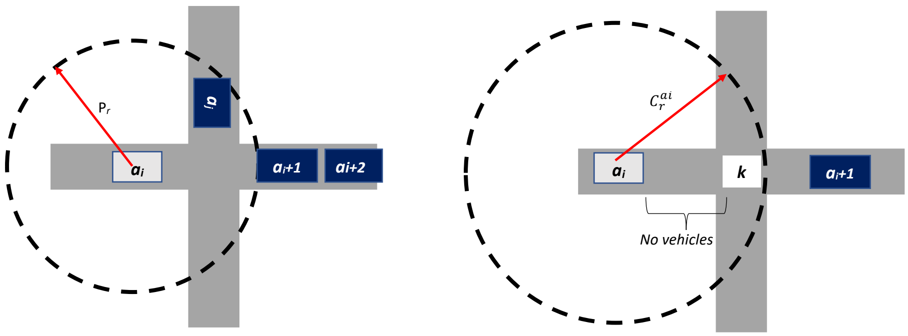
- A vehicle a_i can accelerate as long as exists a distance D_{acc} between this vehicle and the vehicle that comes before a_{i+1}.
- A vehicle a_i keeps its velocity as long as exists a distance $D_{keep} < D_{acc}$ between this vehicle and the vehicle that comes before a_{i+1}.
- A vehicle a_i has to decrease its velocity if exists a distance $D_{brake} < D_{keep}$ between this vehicle and the vehicle that comes before a_{i+1}.

The above three rules provide the mechanism to maintain safe distances among the vehicles, guaranteeing safe driving. As long as safe distances exists between a vehicle and its predecessor, collisions will be avoided between these vehicles.

The LAI model defines three equations to calculate safe distances according to the above rules [103]. These equations are incorporated into the DIM model in order to describe the dynamics of the vehicles on the same trajectory and lane. In addition, we based our distributed model on the Gershenson centralized negotiation model [63], [36], [66] for the design of our distributed rules for autonomous vehicles.

3.1.2 Autonomous vehicles

We assume a group of agents $A = a_0, ..., a_n$ that represent autonomous vehicles moving through the different streets of a city. Each vehicle a_i includes sensors to detect other vehicles that are inside an area. Each vehicle is also provided with a wireless communication system to send messages and request information to other vehicles.



(a) Perception radius. (b) Communication radius.

Figure 3.1: Example of the perception radius and the communication radius.

To represent this, an autonomous vehicle a_i defines two radius: the perception radius and the communication radius. The perception radius P_r defines a detection area inside which, other autonomous vehicles are detected by the sensors of a_i. This radius simulates LiDAR[1] sensors, radars sensors, cameras, etc. (see Fig. 3.1a).

The communication radius C_r defines a communication area inside which, other autonomous vehicles receive messages sent by a_i. Messages can be delivered to specific receivers or can be broadcasted to any receiver inside this area (see Fig. 3.1b).

3.1.3 Communications

In our approach, the communication model relies on the Vehicle-to-Vehicle communication systems (V2V)[160]. This choice is rooted in the focus of the DIM model on vehicle interactions, disregarding infrastructure considerations for addressing the entering, crossing, and exiting of intersections to prevent

[1]https://news.voyage.auto/an-introduction-to-lidar-the-key-self-driving-car-sensor-a7e405590cff

collisions and commute delays. In this context, autonomous vehicles will operate within a Vehicular Ad Hoc Network (VANET) using the IEEE 802.11p protocol [10], along with Dedicated Short-Range Communications (DSRC), a wireless connection based on mutual communications.

In this context, each autonomous vehicle will be equipped with a communication antenna designed to request, receive, and broadcast information within a communication radius C_r (as illustrated in Figure 3.1b) using a DSRC wireless connection.

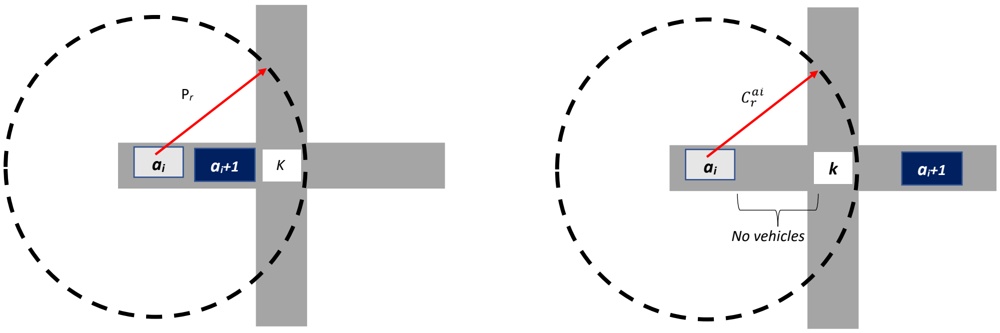
The communication link between autonomous vehicles will be established and maintained as long as the vehicles share their communication radius. When the vehicles move away from each other, the communication link will be automatically disconnected.

3.1.4 Behavioral roles

An autonomous vehicle can play two different roles: Follower and Negotiator. The role played by an autonomous vehicle depends of information that receives and the actions the vehicle can take. This is similar to the approach already proposed in the context of automated highway systems [105].

Follower role

The follower role (represented as F_v) is played by autonomous vehicles that are moving just behind another vehicle. At the beginning of the execution, every autonomous vehicle has associated this role. An autonomous vehicle a_i plays F_v if it detects another vehicle a_{i+1} driving front it, inside the detection area defined by P_r. In this situation, a_i has the goal of keeping its safe distance with a_{i+1}. (See fig. 3.2a).



(a) a_i plays F_v, keeping safe distances with a_{i+1}.

(b) a_i plays N_v.

Figure 3.2: Examples of the roles played by a vehicle

A vehicle a_i playing F_v is able to detect the distance with respect to the vehicle that comes before a_{i+1}. Taking into account its safe distance, it could decide to increase, to keep or to decrease its velocity according to the above commented LAI model rules.

Negotiator role

The negotiator role (represented as N_v) is played by autonomous vehicles that do not detect other vehicles inside their communication areas and before the next intersection k (see fig. 3.2b).

When a vehicle a_i starts playing role N_v, this vehicle broadcasts a message with information of its position and velocity with respect to intersection k. If a vehicle a_i playing role N_v intersects its $C_r^{a_i}$ (communication radius of agent a_i) with the $C_r^{a_j}$ (communication radius of agent a_j) of another agent a_j playing role N_v in a conflict way, they must share the information of velocity and positions in order to negotiate who should be the first to cross at the intersection (see fig. 3.3).

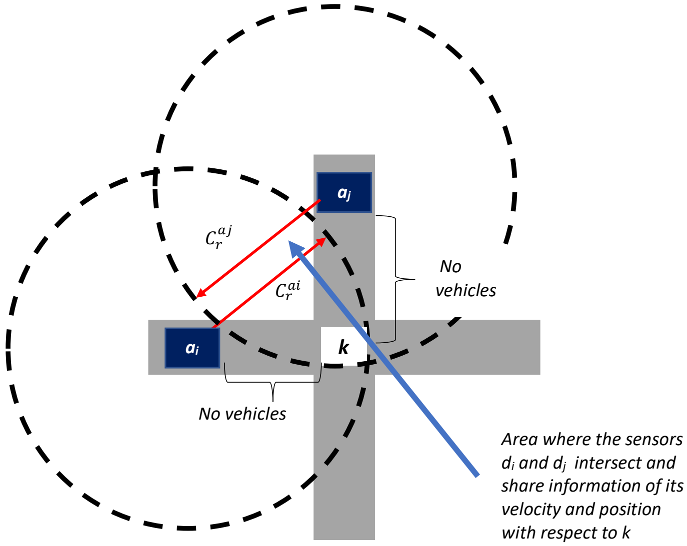


Figure 3.3: vehicle a_i playing role N_v sharing information with vehicle a_j playing role N_v in a conflict way intersecting their communication radius ($C_r^{a_i}$ and $C_r^{a_j}$).

Finally, an agent playing role N_v leaves this role, when it enters in the intersection and shares its messages to the new vehicle with role N_v behind it.

3.1.5 Negotiation between autonomous vehicles

In this section is explained the rules of our algorithm. Hence the autonomous vehicles run the rulers to make the negotiation between conflicting points (adjacent roads or lanes) and to achieve the cross by themselves of cooperative way without collisions and delays. As a consequence, they obtain a priority to cross, contributing cooperatively to achieve the expected behavior of the system.

Reach priority to cross in low densities

If a vehicle a_i assuming the role N_v approaches an intersection k, it will initiate a broadcast within its communication radius $C_r^{a_i}$, transmitting information about its velocity and position with reference to intersection k. This message will be directed towards the adjacent road or lane of type j (conflicting points).

In scenarios with low traffic densities, vehicles assuming the role N_v will engage in a negotiation process based on the "first come, first served" principle. The vehicle closest to the intersection will have the priority to cross first (see figure 3.4), while the other will decelerate and reinitiate the negotiation process through a new broadcast (see equation (3.1)).

(3.1)

$$a_i \text{ cross the intersection} = \begin{cases} \text{if not receive a message from any } a_j = N_v \\ \text{if } a_i = N_v \text{ arrives first before } a_j = N_v \text{ at } k \end{cases}$$

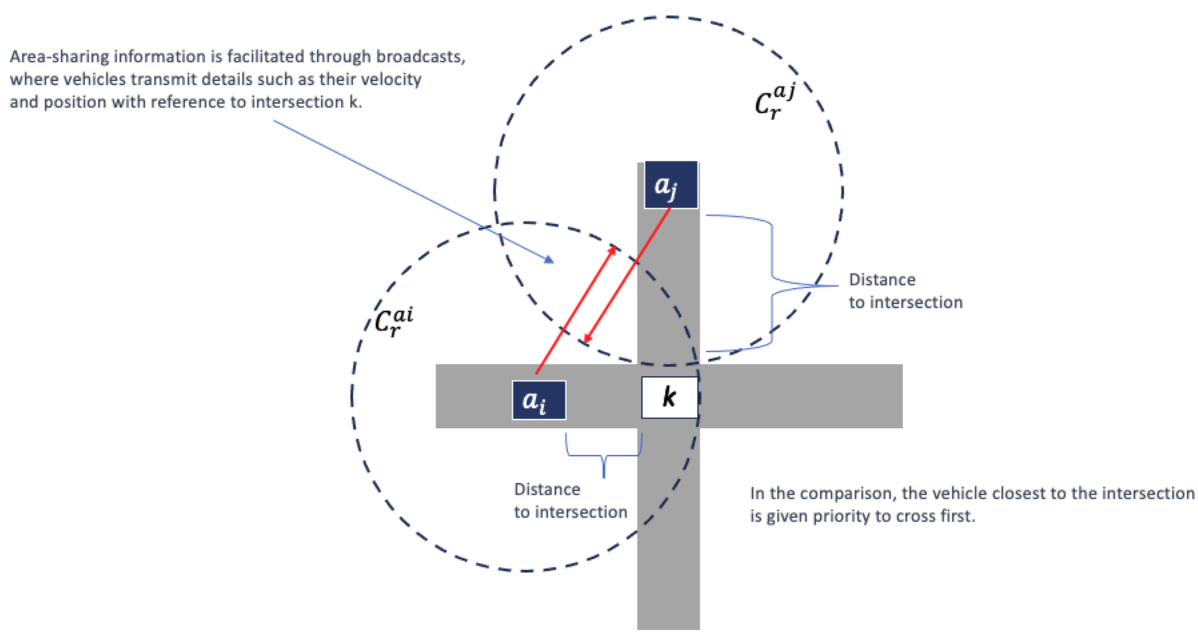


Figure 3.4: Reach priority to cross - low density.

Timeout

If an autonomous vehicle a_i assuming the role N_v loses the negotiation, it transitions into a yielding state. Subsequently, a_i comes to a complete stop before intersection k for a duration of t_{stop}. While stationary, a_i continuously assesses the possibility of gaining priority to cross the intersection (refer to rules for prioritized crossing in both low and high densities) starting from time t_{stop+1} through subsequent intervals until it is deemed appropriate to cross. However, if a_i fails to secure priority within a reasonable time-frame, it will request the right of way from vehicle a_{j+m}, who is currently a N_v at that time. This request is initiated because a_i has surpassed a predefined threshold of time, t_μ, spent in the stationary state without obtaining clearance to cross the intersection.

Avoid intersection blocked

If an agent a_i playing role N_v goes to an intersection k, and detects first in its $C_r^{a_i}$ or in its P_r another autonomous vehicle a_{i+1} that has crossed the intersection k but still is in a distance e with respect the intersection, the vehicle a_i playing N_v must begin to decrease its speed before the intersection. The vehicle a_i will avoid to cross the intersection k until distance e will be free. While distance e isn't free the vehicle a_i playing N_v will come to stop before the intersection (see Fig.3.5).

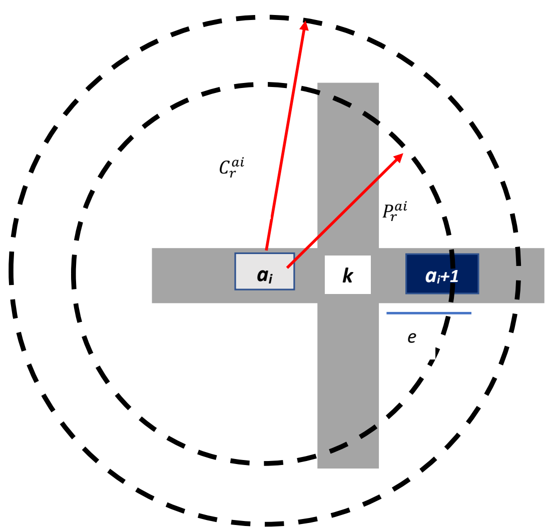


Figure 3.5: a_i will avoid to cross on intersection k if $a_i + 1$ is in e.

If there exists two conflict lanes L_1 and L_2 with an agent in each line $a_n^{L_1}$ and $a_m^{L_2}$ inside the distance e after the intersection k, then the rule about *avoid intersection blocked* will be executed iteratively until any lane inside distance e will be free. If both lanes will be free at the same time, then the vehicle playing role N_v that has been waiting more time is who reaches the priority to cross.

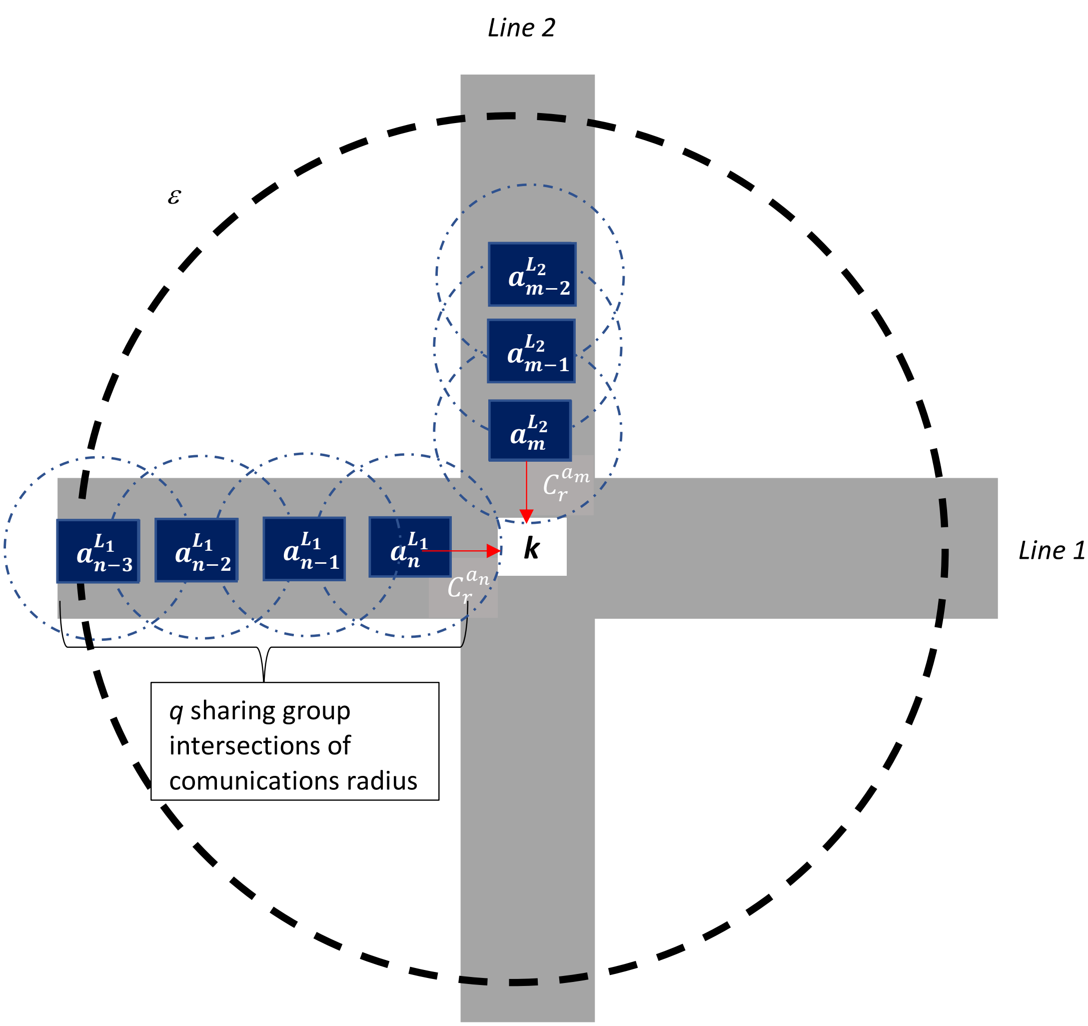


Figure 3.6: The queue of vehicles in lane 1 has priority to cross over vehicles in lane 2 according to the rule *Reach priority to cross in high densities.*

Reach priority to cross in high densities

In this approach we give a higher priority in order to cross to convoys or groups of autonomous vehicles that are in the same lane. According to this, an agent $a_n^{L_1}$ playing role N_v in line 1 reaches priority to cross over the rest of lanes in conflict, if the quantity of autonomous vehicles behind to it (q) (e.g. $a_{n-1}^{L_1}$, $a_{n-2}^{L_1}$, $a_{n-3}^{L_1}$, ...) is the higher respect the rest of the lanes in conflict. To calculate this q we introduce a threshold ϵ which indicates the quantity limit of a queue of vehicles in the same lane before an intersection (see fig. 3.6). Thus, the crossing priority each street when there is high densities depending on the vehicle playing role N_v that complete a convoy of vehicles q_t such that:

$$q_t = \sum_{i=1}^{n} c \tag{3.2}$$

Where c is the number of vehicles detected by N_v in each step of time i and n represents the number of steps required in order to change the lane (See equation (3.2)).

$$\gamma - q_t < 0 \tag{3.3}$$

Where γ represents a threshold such that if it is exceeded, the priority of crossing is changed to another street (See equation (3.3)).

Finally, if there are two conflicting lanes, L_1 and L_2, each with agents in lines $a_n^{L_1}$ and $a_m^{L_2}$, acting in N_v roles, and an equal number of autonomous vehicles behind them, the priority for crossing will be randomly assigned to one of the two streets with a convoy to cross first.

3.2 Experiments

In this section, we show the experiments to validate our DIM model by using the simulator developed by Zapotécatl [180], which is a simulator based in cellular automatons. This tool, simulates the dynamic of vehicular traffic in cities composed by streets and intersections. This simulator is developed following the rules of LAIE's[2] model [180, 66, 186]. where each vehicle keeps a safe distance with its predecessor and no collisions are produced.

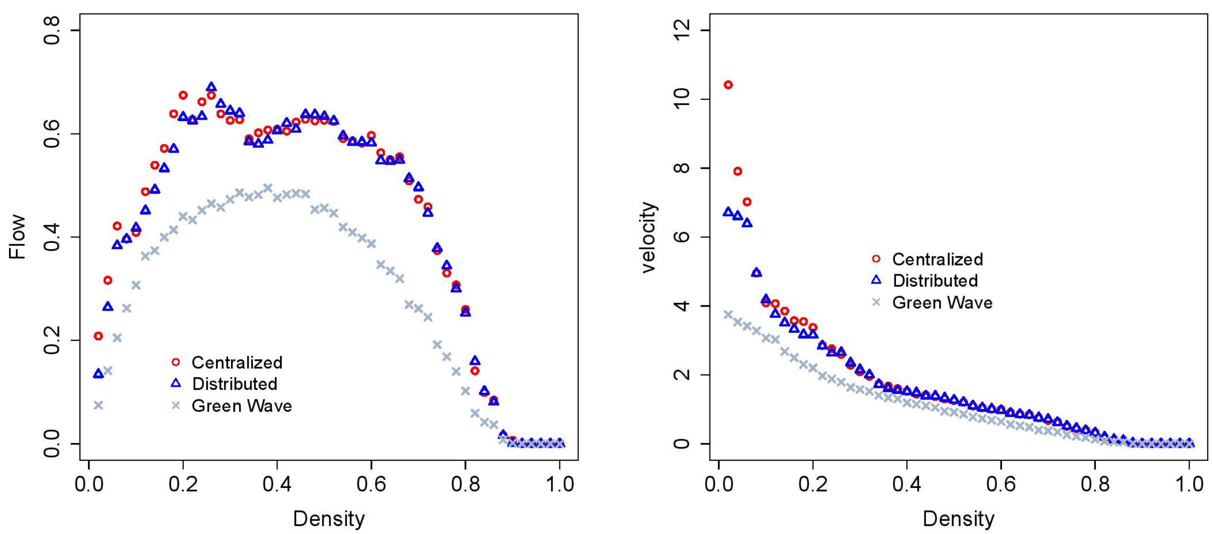
We compare the performance of our DIM model with two other traffic intersection management systems. The first system (Green Wave) is the traditional approach in which traffic lights are the responsible of setting the priority in each intersection. In this approach, the traffic light switches between green and red light every period of time, giving priority to the vehicles located in the line with green light. The second system (Centralized) is the centralized proposal developed by [66, 36, 63]. The experiments evaluate performance of the three systems in a Manhattan-style grid with a first setting of 4 intersections, afterward 25 intersections, 100 intersections and finally a setting with 225 intersections. We start from a traffic density of 0.02 and we increase this density until reaching 1 (that means a collapse where any vehicle is moving). Each execution was repeated 20 times.

Now, to begin, the first experiment (see figure 3.7) will showcase the behavior of flow, velocity, and waiting time of our DIM model in comparison with the centralized model described above in a city with 4 intersections. In Figure 3.7a, the results illustrate the performance of the three systems in terms of traffic flow. The behavior is comparable at low traffic densities, but as density increases, the Green Wave system exhibits significantly lower performance compared to the other two approaches. Specifically, the maximum flow achieved by Green Wave is 0.45 at a density of 0.5, while the DIM system and the Centralized approach maintain a traffic flow of 0.7, with similar values across a density range from 0.2 to 0.6. Notably, the performance of the DIM system closely resembles that of the Centralized approach.

In figure 3.7b, the performance of the systems in terms of the average velocity at intersections per vehicle during the simulation is depicted. It is evident that the performance of the Green Wave system is consistently lower than the other systems for density values ranging from 0.02 to 0.5, mainly because each vehicle stops when the traffic light is red. For densities greater than 0.5, the performance of all three systems becomes relatively similar. This

[2] The LAIE's model is an extension of the LAI model, which introduces conflict ways but maintaining the same dynamic model

trend emerges because, with increasing density, the average velocity tends to decrease until the city experiences a collapse of traffic, leading to a velocity of 0.



(a) Flow vs Density. City Manhattan style of 4 intersections.

(b) Velocity vs Density. City Manhattan style of 4 intersections.

Figure 3.7: Experimental Results: City Simulation with 4 Intersections.

Finally, figure 3.8 illustrates the performance of the three systems in terms of the average waiting time at intersections during the simulation. Similar to the previous figures, the Green Wave system exhibits the lowest performance. This difference is particularly noticeable at lower density values, where cars frequently come to a halt due to red traffic lights. In contrast, both the DIM and Centralized systems show very short waiting times at low densities. This is attributed to dynamically changing traffic lights in the case of the Centralized approach and reactive negotiation in intersections for the DIM system. For densities exceeding 0.5, the performance of the three systems converges, as the increasing traffic leads to city congestion.

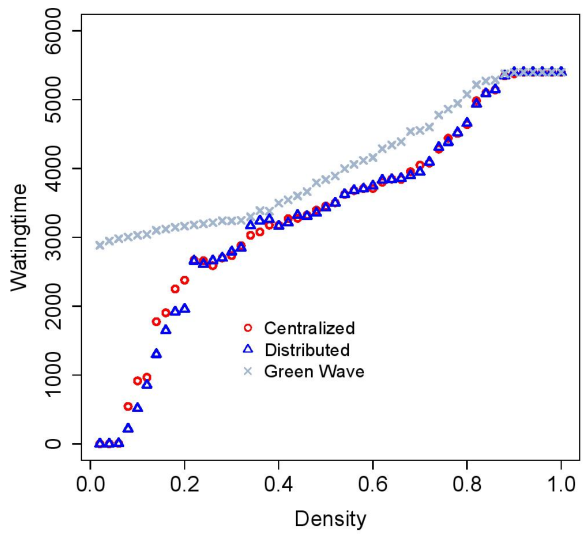
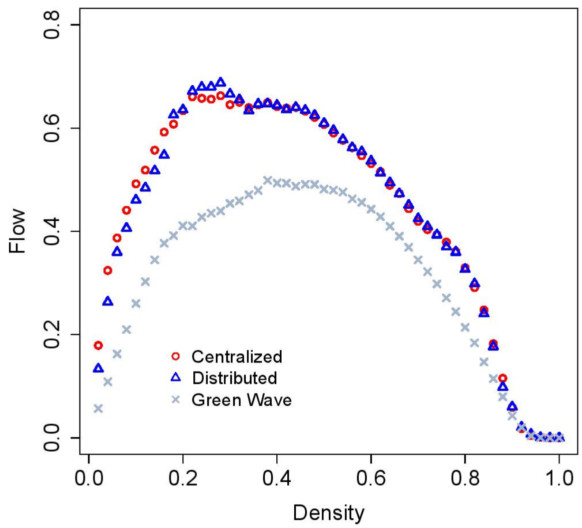


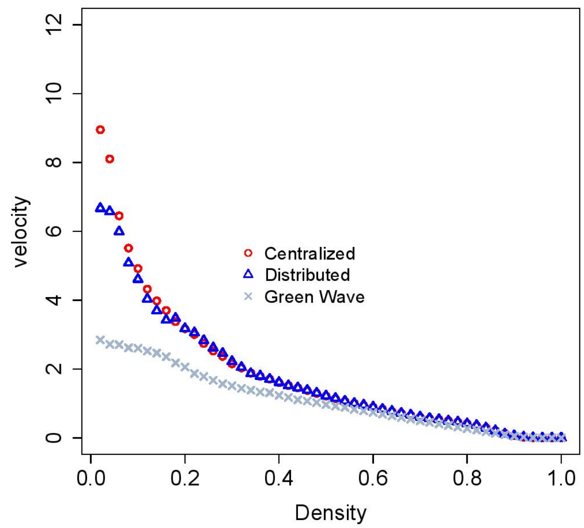
Figure 3.8: WaitingTime vs Density. City Manhattan style of 4 intersections.

Now, for the second experiment (refer to Figure 3.9), the performance of the same three variables (flow, velocity, and waiting time) for the aforementioned models is demonstrated, but in a city with 25 intersections. Figure 3.9a illustrates the performance of the three systems concerning traffic flow. The behavior is comparable at low traffic densities; however, as density increases, the Green Wave system exhibits significantly lower performance than the other two approaches. Specifically, the maximum flow achieved by the Green Wave is 0.47 for a density of 0.5, while the other two systems achieve a traffic flow of 0.69, maintaining similar values for densities ranging from 0.2 to 0.6. Notably, the performance of the DIM system closely resembles that of the Centralized approach.

In figure 5.8, the performance of the systems in terms of the average velocity reached at intersections per vehicle during the simulation is depicted. It can be observed that the performance of the Green Wave is again lower than the other systems for density values from 0.02 to 0.5 (since each vehicle stops while the traffic light is red). For densities greater than 0.5, the performance of the three systems is quite similar. This is due to the fact that as the density increases, the average velocity tends to decrease until the city is collapsed by vehicles, and the velocity reaches 0.



(a) Flow vs Density. City Manhattan style of 25 intersections.



(b) Velocity vs Density. City Manhattan style of 25 intersections.

Figure 3.9: Experimental Results: City Simulation with 25 Intersections.

Finally, in figure 3.10, the performance of the three systems in terms of average waiting time at intersections is presented. Similar to the previous figures, the performance of the Green Wave system is the lowest. This difference is most pronounced at lower density values, as cars frequently come to a halt due to red traffic lights. In contrast, both the DIM and Centralized systems exhibit very short waiting times at low densities. This can be attributed to the dynamic traffic light changes in the Centralized approach and the reactive negotiation in intersections for the DIM system. For densities greater than 0.5, the performance of the three systems becomes similar, as the traffic tends to overwhelm and collapse the city.

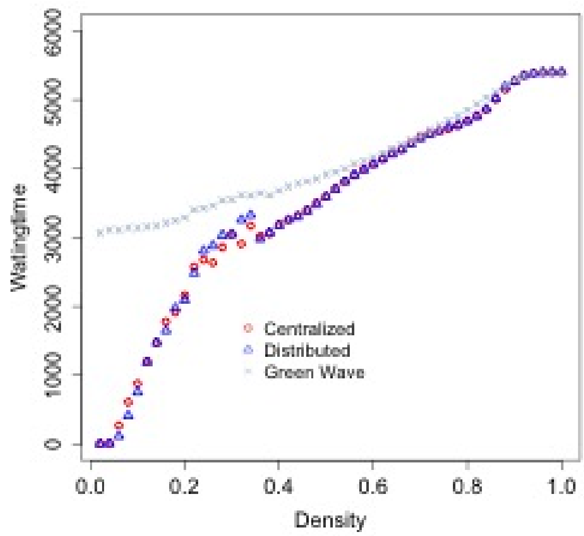
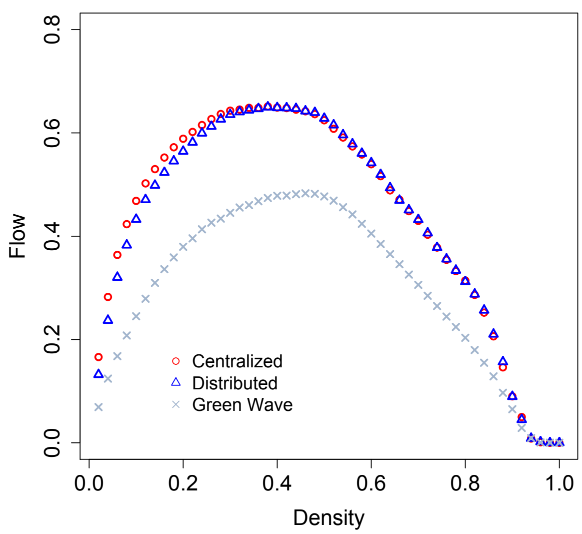


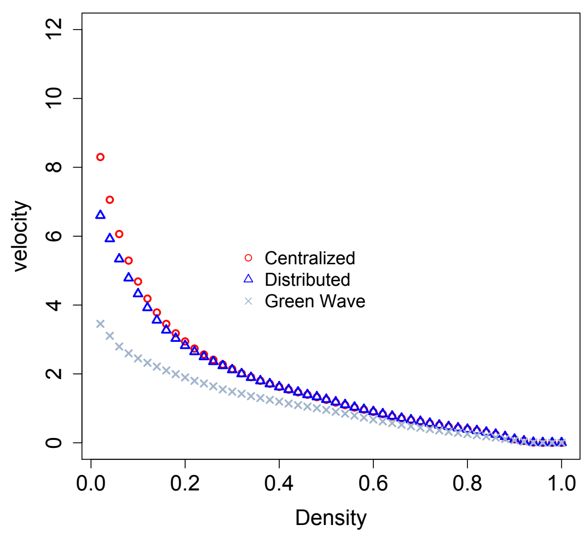
Figure 3.10: WaitingTime vs Density. City Manhattan style of 25 intersections

Now, for the third experiment (refer to Figure 3.11), we explore the performance of the same three variables (flow, velocity, and waiting time) for the previously mentioned models, but this time within a city featuring 100 intersections. Figure 3.11a depicts the performance of the three systems in terms of traffic flow. As observed, the behavior is comparable for low traffic densities. However, with increasing density, the Green Wave system exhibits significantly lower performance than the other two approaches. Specifically, the maximum flow achieved by the Green Wave is 0.48 for a density of 0.5, while the other two systems achieve a traffic flow of 0.65, maintaining consistent values for density ranging from 0.2 to 0.6. Notably, the performance of the DIM system closely resembles that of the Centralized approach.

The figure 3.11b illustrates the system's performance in terms of the average velocity reached at intersections per vehicle during the simulation. It is noticeable that the Green Wave system's performance is once again lower than the other systems for density values ranging from 0.02 to 0.5, as each vehicle stops when the traffic light is red. For densities exceeding 0.5, the performance of the three systems becomes quite similar. This is attributed to the fact that, as density increases, the average velocity tends to decrease until the city experiences a collapse due to the congestion of vehicles, ultimately reaching a velocity of 0.



(a) Flow vs Density. City Manhattan style of 100 intersections.



(b) Velocity vs Density. City Manhattan style of 100 intersections.

Figure 3.11: Experimental Results: City Simulation with 100 Intersections.

Finally, figure 3.12 illustrates the performance of the three systems concerning the average waiting time at intersections during the simulation. Similar to the previous figures, the Green Wave system exhibits the lowest performance. This difference becomes more pronounced with lower density values as cars frequently come to a halt due to red traffic lights. In contrast, both the DIM and Centralized systems show very short waiting times at low densities, attributed to dynamically changing traffic lights in the case of the Centralized approach and reactive negotiation in intersections for the DIM system. For densities exceeding 0.5, the performance of the three systems converges as traffic tends to overwhelm the city.

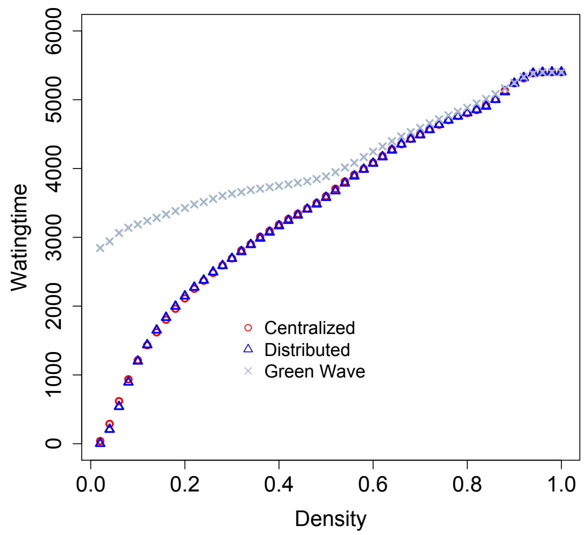
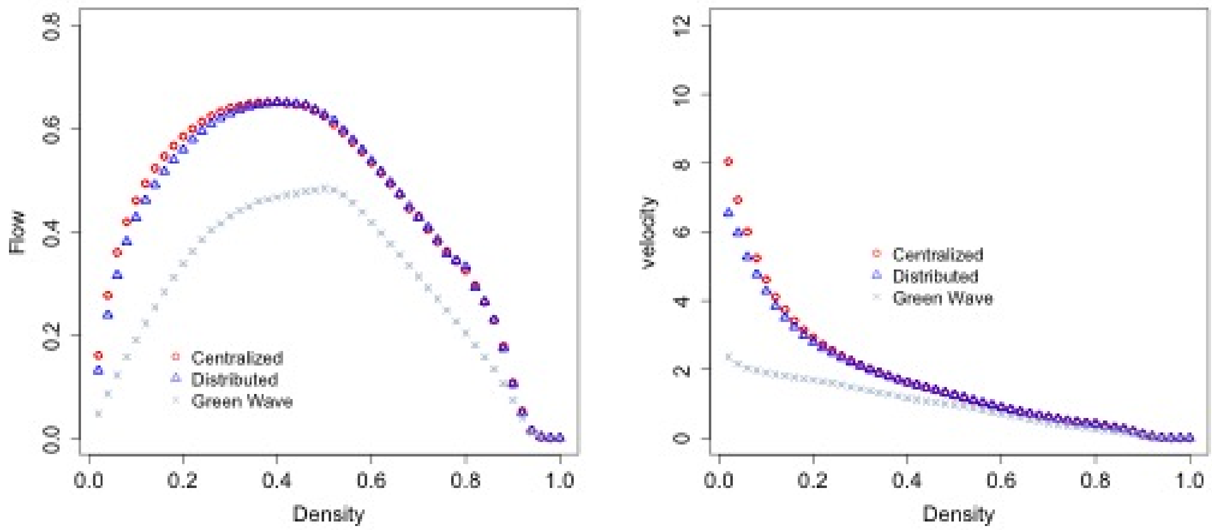


Figure 3.12: WaitingTime vs Density. City Manhattan style of 100 intersections

Now, in the final experiment (refer to Figure 3.13), we examine the performance of the same three variables (flow, velocity, and waiting time) for the previously mentioned models, but this time within a city featuring 225 intersections. In figure 3.13a, the performance of the three systems in terms of traffic flow is presented. It is evident that the behavior is analogous for low traffic densities. However, with increasing density, the Green Wave system exhibits significantly lower performance compared to the other two approaches. Specifically, the maximum flow achieved by the Green Wave system is 0.46 for a density of 0.5, while the performance of the other two systems attains a traffic flow of 0.64. These systems maintain similar values for density ranging from 0.2 to 0.6. Notably, the performance of the DIM system closely aligns with that of the Centralized approach.

In figure 3.13b, the performance of the systems in terms of the average velocity reached at intersections per vehicle during the simulation is depicted. Notably, the Green Wave system exhibits lower performance for density values ranging from 0.02 to 0.5, as each vehicle comes to a stop during red traffic lights. However, for densities surpassing 0.5, the performance of the three systems converges to a similar pattern. This can be attributed to the increasing density, causing a reduction in average velocity until the city experiences a collapse, leading to a velocity of 0.



(a) Flow vs Density. City Manhattan style of 225 intersections.

(b) Velocity vs Density. City Manhattan style of 225 intersections.

Figure 3.13: Experimental Results: City Simulation with 225 Intersections.

Finally, in Figure 3.14, the performance of the three systems in terms of average waiting time at intersections during the simulation is presented. Similar to the previous figures, the Green Wave system exhibits the lowest performance, especially at lower density values. This is attributed to cars frequently stopping due to red traffic lights. In contrast, both DIM and the Centralized system demonstrate very short waiting times at low densities. This is attributed to the rules governing the dynamic change of traffic lights in the Centralized approach and the reactive negotiation in intersections in the DIM system. For densities greater than 0.5, the performance of the three systems becomes similar as traffic tends to congest and eventually collapse the city.

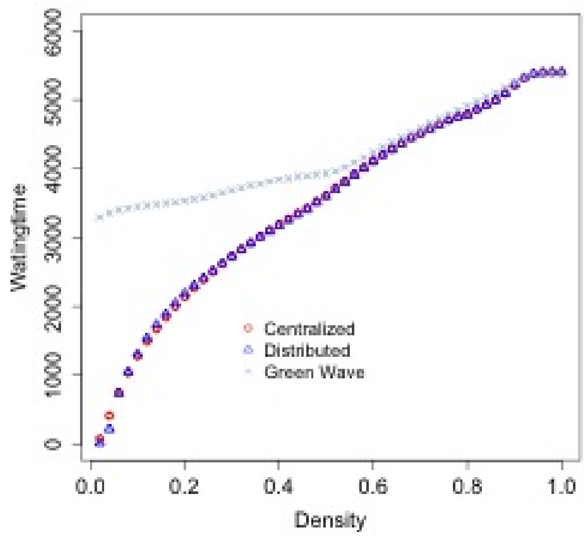


Figure 3.14: WaitingTime vs Density. City Manhattan style of 225 intersections.

3.3 Conclusions

In this chapter, we proposed the DIM model for distributed management of traffic intersections. The performance associated to vechicles of DIM is quite similar to other centralized approaches such as the Gershenson. At the same time, our proposal outperforms a conventional traffic system control like Green Wave in terms of velocity, waiting time and traffic flow, specially, when the size of the city and the number of intersections increase. In our proposal, each autonomous vehicle that reaches an interaction coordinates with the rest of vehicles for crossing safely and efficiently.

The coordination of autonomous vehicles in DIM does not need a central control for management [50]. Therefore, this distributed system is more scalable since there is not any centralized manager that could become a bottleneck. What is more, DIM is much tolerant to changes in the conditions in the environment and device failures.

With regard to a centralized model systems like the proposed by Gershenson, the DIM model requires less hardware and vial infraestructure to keep the traffic control management. Due to the roles defined for the vehicles, the negotiation rules are considered to cross intersections in a safe way without obstructing the intersections.

After proposing our DIM algorithm with a distributed approach, the next step involves further exploration of complex scenarios inherent in a real-world context. Hence, Chapter 4 presents an extension of our algorithm that introduces communication faults into the system, aiming to assess its operational performance in comparison to other existing systems with centralized approach.

Chapter 4

Extension of the DIM algorithm for implementing control failures

"Failure is simply the opportunity to begin again, this time more intelligently." – Henry Ford.

Abstract

This chapter introduces an extension of our algorithm, which focuses on interactions among autonomous vehicles at intersections through a distributed approach. In this extension, we have incorporated a new behavior to address a more complex interaction scenario, simulating communication failures among vehicles. This showcases the robustness of our algorithm in the face of failures in global control over intersection crossings. Such failures would render centralized control approaches ineffective, highlighting the advantages of a distributed approach. The experiments are conducted through computational simulations, and the performance of our model is compared with two centralized models. The first model is the traditional "Green Wave" system utilizing traffic lights, while the second is called a "semi-centralized" approach proposed by [182, 66], which employs traffic lights with a self-organization approach to control intersection crossings. The comparison is carried out in single-lane city scenarios.

As discussed in Chapter 3, our approach is founded on vehicular interactions, giving rise to various behaviors, with the goal of the ensure the smooth flow of traffic on both streets and intersections, preventing collisions and traffic obstructions. In this sense when the interactions between autonomous vehicles will be more complex (multiple lanes, types of vehicles, etc.), our algorithm will grow into more behavioral roles.

As observed, communication and perception systems in our algorithm, serve as the conduits through which vehicular interactions are managed. If these channels fail, interactions may become susceptible to disruptions, resulting in the absence of emergent behaviors. In contrast to traditional traffic control systems, such as traffic lights, a failure in this control system could lead to the collapse of intersection flow.

Although the majority of proposals discussed in 2.3 have highlighted the benefits of centralized strategies for managing traffic systems at vehicular intersections, these approaches exhibit limited fault tolerance.

In this context, the current chapter presents an extension of our algorithm wherein autonomous vehicles with failures in their communication systems (the main channel of interaction at intersections) are incorporated, while retaining an active perception system. Once again, our proposal is validated using a cellular automata-based simulator. Various experiments will be conducted to compare our approach with other centralized strategies. The introduction of autonomous vehicles with communication system failures into the simulation is implemented progressively, starting from low densities and increasing to different levels, ultimately reaching one hundred percent of vehicles with communication system failures in the simulation.

4.1 Model DIM Implementation in the Presence of Communication Failures

In this section, we will be working with the model implemented in Chapter 3.1. This model comprises four essential components: the traffic flow model, the autonomous vehicle model, the communications model, and behavioral roles. It is crucial to emphasize that through interactions among autonomous vehicles on both streets and intersections, emergent behaviors play a pivotal role in maintaining a collision-free and unobstructed traffic flow.

Utilizing the DIM model [68] at the macroscopic level of road traffic enables the emergence of the capability to negotiate safe vehicle crossings at intersections. This model is designed with a focus on scalability and flexibility, aiming to achieve efficiency levels comparable to those of a centralized system. Additionally, it will incorporate fault tolerance to effectively respond to vehicle failures.

4.1.1 Communication failures

Many distributed systems for managing intersections typically assume the proper functioning of all elements involved in the management process. However, these systems can become unpredictable when failures occur in certain devices, such as autonomous vehicles. In this context, interactions may not be monitored with the same accuracy as in centralized approaches, potentially leading to collisions. Considering the importance of efficiency, scalability, fault-tolerance, and robustness against failures, distributed systems, including the DIM model, must address these aspects. The DIM model, in particular, incorporates support for communication failures among autonomous vehicles. The sensors described in Section 3.1.2, play a crucial role in detecting and addressing these failures.

We denote the role played by an autonomous vehicle a_i experiencing a communication failure as Cf_v, indicating that the vehicle is unable to send or receive messages from other vehicles. In this situation, a_i activates only its $P_r^{a_i}$, utilizing the perception radius to safely navigate and cross the intersection (see equation (4.1)).

$$
Cf_v \text{ cross the intersection} = \tag{4.1}
$$

$$
a_i = \begin{cases} \text{if not detect other vehicle from any } a_j = N_v \text{ before } k \\ \text{if not detect other vehicle } a_{i+1} \text{ before } k \text{ in distance } e \\ \text{if } a_i \text{ detect any vehicle } a_j = N_v, Cf_v \text{ stopped before } k \end{cases}
$$

Otherwise, vehicle $a_i = Cf_v$ stops before the intersection k for safety. It then reassesses the situation to determine whether it can safely proceed through intersection k (see equation (4.1)).

Crossing for Cf_v in high densities scenarios

Each autonomous vehicle a_i that is playing the role Cf_v must stop before intersection k for safety. If an autonomous vehicle a_j commuting by conflicting lane L_2 and with rol of N_v detected to a Cf_v stopped in L_1 (see equation (4.2)):

$$(4.2)\quad a_j = N_V \text{ should let } Cf_v \text{ cross the intersection} =$$
$$\begin{cases} \text{if it has not convoy or it can stop} \\ \text{Otherwise, send a message upstream to next vehicle behind it } a_{j-m} \text{ to stop} \end{cases}$$

In equation (4.2) in the otherwise case the vehicle that send a message upstream will be the last vehicle convoy or the vehicle can not stop.

Finally, if all the vehicles are playing the role Cf_v, then the crossing would be carried out one by one, giving the priority to one of the lanes.

4.2 Experiments

In this section, we present various experiments conducted to test the DIM model. For these experiments, we utilize the simulator tool developed by Zapotécatl [181], which is based on cellular automata. This tool simulates the traffic dynamics in cities with streets and intersections, following the rules of LAIE's model. Notably, the LAIE's model is an extension of the LAI model, introducing conflict ways while maintaining the same dynamic model [181, 66, 186].

We evaluate the performance of our DIM model by comparing it with other traffic intersection management systems. The system, referred to as "Centralized", is a self-organizing proposal developed by Gershenson et al. [63, 66, 36]. This system can adapt traffic lights to prioritize lanes based on features such as clustering of vehicles or convoys, free lanes leading to the intersection, and empty intersections.

The experiments assess the performance of the two systems in a Manhattan-style grid. We initiate the experiments with a traffic density of 0.02, gradually increasing it up to 1 that is the point of collapse where no vehicle can move due to all spaces being occupied. Each density level is repeated 20 times with varying initial random positions of vehicles.

4.2.1 Experiments on communication failures

In this section, it shown the test the performance of the system when some communication failure occurs. We compare the performance of our DIM model with the centralized system. In the case of the centralized approach, communication failures are represented as fails in the traffic lights. Therefore, vehicles are expected to cross the intersection without stopping. In the case of DIM, communication failures are represented as communication problems in the vehicles. Therefore, a vehicle with communication failures is not able to coordinate the crossing with other vehicles.

The experiments evaluate the performance of both approaches in a city represented as a Manhattan-style grid with 100 intersections. We test different percentages of vehicles with communication failures, from 25% (i.e. most of the vehicles can communicate properly) to 100% (i.e. all the vehicles have communication problems). The vehicles with communication failures are randomly selected.

Figure 4.1 and 4.2 show the performance of both approaches. As it can be observed, the vehicles flow of the semi-centralized approach is influenced by the percentage of failures. For a percentage of 25%, the maximum flow does not exceed 0.4 and this flow abruptly decreases between 0.5 and 0.7, becoming close to 0 from density 0.8 on. As this percentage is increased, the results get dramatically worse. As an example, for 50% of failures, the maximum flow is around 0.3 for values of density lower than 0.3. From densities values greater than 0.5, the flow is practically null. In contrast, the DIM system shows a better behavior against failures.

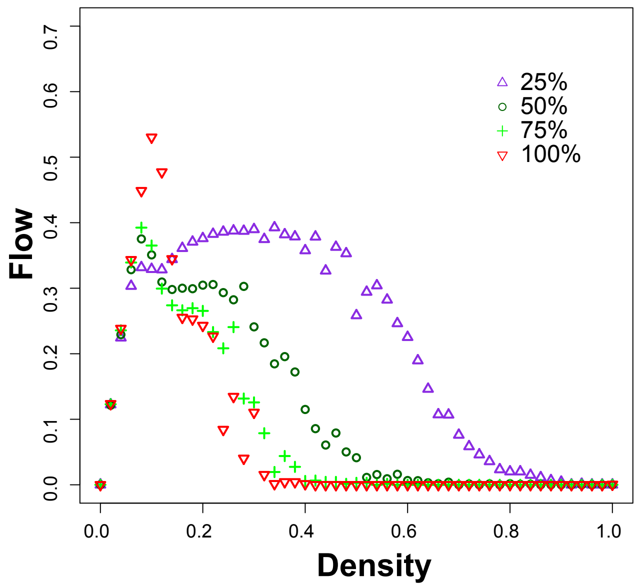


Figure 4.1: Semi-centralized model.

As it can be observed in the figure, for a percentage of 25%, the flow achieves values around 0.6 for densities values from 0.2 to 0.6. This shows a more stable behavior compared to the semi-centralized approach. What is more, this stability against failures can be observed for any percentage of failures. Although flow values are lower as the percentage of failures is increased, these values are quite similar for density values ranged between 0.2 and 0.6. In contrast to the semi-centralized approach, the abruptly decrease does not occur until large values of density (greater than 0.7). Therefore, the distributed approach provides more tolerance against failures.

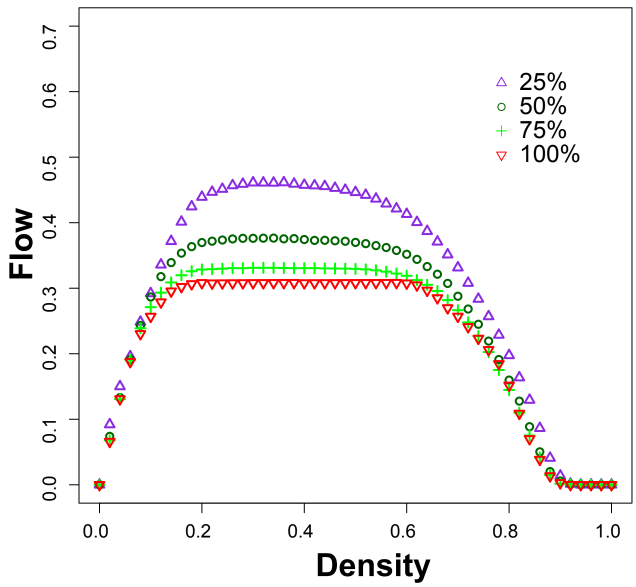


Figure 4.2: DIM model.

4.3 Conclusions

We introduce the DIM model to facilitate the distributed management of traffic intersections. In this model, each autonomous vehicle utilizes message exchange to coordinate with others, ensuring a safe and efficient crossing of intersections. Through the conducted tests, it is evident that the performance of the DIM model closely resembles that of centralized adaptive approaches, such as the one proposed by Gershenson et al. Furthermore, being a distributed approach, the DIM model exhibits greater robustness against failures. Simultaneously, our proposal surpasses conventional traffic control systems like Green Wave in terms of velocity, waiting time, and overall traffic flow.

The coordination of autonomous vehicles in DIM does not rely on central control for management. Consequently, this distributed system boasts superior scalability, eliminating the presence of a centralized manager that might otherwise become a bottleneck. Moreover, DIM exhibits greater tolerance to changes in environmental conditions and potential device failures.

Compared to adaptive centralized systems, the DIM model demands less hardware and road infrastructure for efficient traffic management. The predefined roles for vehicles in DIM ensure that negotiation rules are well-suited for safe intersection crossings, avoiding obstruction of critical areas.

Furthermore, based on the experiments, the DIM model demonstrates greater robustness than the semi-centralized model against failures. As observed, our proposal enables the system to sustain a consistent vehicle flow even with 50% of vehicles experiencing communication failures. In contrast, the performance of the semi-centralized model diminishes in the presence of communication failures, even at low levels of traffic density.

As part of future work, we plan to enhance our model by incorporating the consideration of multiple lanes and directions. Additionally, the model will be extended to accommodate vehicles with different priorities, allowing for the definition of vehicles with varying levels of preference at intersections.

Chapter 5

Managing emergencies in DIM algorithm model

"Information redundancy is not only inevitable but also essential for the reliability of communication.." – Claude Shannon.

Abstract

This chapter introduces an extension of our algorithm focusing on emergency handling, specifically for priority vehicles. A new behavioral role is introduced to address interactions with vehicles prioritized for crossing over regular vehicles. While existing proposals have typically granted emergency vehicles the capability to interrupt all intersections until they complete their journey, our approach outlines rules of interaction for seamless intersection crossing without disrupting the flow of other vehicles. The chapter employs a new simulator for two sets of experiments, evaluating the performance of our algorithm under both low and high complexity scenarios. Comparative analysis is conducted against a traditional centralized model known as the "Green Wave" for intersection control.

This chapter introduces an extension of our proposal regarding the implementation of autonomous emergency vehicles. The chapter is divided into two sections focusing on experimentation (Experiments with low complexity and their conclusions - Experiments with high complexity and their conclusions). At this point, it is crucial to emphasize in our proposal that the priorities are outcomes emerging from interactions among vehicles as they navigate their routes. Consequently, autonomous vehicles, at the conclusion of their interaction, assume a behavioral role. This role establishes both temporal and spatial considerations for safely crossing intersections, thereby mitigating the risk of collisions and traffic blockages.

However, there are instances where the standard temporal and spatial considerations for safe intersection crossing may be overridden. This occurs when certain vehicles, designated for emergency response within a city, are granted priority without the need for preliminary interactions with other vehicles.

In light of the above, our scenario suggests that the behavioral role for a vehicle interacting with an autonomous emergency vehicle at an intersection includes a temporary pause to allow its passage, thus ensuring safety. This interruption should occur exclusively when the emergency vehicle is within the range of a radio communication broadcast by a vehicle assuming the "Negotiator" role. This approach aims to minimize disruptions to the regular traffic flow, as the new algorithm gives precedence to emergency vehicles.

Additionally, in this chapter, we will introduce a new simulator for vehicular traffic named SUMO (Simulation of Urban MObility). This open-source software provides a significant advantage in simulating microscopic traffic since it allows for individual modeling of each vehicle, complete with unique characteristics that allow us to introduce the management of priorities.

5.1 Emergency Vehicles Model

In this section, we will introduce the coordination model for emergency vehicles. As a refresher, the Distributed Interaction Model (DIM) has been described in Chapter 3.1. This model outlines how behavior roles emerge from interactions between autonomous vehicles. According to the DIM, vehicles are capable of following others and navigating intersections without predetermined priority, thereby avoiding collisions and blockages during their journeys.

In our specific context, the Emergency Vehicle Model maintains the same four-part composition discussed in Chapter 3.1. The following Algorithm 1 provides a succinct overview of the coordination process for crossing intersections, derived from interactions between autonomous vehicles. This is prior to the introduction of emergency scenarios. The algorithm specifically addresses how to determine which autonomous vehicle should proceed through an intersection in the event of a potential conflict with other vehicles.

5.1.1 Emergency Vehicles

An emergency vehicle a_E is designated with an emergency behavior role (E), granting it priority for intersection crossing over other vehicles. It is important to note that our assumption involves only two lanes in conflict at each intersection, without overtaking.

To define the behavior of emergency vehicles, it is essential to note that an emergency vehicle possesses the same communication systems as other regular vehicles. In other words, it is equipped with both a perception radius and a communication radius. Specifically, the perception radius P_r of an emergency vehicle a_E assuming a behavior role of (E) will be denoted as $P_r^{a_E}$, and the communication radius C_r of the same emergency vehicle a_E playing the behavior role of (E) will be denoted as $C_r^{a_E}$.

Algorithm 1 Coordination intersection crossing

Require: An autonomous vehicle a_i with role N_v.
Ensure: Cross the intersection; otherwise stop.

while a_i arrives at intersection k **do**
  Broadcast its distance and velocity over k
  if There is not a response by any vehicle **then**
    a_i can cross with priority the intersection k
  else
    a_i should evaluate crossing for avoiding collisions and block the intersection k
    if There is a fleet of autonomous vehicles crossing the intersection k in a conflicting way **then**
      a_i must remain stopped until the intersection k becomes clear
    else if There is a vehicle a_j that answers the broadcast message with 0 velocity and e position regarding the intersection k **then**
      a_i must remain stopped until the position e becomes clear to avoid blocking the intersection
    else if There is a vehicle a_j that answers the broadcast message with exactly the same conditions as a_i regarding the intersection k **then**
      a_i and a_j apply a negotiation protocol to decide which one gets the priority to cross the intersection.
    end if
  end if
end while

When an emergency vehicle a_E approaches an intersection k, it is granted priority for crossing the intersection, unless other vehicles are already crossing in a conflicting manner. To depict this behavior, a_E sends a broadcast message to vehicles within its communication radius $C_r^{a_E}$, identifying itself as an emergency vehicle. In response to this, the following situations may arise:

- If, after assuming a behavior role like N_v, the emergency vehicle a_E receives no response to its broadcast message, it proceeds to cross the intersection with priority.

- If other vehicles a_j, a_{j-1}, a_{j-2}, ..., a_{j-m} are already crossing the intersection in a street L_2, and an emergency vehicle a_E assumes a behavior role N_v or arrives within the communication radius of a vehicle N_v on its own lane L_1, the vehicle $N_v^{L_1}$ will send a priority message within its communication radius $C^{a_i}r$ to request emergency crossing to the vehicle $aj - m$ with a behavior role of $N_v^{L_2}$. If $N_v^{L_2}$ can stop before reaching the intersection k, the vehicle in lane L_1 will proceed. If $N_v^{L_2}$ cannot stop, an iteration will be made with the 'priority message' among the subsequent vehicles behind it until finding a $N_v^{L_2}$ vehicle that can stop.

- If two emergency vehicles arrive at the same time at the intersection k, each one in a different conflict way, therefore:

  1. If there are not any other vehicle already waiting at the intersection, then, both emergency vehicles take the same behavior of a negotiator role (i.e. they apply a negotiation protocol in order to take the decision about who has the crossing priority).
  2. If there are other vehicles waiting in the intersection, they follow the default behavior of a negotiator role until one of the emergency vehicles crosses the intersection.

It is important to note that emergency vehicles are only considered when they are within a specific radius. Consequently, the flow of the global traffic system is not influenced by emergency vehicles.

In high densities, when a street L_1 gains crossing priority for an emergency vehicle a_E over a conflicting street L_2, the behavior "stopped until" emerges. This implies that the vehicle $N_v^{L_2}$ will resume its movement only when a_E completes the intersection crossing.

5.2 Experiments

As described at the beginning of this chapter, the experiments section is divided into two subsections. Both experiments address the management of emergency vehicles in cities with varying densities to evaluate the performance of our algorithm compared to the ”Green Wave” model, (a centralized strategy). The difference lies in the additional parameters evaluated in the second subsection, where besides assessing our model, we investigate whether our model performs better in terms of waiting time at higher densities when the distance between intersections is increased, consequently generating more vehicle queues.

5.2.1 Results with low complexity

In this section we show several experiments focused on testing the performance of the emergency vehicles model. We used the SUMO simulator for urban mobility. SUMO provides functionalities to simulate traffic in cities composed by streets and intersections (Figure 5.1). For the purpose of these experiments, we considered four intersections for different traffic densities, ranging from 0 to 1. Emergency vehicles may appear with a prior probability of 1 vehicle per each 3600 vehicles.

In order to test the performance of the model proposed, we compare our DIM model for emergency vehicles with a Green Wave model, which is the traditional approach that provides a traffic intersection management based on traffic lights.

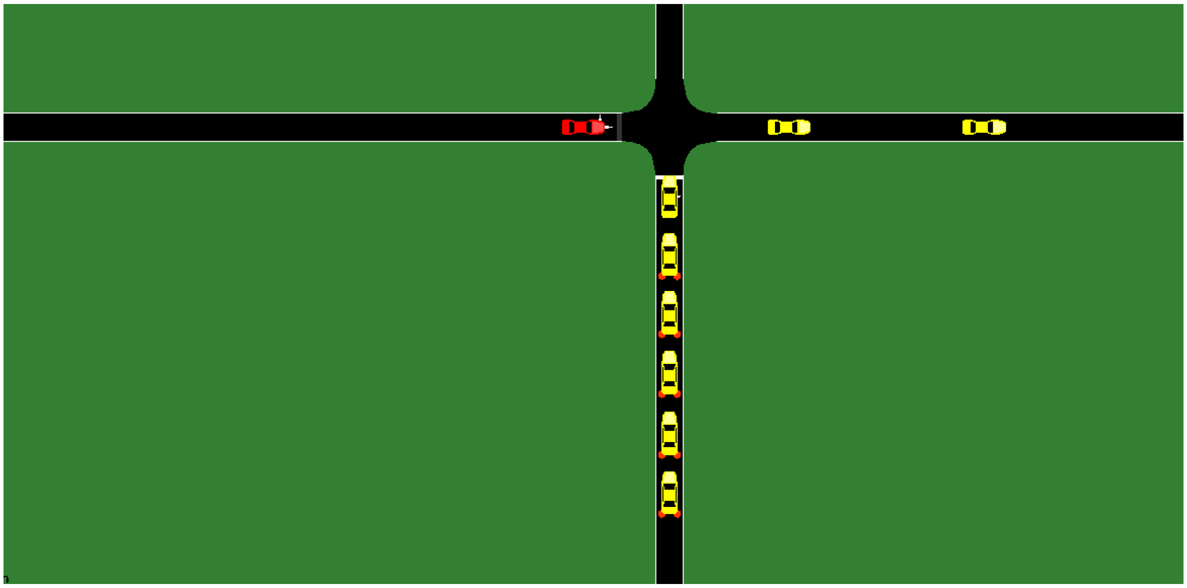
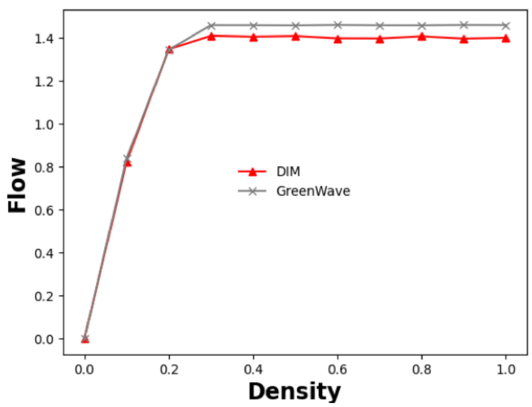


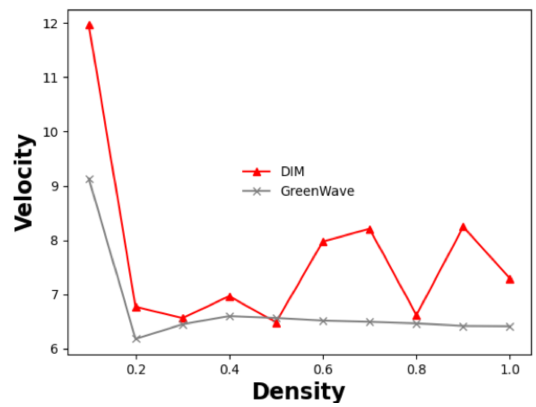
Figure 5.1: SUMO simulator showing an intersection with regular vehicles (yellow) and emergency vehicles (red).

In Figure 5.2, we show the performance of both models in cities without emergency vehicles. Figure 5.2a represents the traffic flow depending on the density of the city. As it can be observed, the flow increases in both models until a density of 0.3. From this density on, the traffic flow stabilizes. This can be explained since the intersections may be blocked for large values of traffic flow.

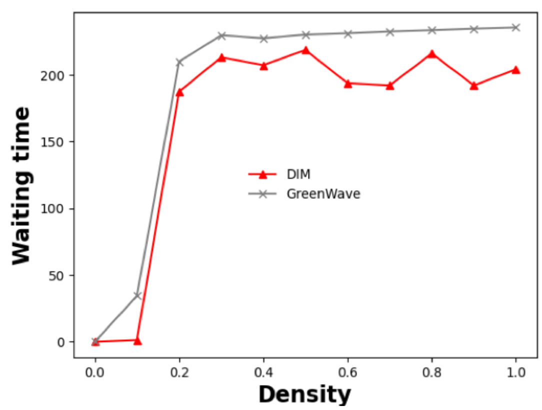
As it can be appreciated, the performance of the Green Wave model is slightly worse than DIM. This behavior is repeated in Figure 5.2b, which shows the average velocity of vehicles and in Figure 5.2c, which shows the average waiting time. Both variables, velocity and waiting time are slightly worse for the Green Wave model. This can be explained since the DIM model provides a coordination mechanism based on the traffic, which is adapted depending on the traffic scenario. In contrast, the Green Wave considers a fixed amount of time to give crossing priorities. This strategy may penalize blocked lines.



(a) Traffic flow.



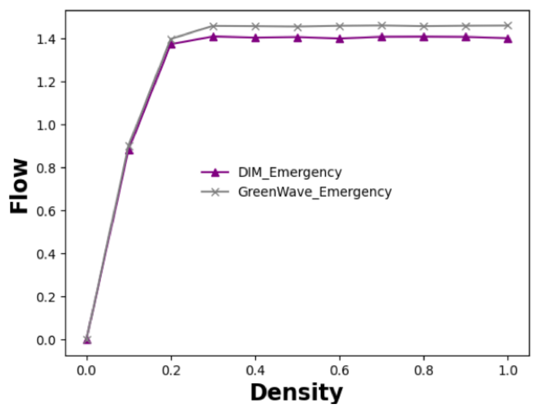
(b) Velocity.



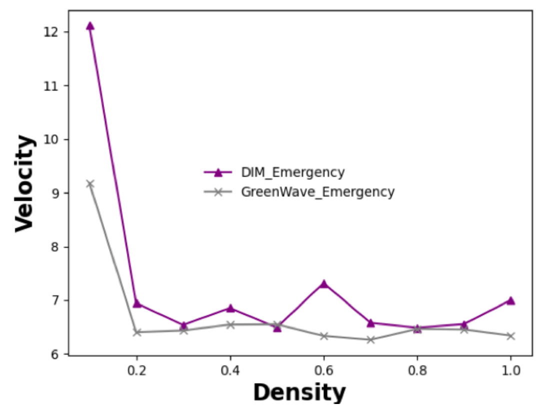
(c) Waiting time.

Figure 5.2: Models comparison without emergency vehicles

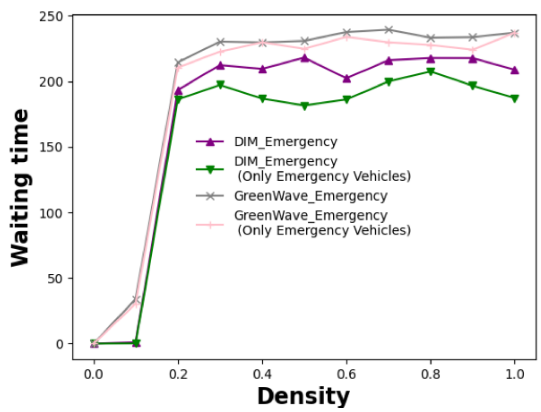
In Figure 5.3, it can be observed the performance of both models when emergency vehicles are introduced. Similar to the previous experiment, both the traffic flow and the velocity are quite stable from densities values higher than 0.2. In Figure 5.3c we can observe the average waiting time of emergency vehicles and the average waiting time of regular vehicles (i.e. non-emergency vehicles). As it can be observed, the Green Wave model does not give significant priority to emergency vehicles. In contrast, the DIM model provides a mechanism that allows the emergency vehicles to considerably reduce the average waiting time compared with the rest of vehicles. Moreover, these differences become significant when the traffic density is higher than 0.2.



(a) Traffic flow.



(b) Velocity.



(c) Waiting time.

Figure 5.3: Models comparison with emergency vehicles

Conclusions for low complexity experiments

Intersections represent point of conflict since autonomous vehicles from different lines need to cross. Centralised solutions provide coordination mechanisms in order to determine priorities for crossing. In addition, emergency vehicles are required to get the highest priority as possible when crossing the intersection. Therefore, distributed solutions that can adapt to changes in the environment (such as, traffic densities) are required.

In this chapter, we propose a distributed coordination management system that considers emergency vehicles. This system provides crossing mechanisms at intersections in a distributed fashion. According to the experiments, this model provides a better performance than other centralised approaches managed by traffic lights regarding variables such as traffic flow, velocity and waiting time. What is more, this performance is eventually better for emergency vehicles that require highest priorities than the rest of vehicles.

One assumption of our work is the consideration of one-way lines. In future works, we plan to extend this approach in order to consider several lines for each direction. This would be specially interesting when emergency vehicles are considered.

In general, in this algorithm, vehicles manage the crossing process by considering their proximity to the intersection and vehicle priority. As the density increases, vehicles initiate an initial negotiation, leading to the formation of a queue when a vehicle comes to a stop. When this queue surpasses a predefined threshold, the negotiator vehicle engages with the conflicting lane to announce the presence of a waiting convoy of vehicles. Subsequently, this convoy will proceed to cross the intersection. This approach ensures that the decongestion of the road is tailored to the queues of vehicles awaiting intersection crossing. The adaptability of this decongestion process is contingent upon the specific density of vehicles in that lane.

5.2.2 Results with high complexity

In this section, we show several experiments focused on testing the performance of the emergency vehicles model. We used again the SUMO simulator for the modelling of intermodal traffic systems. SUMO is an open-source, highly portable, microscopic, and continuous road traffic simulation package designed to handle large road networks. It allows for intermodal simulation, including pedestrians, and comes with a large set of tools for scenario creation. We used the 1.6.0 version of the simulator. SUMO provides functionalities to simulate traffic in cities composed of streets and intersections. For these experiments, we considered different types of cities. Firstly, we carried out experiments with cities with four and twenty-five intersections and different traffic densities, ranging from 0 to 1. Regarding emergency vehicles, we used two different percentages (1% and 9%) of emergency vehicles, which correspond to a prior probability of 36 per every 3600 vehicles, and 332 per every 3600 vehicles, respectively.

In order to test the performance of the model proposed, we compare our DIM model for emergency vehicles with a Green Wave model, which is the traditional approach that provides a traffic intersection management based on traffic lights.

In Figures 5.4, 5.5, 5.6, 5.7, 5.8 and 5.9, we show the performance of both models in cities without emergency vehicles. Figures 5.4, 5.5 and 5.6 represents the city with 4 intersections. The red line, represents the behaviour of the Green Wave model while the blue line represents the behaviour of the DIM model. In both models, three different parameters were evaluated for different ranges of traffic densities: the traffic flow, the velocity (in m/s), and the waiting time (in seconds).

It can be observed that the flow (see Figure 5.4) increases in both models until a density of 0.2. From this density on, the traffic flow stabilises. This can be explained since there are intersections that may be blocked for large values of traffic flow and this limits the traffic flow.

As it can be appreciated, the performance of the Green Wave model is slightly worse than DIM for both the velocity and the waiting time. This behaviour is showed in Figure 5.5 and 5.6, which show the average velocity of vehicles and the average waiting time, respectively.

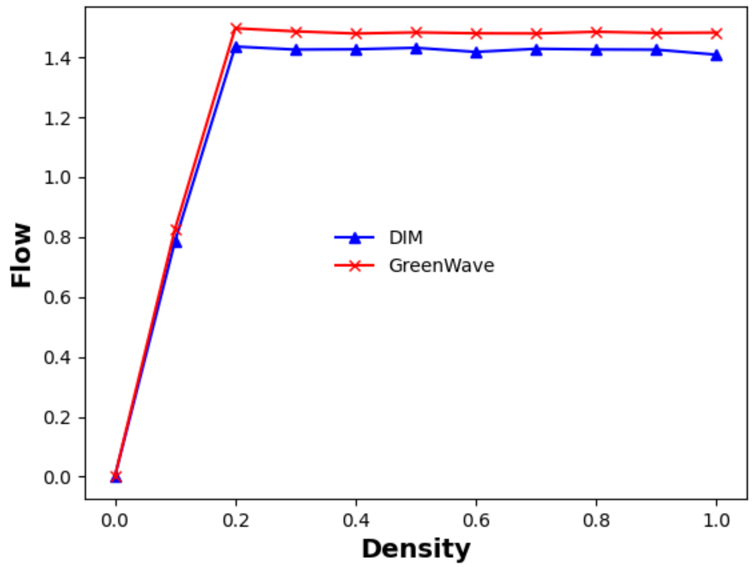


Figure 5.4: Flow vs Density on city with 4 intersections. Models without emergency vehicles.

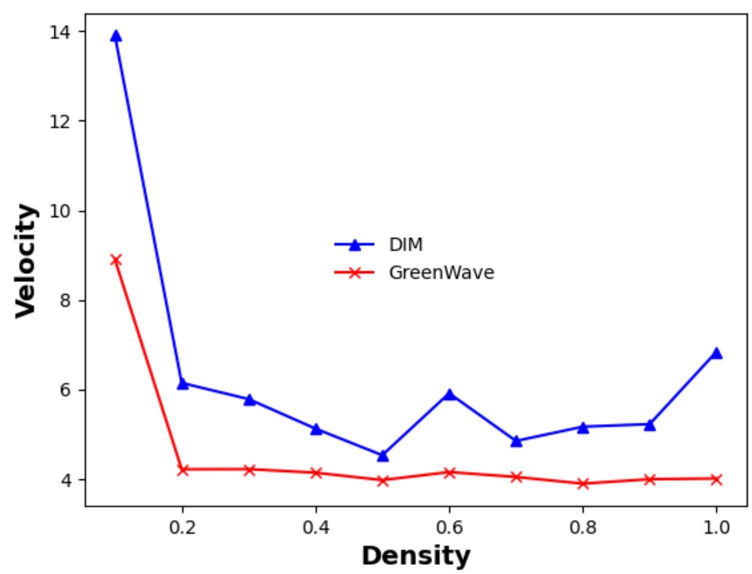


Figure 5.5: Velocity vs Density on city with 4 intersections. Models without emergency vehicles.

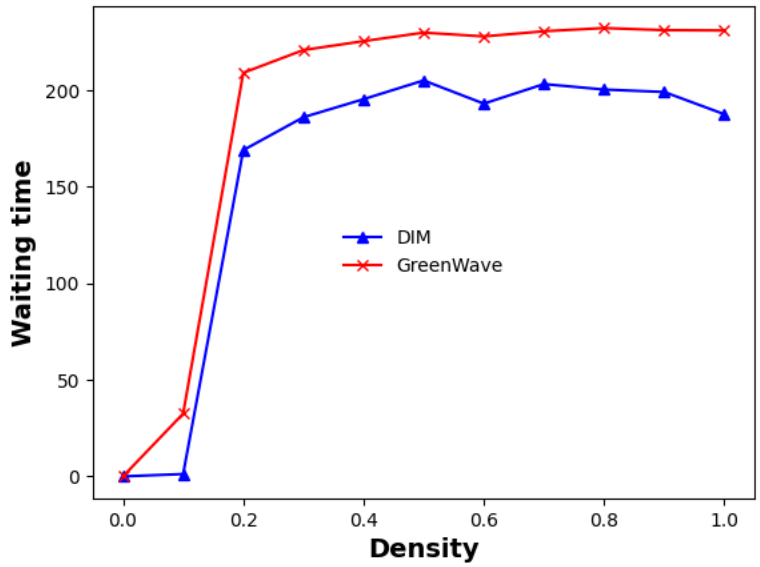


Figure 5.6: WaitingTime vs Density on city with 4 intersections. Models without emergency vehicles.

This can be explained since the DIM model provides a coordination mechanism based on the traffic, which is adapted depending on the traffic scenario. In contrast, the Green Wave considers a fixed amount of time to give crossing priorities. This strategy may penalise blocked lines.

Figures 5.7, 5.8 and 5.9, represents the city with 25 intersections. Regarding the traffic flow, the DIM model reaches a slightly higher flow from densities between 0.2 and 0.5. This can be explained due to the city is bigger than the previous case and therefore, some vehicles do not find blocked intersections in a way conflict, causing that these vehicles do not stop. After a density of 0.5, both models are stabilised by the same condition mentioned for the previous city. Comparing both models, it can be observed that the DIM model is more scalable than the Green Wave since the performance of the later decreases when the size of the city increases.

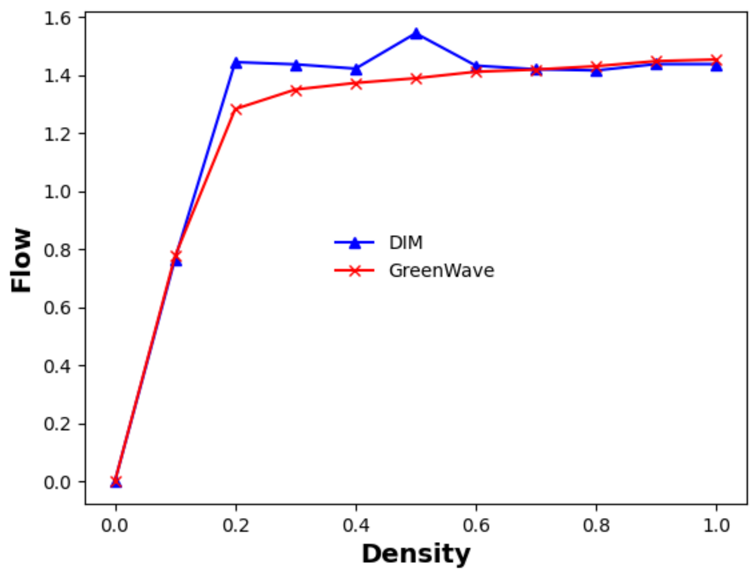


Figure 5.7: Flow vs Density on city with 25 intersections. Models without emergency vehicles.

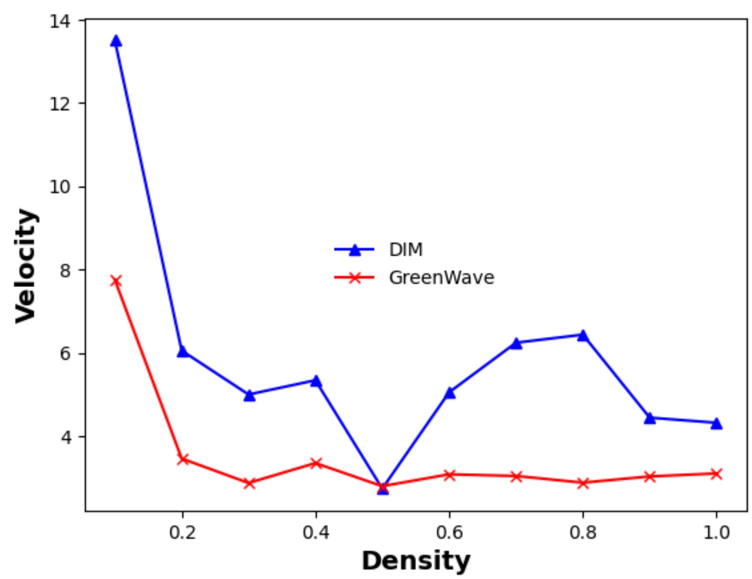


Figure 5.8: Velocity vs Density on city with 25 intersections. Models without emergency vehicles.

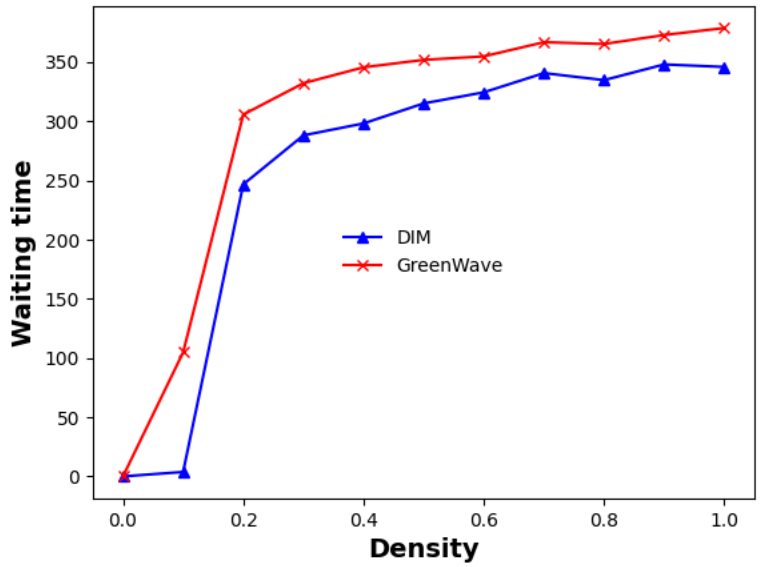
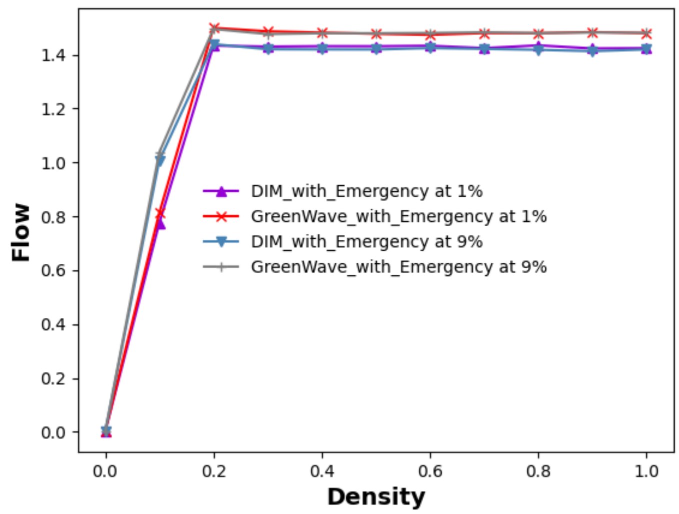


Figure 5.9: WaitingTime vs Density on city with 4 intersections. Models without emergency vehicles.

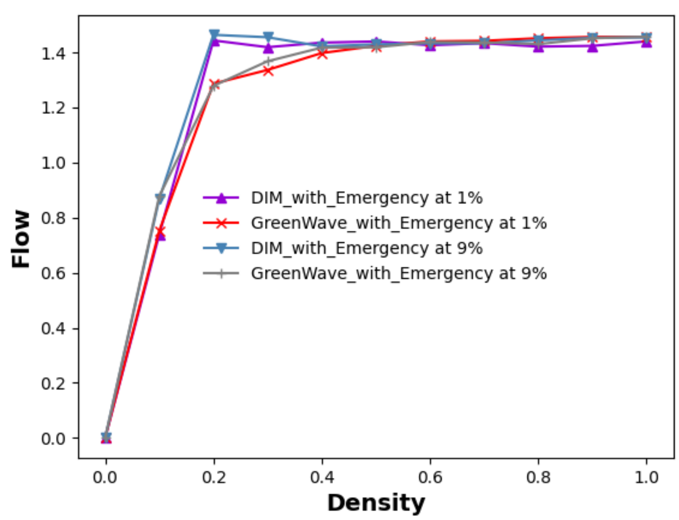
In a similar way than the city of 4 intersections, the performance of the Green Wave model is slightly worse than DIM model for both velocity and waiting time for the city of 25 intersections. However, the trend of the waiting time is to increase as the density increases. This increase in a larger city can be explained since as the density increases, vehicles are required to wait longer periods of time in order to cross each intersection, what causes a higher traffic congestion. Nevertheless, differences between DIM and Green Wave are even considerable.

Figures 5.10 and 5.11 show the performance of both models in cities with emergency vehicles at 1% and 9%. In Figures 5.10a and 5.10b we can observe the traffic flow for cities with 4 intersections and 25 intersections respectively. Similar to the previous experiments, in the city with 4 intersections the traffic flow stabilises from density values higher than 0.2. In addition, the scalability of DIM is better than Green Wave when the city size increases.

Regarding the velocity, the difference between the performance of both models is higher for the city with 25 intersections(See figure 5.11b). As it can be observed, the velocity of DIM increases as the city size increases, while the city size do not affect the performance of the velocity for the Green Wave model. As it can be observed, when the rate of emergency vehicles is higher (9%), the velocity tends to progressively decrease in the largest city.

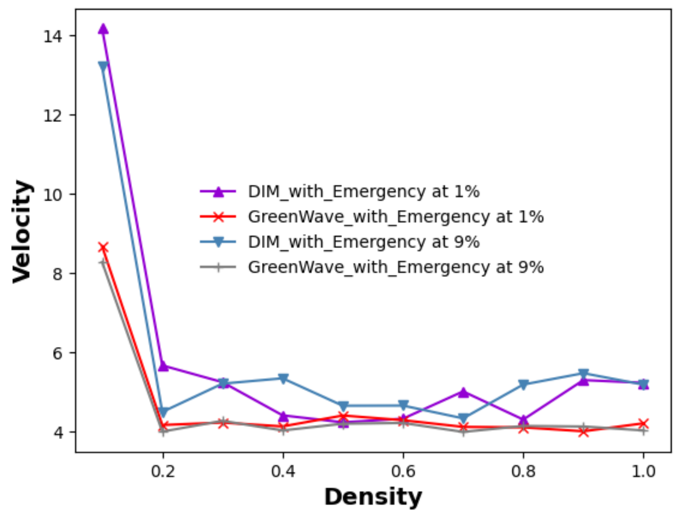


(a) Flow vs Density on city with 4 intersections.

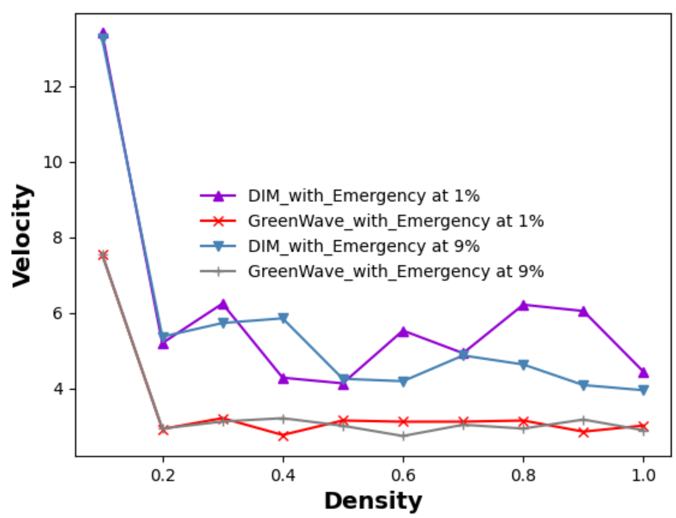


(b) Flow vs Density on city with 25 intersections.

Figure 5.10: Models comparison in flow, with emergency vehicles at 1% and 9% on two different cities.



(a) Velocity vs Density on city with 4 intersections.



(b) Velocity vs Density on city with 25 intersections.

Figure 5.11: Models comparison in velocity, with emergency vehicles at 1% and 9% on two different cities.

In Figures 5.12, 5.13, 5.14, and 5.15, we show the average waiting time of emergency vehicles and regular vehicles (i.e. non-emergency vehicles) for the two sizes of cities and for 1% of emergency vehicles (See figures 5.12 and

5.13) and 9% of emergency vehicles (See figures 5.14 and 5.15).

In the city with 4 intersections, the Green Wave model does not give significant priority to emergency vehicles. In contrast, the DIM model provides a mechanism that allows the emergency vehicles to considerably reduce the average waiting time compared with the rest of vehicles. Moreover, these differences become significant when the traffic density is higher than 0.2. In the largest city, the waiting time of both models increase as the density increases.

In a similar way to the previous experiments, the increase in traffic causes that vehicles need to wait larger amounts of time, even emergency vehicles. This may be a limitation when only one-way lines are considered. In addition, it can be also appreciated that for the DIM model, differences between emergency and regular vehicles are shorter when the city size increases. The percentage of emergency vehicles does not considerably influence the differences between both models.

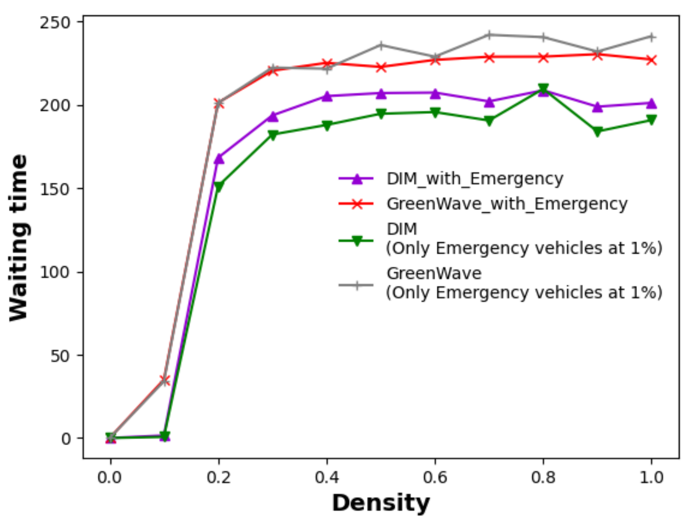


Figure 5.12: WaitingTime vs Density on city with 4 intersections and 1% Emergencies

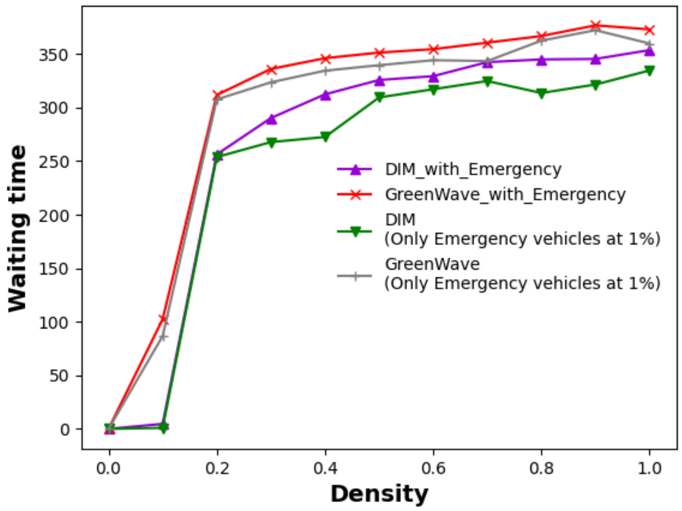


Figure 5.13: WaitingTime vs Density on city with 25 intersections and 1% Emergencies.

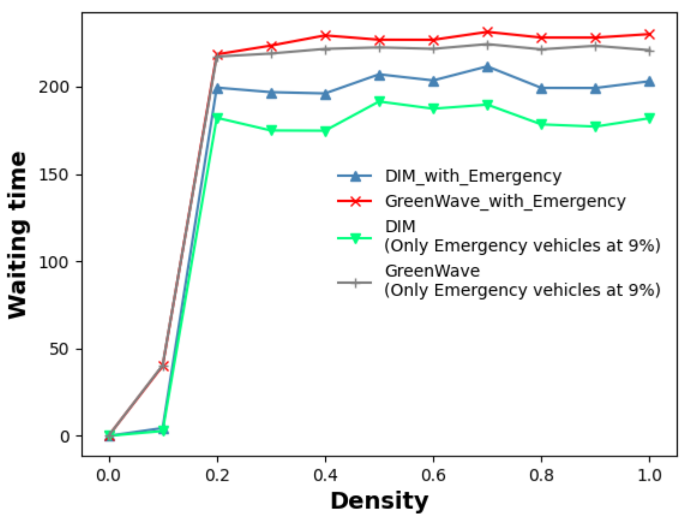


Figure 5.14: WaitingTime vs Density on city with 4 intersections and 9% Emergencies.

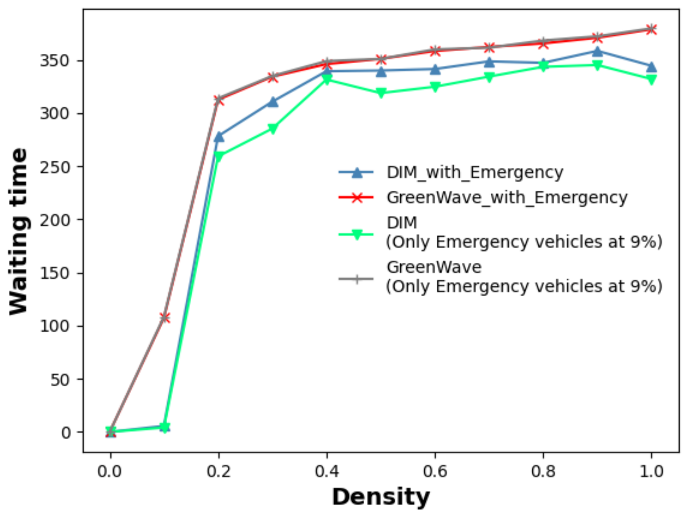


Figure 5.15: WaitingTime vs Density on city with 25 intersections and 9% Emergencies.

Following, we carried out different experiments in order to test the queues and halted vehicles. To do this, we used cities of four and sixteen intersections with high density values (0.7 and 0.9). In addition, we also changed the distance between intersections for 200, 500, and 700 meters between each intersection. In these experiments, we fixed the value of emergency vehicles to 1%.

In these experiments, we measured the following parameters:

- Queue length: this parameter shows the average length of queues when a negotiator vehicle (the first of the queue) starts the movement to cross the intersection.

- Halted vehicles: this parameter shows the percentage of vehicles halted (velocity = 0) from the whole number of vehicles of the city. This value is obtained as an average from each step of the execution.

Tables 5.1, 5.2, and 5.3 show the queue lengths and halted vehicles in cities with 200, 500, and 700 meters between intersections, respectively. According to these results, the distance between intersections does not influence the

		DIM		Green Wave	
		Densities			
Size	Parameters	0.7	0.9	0.7	0.9
4	Queue length	1.805 ± 0.009	1.717 ± 0.007	2.981 ± 0.024	3.010 ± 0.024
	Halted vehicles	55.17%	53.57%	60.01%	60.37%
16	Queue length	1.696 ± 0.006	1.733 ± 0.005	2.654 ± 0.02	2.641 ± 0.02
	Halted vehicles	51.58%	61.66%	55.98%	55.76%

Table 5.1: Queue lengths and halted vehicles in cities with 200 meters between intersections.

		DIM		Green Wave	
		Densities			
Size	Parameters	0.7	0.9	0.7	0.9
4	Queue length	1.603 ± 0.009	1.215 ± 0.008	2.791 ± 0.02	2.834 ± 0.02
	Halted vehicles	54.48%	52.81%	59.12%	59.37%
16	Queue length	1.647 ± 0.006	1.758 ± 0.007	2.792 ± 0.018	2.788 ± 0.018
	Halted vehicles	51.74%	52.81%	53.20%	53.28%

Table 5.2: Queue lengths and halted vehicles in cities with 500 meters between intersections.

		DIM		Green Wave	
		Densities			
Size	Parameters	0.7	0.9	0.7	0.9
4	Queue length	1.757 ± 0.009	1.476 ± 0.007	2.449 ± 0.02	2.427 ± 0.02
	Halted vehicles	54.65%	54.10%	59.46%	59.33%
16	Queue length	2.097 ± 0.006	1.907 ± 0.005	2.282 ± 0.02	2.159 ± 0.019
	Halted vehicles	53.16%	53.10%	53.55%	53.35%

Table 5.3: Queue lengths and halted vehicles in cities with 700 meters between intersections.

performance of the DIM model as it influences the performance of the Green Wave. This can be explained since the coordination in the DIM model emerges from the interaction between those vehicles required to cross the intersection, which consists of a balanced fashion depending on the traffic and density of vehicles.

Conclusions for high complexity experiments

In this chapter, a distributed coordination management system that considers the prioritisation of emergency vehicles has been proposed. The proposed system is able to provide a crossing strategy of vehicles at intersections in a distributed manner through the establishment of behavioural rules. According to the experiments, the proposed system provides better performance than other centralised approaches modelled in traffic lights. In particular, the tests have been carried out taking into account aspects such as the traffic flow, the average speed of vehicles, and their waiting time at intersections. The performance obtained is eventually better for emergency vehicles, which have a higher priority than the other vehicles, without generating excessive delays for the rest of the vehicles. The tests were carried out on various configurations with respect to the number of existing intersections. As future work, it would be interesting to include other factors that make the simulation closer to real scenarios, such as unbalanced densities in lines depending on the hour and day, several lines per each direction, or failures and reparation of damages that requires to make useless a lane.

One assumption of our work is the consideration of one-way lines. Even the performance of the distributed model is better than centralised approaches; this may be a limitation when the city size increases. According to the experiments, differences between the waiting time of regular and emergency vehicles are shorter for large cities and densities. Therefore, we plan to extend this approach to consider several lines for each direction in future works. This would be especially interesting when emergency vehicles are considered since the traffic could be released in one line when needed to prioritise emergency vehicles.

5.3 Conslusions

In the first section, we introduced an extension of our DIM algorithm to accommodate emergency vehicles, proposing a new behavior arising from interactions with such vehicles. One key aspect of these interactions is the recognition of emergency vehicles only when they are within the communication radius of the N_v vehicle. By employing this approach, our algorithm ensures that the balance of vehicle queues is maintained even when priority is assigned to streets with emergencies. This mechanism allows for efficient traffic flow management, as it minimizes disruptions caused by emergency vehicles while still ensuring timely responses to emergency situations. By integrating this feature into our algorithm, we enhance the overall robustness and adaptability of our traffic control system.

In the second part of our study, we delve into two comprehensive experiments aimed at evaluating the efficacy of our emergency management system compared to the traditional centralized “Green Wave” approach. Our investigations shed light on the nuanced dynamics of urban traffic control, particularly in scenarios where emergencies play a crucial role.

In the first experiment, we meticulously analyze the performance of our model across different city layouts, focusing on Manhattan-style configurations. Our findings reveal a compelling advantage of our approach: significantly reduced waiting times for both normal vehicular traffic and emergency vehicles when compared to the centralized “Green Wave” model. This outcome underscores the efficiency and adaptability of our distributed algorithm in dynamically managing traffic flows and prioritizing emergency response.

Building upon these results, our second experiment into more complex scenarios, exploring the impact of varying emergency vehicle percentages, street lengths, and high-density conditions. Despite the heightened challenges posed by these factors, our model consistently outperforms the traditional approach across all metrics, particularly in mitigating waiting times. Importantly, we observe that the extension of street lengths does not significantly affect our model’s ability to handle queues and emergencies efficiently.

Overall, these comprehensive experiments provide robust evidence of the effectiveness and scalability of our proposed algorithm. By seamlessly integrating emergency management capabilities into our distributed framework, we offer a promising solution to the evolving challenges of traffic control at intersections.

Chapter 6

Implementation of DIM algorithm in high-complexity environments: Multi-lane cities.

"The complex develops out of the simple." – Colin Wilson.

Abstract

This chapter presents an extension of our proposed algorithm to accommodate environments with a higher quantity of interactions, transitioning from single-lane cities to multi-lane cities. The algorithm incorporates new behavioral roles resulting from interactions between vehicles on the same street and vehicles on adjacent streets (conflicting points). These additional interactions contribute to the emergence of a global behavior, where vehicles, depending on density, cross intersections in groups of two different sizes. The simulations implement three different density distributions to observe the algorithm's global performance in controlling traffic at intersections.

Building upon the insights gained from the previous chapters, which demonstrated the evolution of our DIM algorithm across various scenarios of interactions among autonomous vehicles in single-lane cities, this chapter expands the scope by introducing a greater variety of interactions through an increase in the number of lanes per street.

Considering the dynamic nature of vehicular traffic in real-world scenarios, traffic flow shows varying densities, particularly during peak hours. The tests conducted on our algorithm will adhere to this realistic behavior, maintaining the logic that includes evaluating its global performance by introducing several lanes per street. This assessment encompasses efficient queue management, especially in high-density conditions.

Therefore, for the experiments, we introduce three types of probability distributions for the appearance of autonomous vehicles on simulation lanes —termed “biased”, “uniform”, and “random”— will be introduced. This will allow us to observe the global emerging behavior in traffic flow performance as the density of vehicles increases from low to high.

6.1 Multi-lanes

As mentioned earlier, the objective of this chapter is to explore a greater quantity of interactions between autonomous vehicles to understand the capabilities of our algorithm in complex environments. Consequently, in the simulation, cities will be constructed with three lanes (see Figure 6.1) on each street. All lanes will share the same features within the city, without any form of priority. This ensures that every autonomous vehicle will commute through the lanes without overtaking and without having an advantage over others.

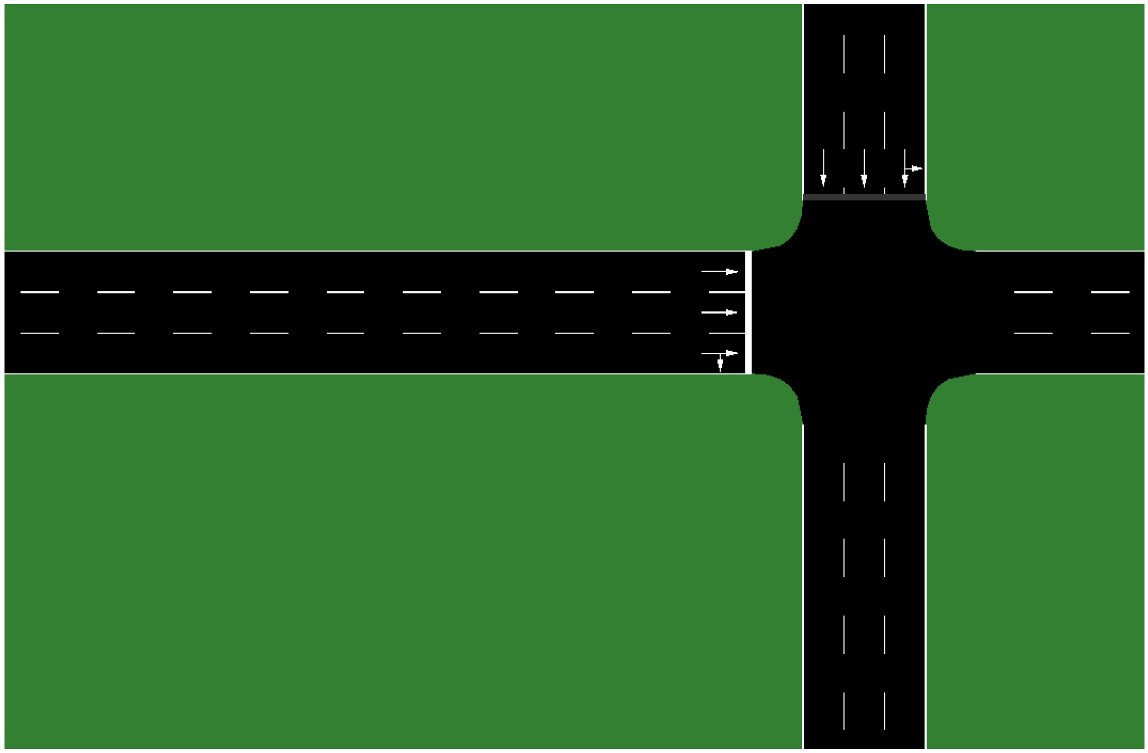


Figure 6.1: A multi-lane street in the SUMO simulator.

While our model is not constrained by a specific number of lanes due to its scalability in environments with high interaction complexity, the decision to incorporate three lanes in the road networks of all cities for testing purposes was motivated by the aim to achieve a more comprehensive understanding of interactions. In this instance, the motivation behind this decision was to establish an initial version capable of exploring a broader range of interactions, beyond simply adding one extra lane to our initial implementation.

6.2 DIM algorithm in multi-lanes

In this section, additional behaviors and necessary interactions for safely navigating intersections without collisions or blockages will be presented. This discussion is based on the algorithm introduced in Section 3.1 of Chapter 3.

6.2.1 New behavioral role

As seen in Section 3.1.4, an autonomous vehicle can assume two different roles: Follower F_v and Negotiator N_v. In the case of multiple lanes, it becomes necessary to introduce a new behavioral role, where autonomous vehicles can achieve enhanced information management and deduce situations about the "street status".

Super negotiator role

The Super Negotiator role (represented as SN_v) is very similar to a N_v, with the distinction that a N_v can transition to the SN_v status by checking through a broadcast message if there are no other autonomous vehicles in different lanes of the same street closer to intersection k in comparison to itself (see Figure 6.2).

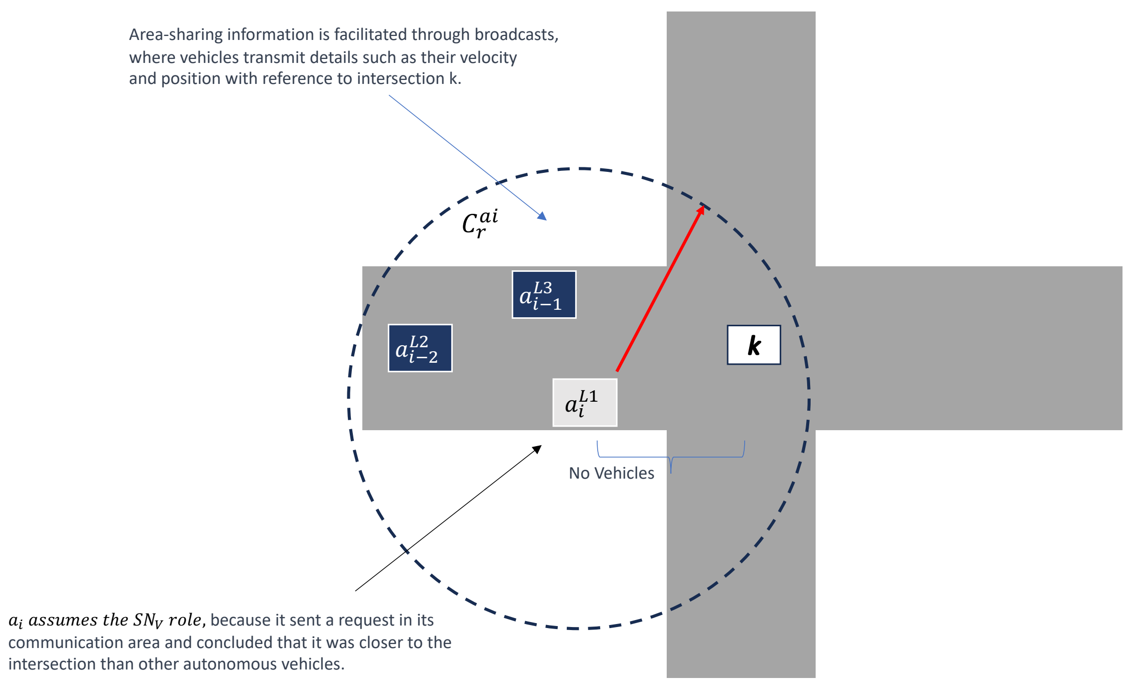


Figure 6.2: a_i is a vehicle in role SN_v

Now, for a street with multiple lanes, the characteristics shown in Equation (6.1) will be considered.

$$a_i \text{ with role } = \begin{cases} SN_v \text{ in a lane } a_i^{L_1} \\ \text{as many } N_v\text{'s as there are remaining lanes} \neq a_i^{L_1} \end{cases} \tag{6.1}$$

Therefore, each street will have multiple N_v, corresponding to the number of lanes it has. However, it will only have one SN_v if it fulfills the specified conditions.

6.2.2 Negotiation between autonomous vehicles (multi-lanes)

In this section, additional interactions primarily involving vehicle $a_i = SN_v$ with its own street and the conflicting street will be presented. Although other autonomous vehicles with the role $a_i = N_v$ and role $a_i = F_v$ will remain the same interactions as in single-lane cases (see section 3.1.5), the negotiation with the other conflicting street will be exclusive to $a_i = SN_v$. This allows SN_v to deduce, based on the density of vehicles, whether to request to cross with different-sized groups of autonomous vehicles or convoys.

Thus, attention will only be put to interactions linked to the behavior of SN_v, which oversees the negotiation process for crossing intersections (low and high densities) and facilitates consensus among vehicles on the same street, preventing isolated decision-making (Timeout, Free to pass, Avoid intersections blocking, Safe crossing).

Reach priority to cross in low densities (multi-lanes)

If a vehicle a_i assumes the role of SN_v in lane L_1, it will initiate the same interaction as detailed in Section 3.1.5, initiating a broadcast to start the negotiation process based on "first come, first served" (FCFS). However, in addition to this, SN_v will also broadcast within its communication radius $SC_r^{a_i}$ downstream, with the intention of transmitting its status to the other

N_v vehicles in the remaining lanes of its street. This is because the other N_v vehicles in the remaining lanes (L_2, L_3,...,L_u) will adopt the same status as the SN_v (see Equation (6.2)).

In addition, the crossing of Super negotiator follows Equation (6.2).

$$a_i = SN_v = \begin{cases} \text{Crossing the intersection, If it gains the priority} \\ \text{Stop before of the intersection, If it loses the priority} \end{cases} \tag{6.2}$$

In both scenarios, the SN_v in equation (6.2) broadcasts its status to the other N_v vehicles on its street, signaling them to proceed or stop accordingly. The reason for this is that, despite operating on a first-come, first-served basis in low-density scenarios, multi-lane streets that lose priority for quick crossing begin to form queues.

Reach priority to cross in high densities (multi-lanes)

As seen in Section 3.1.5, the resolution of priority crossings at intersections in single-lane scenarios is similar to the approach in multi-lane situations. However, there are some differences since each N_v vehicle iterates to check its own lane through a request message within its communication radius. Simultaneously, the SN_v sends a request message within its communication radius to know the status of its N_v vehicles on its street.

With the above, the crossing of intersections with streets in high densities is divided into two parts:

Now, there are two types of thresholds. The first one is ϵ (used in single-lane) to determine if the number of responses from F_v vehicles behind either N_v or SN_v has exceeded the ϵ threshold, indicating a complete convoy. The second threshold is ω, which indicates if there are a number of responses in all lanes of the street. It should be less than the sum of the thresholds ϵ but greater than 75% of the total.

Thus, in terms of global behavior, the threshold ϵ helps to assess if there is a convoy in any lane, while the threshold ω helps to evaluate if there is a number of autonomous vehicles in a jam throughout the entire street, without completing a convoy in any lane.

The interest in using the proposal of these two thresholds (ϵ and ω) lies in giving the SN_v vehicle the ability to deduce the type of request it should send in the broadcast message to the conflicting street to achieve the priority of crossing with a certain size of a group of vehicles or others.

Timeout (multi-lanes)

In the case of a timeout in multi-lanes, the resolution is equivalent to the timeout resolution in a single lane, with the unique difference that the SN_v transfers its status to the other autonomous vehicles with the role N_v in the same street (see Equation (6.3)):

$$a_i = SN_v = \begin{cases} \text{If it loses the negotiation, it signals other } N_v \text{ vehicles in its street to yield} \\ \text{If it exceeds time threshold } t_\mu \text{, signals other } N_v \text{ vehicles to prioritize crossing} \end{cases} \tag{6.3}$$

The threshold t_μ signifies the maximum stop time for SN_v, indicating that it has not found the required quantity of interactions (messages) with other vehicles in its street to prioritize crossing the intersection.

Avoid intersection blocked (multi-lanes)

As explained in Section 3.1.5, the interactions for avoiding blocked intersections involve checking, either through communication or within the perception radius, if, after intersection k in the next street, there is a stationary autonomous vehicle within a short distance e.

In the case of multi-lanes, if the autonomous vehicle with the role of SN_v in lane L_1 detects a stopped autonomous vehicle in the distance e while approaching the intersection, regardless of the lane, SN_v will be stopped before intersection k.

This vehicle then sends a downstream broadcast on its street to the other N_v vehicles in the remaining lanes (L_2, L_3,...,L_u), signaling to yield. Additionally, even if any lane L_{u+1} is free after intersection k, if there is still a stationary vehicle within the distance e, SN_v will maintain its stopped status.

In other words, the street will remain stopped until space e is cleared in one or more lanes of the street in front of intersection k. Finally, if in both directions or streets there are autonomous vehicles stopped within their distances e, regardless of the lane, both streets will remain closed (even though any SN_v has surpassed the threshold stopped time t_μ) until space is released.

Free to pass

This section will explain the type of interaction added to our algorithm to enhance its robustness against autonomous vehicles with higher velocity that arrive late to a group or convoy that has started or is crossing the intersection but has not yet completed the crossing.

From a global perspective of traffic, it can be observed how a vehicle needs to determine before a group of vehicles finishes crossing the intersection if it can integrate into that group or convoy to facilitate its passage through the intersection.

In this way, after checking if the vehicle, which has a certain velocity and travels through an uncongested lane, meets the necessary conditions, it could join the group of vehicles and facilitate its passage; otherwise, it will have to start slowing down before the intersection.

Therefore, when an autonomous vehicle a_{i-n} (traveling at a constant velocity) is moving along a lane L_u without congestion and appears to be able to reach a group or convoy of vehicles that is either starting or finishing crossing the intersection but has not yet completed the crossing:

$$a_{i-n} = \begin{cases} \text{Cross the intersection, If } Len(a_{i-n}) \leq (\delta_{Pass} + \theta) \\ \text{Stop before intersection } k, \text{ If } Len(a_{i-n}) > (\delta_{Pass} + \theta) \end{cases} \tag{6.4}$$

For Equation (6.4), it is necessary to clarify that the threshold δ_{Pass} represents the distance comparison between the last vehicle $Last_{veh}$ of the group or convoy and the intersection k. Additionally, $Len(a_{i-n})$ is the distance of the a_{i-n} with respect to the intersection k. In our case, to achieve the "Free to Pass" status, an additional factor θ (additional distance or minimum gap) is introduced. Therefore, by setting $\delta_{Pass} = Len(Last_{Veh})$, if $Len(a_{i-n})$ is less than or equal to $Len(Last_{Veh}) + \theta$, then the a_{i-n} vehicle can attain the "Free to Pass" status (See Equation (6.5)).

$$(Len(Last_{Veh}) + \theta) - Len(a_{i-n}) \geq 0 \tag{6.5}$$

Safe crossings

When any autonomous vehicle, either a_i or a_j, playing the role of SN_v, sends a broadcast downstream to their N_v counterparts to come to a stop, and if any N_v cannot stop before intersection k, the SN_v does not stop. Before crossing the intersection, it will send a message downstream to the next SN_{v-1} and so on, until the message can find a SN_{v-z} with responses from all N_v vehicles that they can stop.

While this is happening, the SN_v in the conflicting street, who obtained the "priority pass" to cross the intersection k, remains stopped without relaying the message to their N_v vehicles to proceed.

In conclusion, in the algorithm 2 is described the interactions of our model by autonomous vehicles in cities with multi-lanes including all the new rules.

As observed in Algorithm 2, the behavior of the SN_v vehicle involves broadcasting its status after evaluating its interactions with SN_v vehicles from adjacent streets in conflict, as well as interactions with its N_v vehicles on its street and the F_v vehicles beyond the intersection within a distance e.

Depending on the outcome of these interactions, the status of the SN_v vehicle is determined as either "gaining priority" or "yielding".

Algorithm 2 Coordination intersection crossing in cities with multi-lane

Require: Autonomous vehicles $a_i^{L_1}$ and $a_j^{L_1}$ with role SN_v respectively.
Require: Autonomous vehicles $(a_{i-1}^{L_2}, a_{i-2}^{L_3}) and (a_{j-1}^{L_2}, a_{j-2}^{L_3})$ with role N_v respectively.
Ensure: Cross the intersection; otherwise stop.

while $a_i^{L_1}$ arrives at intersection k **do**
  Broadcast message about its distance and velocity over k
  if There is not a response by any vehicle **then**
    $a_i^{L_1}$ change its status to cross with priority the intersection k
    $a_i^{L_1}$ broadcasts a message downstream, conveying its status to the N_v vehicles for them to replicate its status.
  else
    $a_i^{L_1}$ should evaluate crossing with its interactions rulers for avoiding collisions, block the intersection k or if it exceeds time threshold t_μ
    if There is a $a_{i-n}^{L_u}$ vehicle appears to be able to reach a group or convoy of vehicles and the distance $Len(a_{i-n})$ is less than or equal to $Len(Last_{Veh}) + \theta$ **then**
      the $a_{i-n}^{L_u}$ vehicle can achieve the "Free to Pass" status and cross while attached to the convoy.
    else
      the $a_{i-n}^{L_u}$ stop before intersection k
    else if There is a group or convoy of autonomous vehicles crossing the intersection k in a conflicting way **then**
      $a_i^{L_1}$ must remain stopped until the intersection k becomes clear
      $a_i^{L_1}$ broadcasts a message downstream, conveying its status to the N_v vehicles for them to replicate its status.
    else if $a_i^{L_1}$ detects a stopped autonomous vehicle in the distance e while approaching the intersection, regardless of the lane. **then**
      $a_i^{L_1}$ must remain stopped until the position e becomes clear to avoid blocking the intersection
      $a_i^{L_1}$ broadcasts a message downstream, conveying its status to the N_v vehicles for them to replicate its status.
    else if There is a vehicle $a_j^{L_1}$ that answers the broadcast message with exactly the same conditions as $a_i^{L_1}$ regarding the intersection k **then**
      $a_i^{L_1}$ and $a_j^{L_1}$ apply a negotiation protocol to decide which one gets the priority to cross the intersection.
      $a_i^{L_1}$ and $a_j^{L_1}$ broadcasts a message downstream, conveying its status to the N_v vehicles for them to replicate its status.
    end if
  end if
end while

6.3 Experiments

6.3.1 Vehicle occurrence density distribution per lane.

In contrast to experiments conducted on a single lane, the use of multiple lanes intensifies the quantity of interactions between autonomous vehicles, even without lane changes. To comprehensively evaluate the global performance of our algorithm as vehicle density increases from low to high levels, three types of *density distributions* were proposed for the occurrence of autonomous vehicles in each lane:

- The first type of density distribution is termed "Uniform". This designation arises from the fact that, for a given street density ρ_i, each lane independently and belonging to that street exhibits the same density trend, denoted as ρ_i, with some variability (see Figure 6.3).

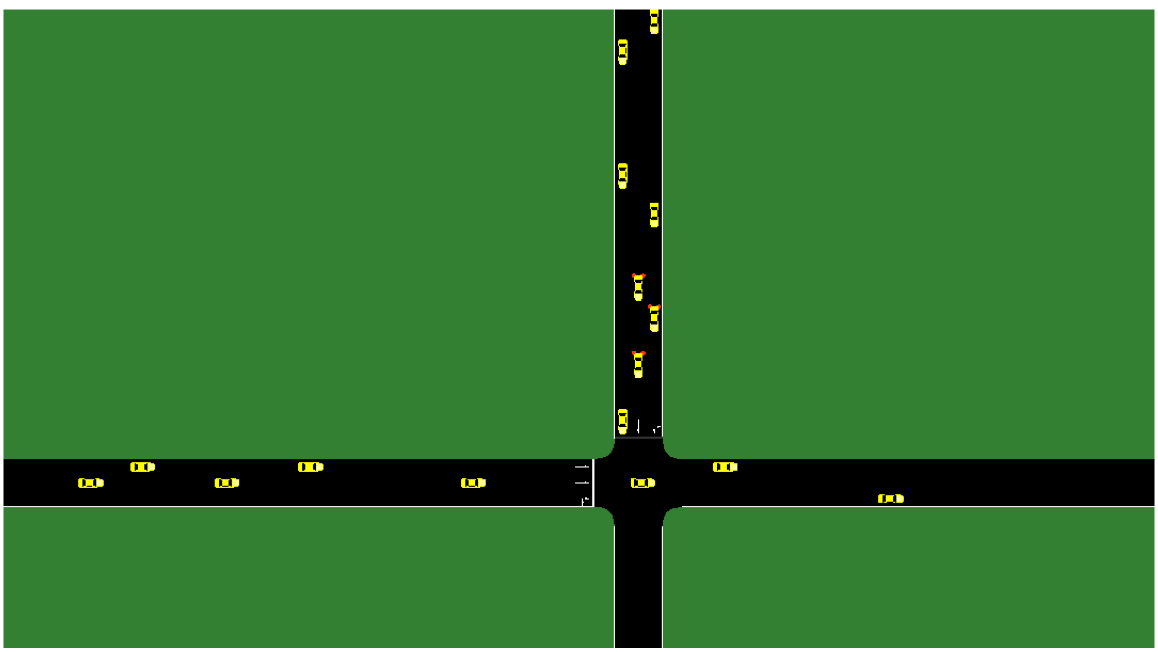


Figure 6.3: "Uniform" density distribution at 30% per street

- The second type of density distribution is termed "Biased". This nomenclature is chosen because, to generate a certain density ρ_i for a street, a specific lane (always the right lane) will consistently have a higher proportion (bias factor = ϕ) over ρ_i, while the remaining density is distributed in the same proportion across the other lanes, respectively, and with variability in all lanes (see Figure 6.4).

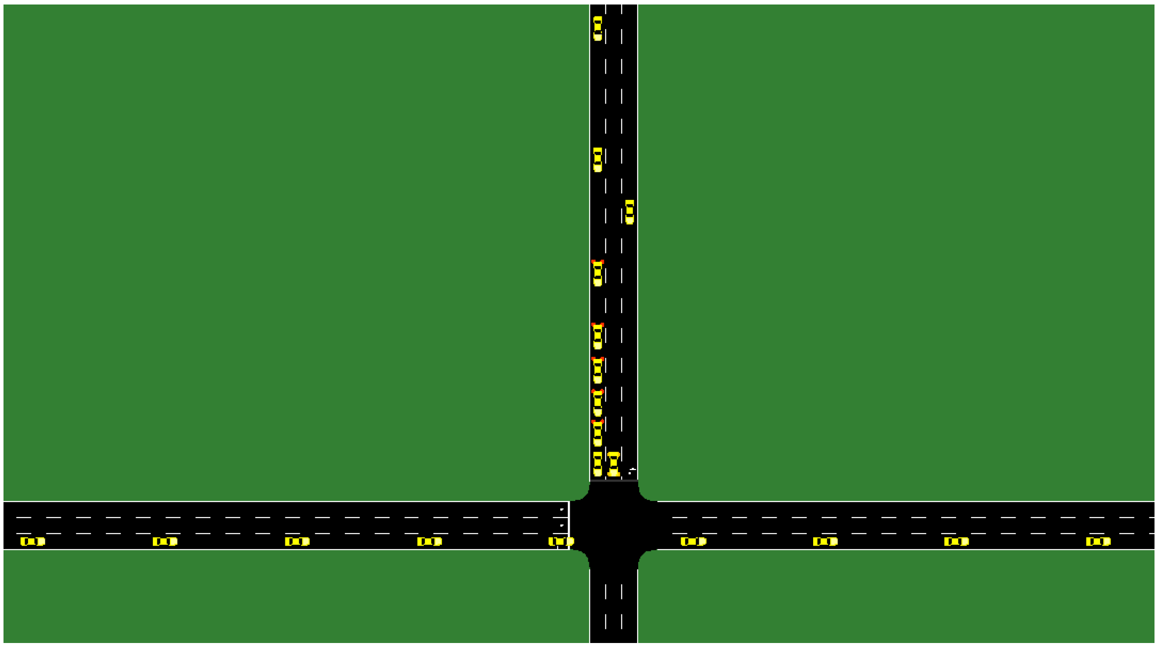


Figure 6.4: "Biased" density distribution at 30% per street

- The last type of density distribution is termed "Random". This name is derived from the approach of selecting densities for lanes within a given street. For a specified street density ρ_i, a random function with a uniform probability distribution between the range $[0, 1]$ is employed for the first lane according to ρ_i. In subsequent iterations, the density of the next lane takes into account the remaining density, applying the same probability distribution to assign the density according to ρ_i and so on and so forth with the other lanes (see Figure 6.5).

By employing these three types of density distributions in our algorithm, it is possible to observe the transitions of behaviors in queue management for each lane in low densities and in group management (for the total sum of vehicles across all lanes) in intermediate and high densities.

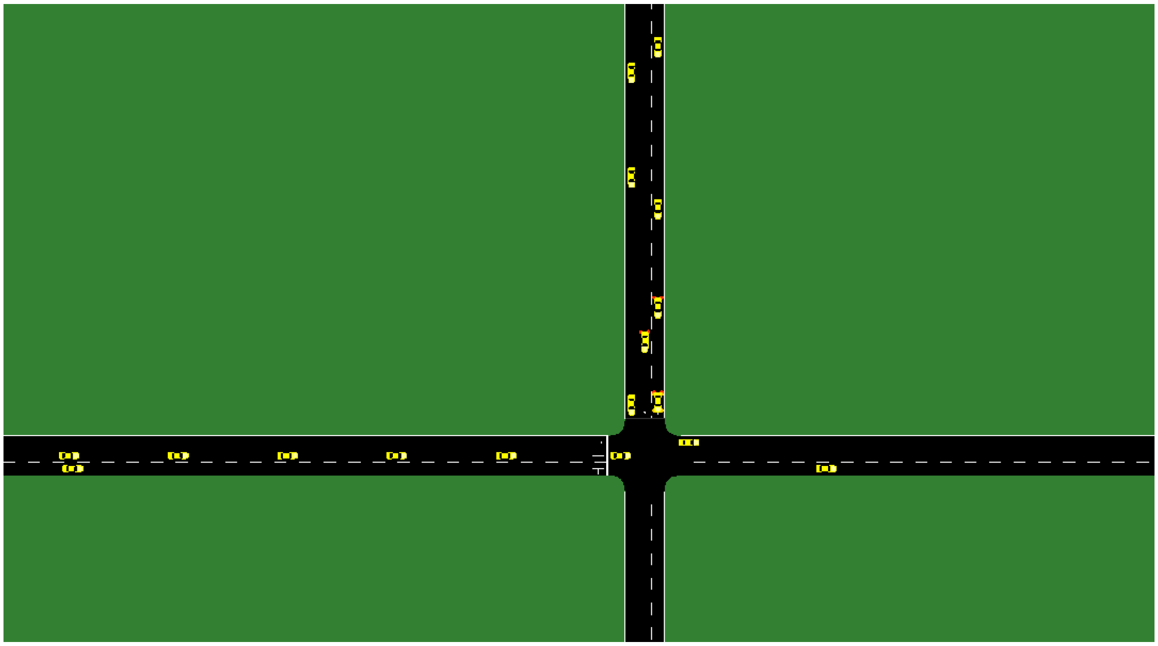


Figure 6.5: “Random” density distribution at 30% per street.

Although, autonomous vehicles initially start with any type of density distribution, at high densities, congestion across all lanes will lead to near-intersection vehicles exhibiting behavior similar to a density distribution called “Uniform”.

Based on the above, we will conduct various experiments using the three different density distribution types to observe emergent behaviors. These experiments will determine whether autonomous vehicles pass intersections in small or large groups, aiming to evaluate the performance of the proposed algorithm extension in a complex environment. Once again, we will utilize the SUMO simulator.

The cities, designed in a Manhattan style for experimentation in a multi-lane environment, have streets with a length of 500 meters, each equipped with three lanes. One city was implemented with 4 intersections, while the other city was implemented with 16 intersections. All autonomous vehicles within the simulation are normal vehicles, with no inclusion of emergency vehicles or vehicles with failures.

For these experiments, our DIM algorithm will be compared with a traditional centralized traffic system employing the "Green-wave" effect in traffic lights. This comparison aims to assess the overall performance of traffic management at the crossing intersections.

6.3.2 Experiment applying the "Uniform" density distribution.

In Figures 6.6, 6.7, 6.8, 6.9, 6.10, and 6.11, the behavior of the "Uniform" density distribution is depicted for a city with 4 intersections and a city with 16 intersections, respectively. In Figure 6.6 with 4 intersections and Figure 6.7 with 16 intersections, a similar growth in flow is observed in "DIM" and "Green Wave" models.

However, at around 10% density in both city types, the "DIM model" maintains a higher flow compared to the "Green Wave" model. Additionally, it can be observed that our "DIM model" shows slightly better queue management in large cities with high-density levels compared to the "Green Wave" model in both city types.

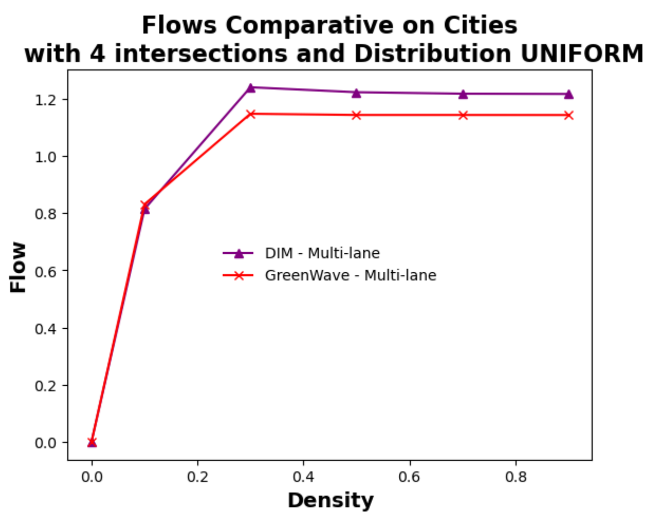


Figure 6.6: Flow results with "Uniform" density distribution: city with 4 intersections

This is due to the fact that our model maintains average flow values of 1.24 in both city types, even with a slight increase in the city with 16 intersections.

Meanwhile, the “Green Wave” model, in both city types, continues with an average flow value of 1.14. In other words, there are, on average, 9% more vehicles commuting through both cities in high-density scenarios (from 30% to 90%).

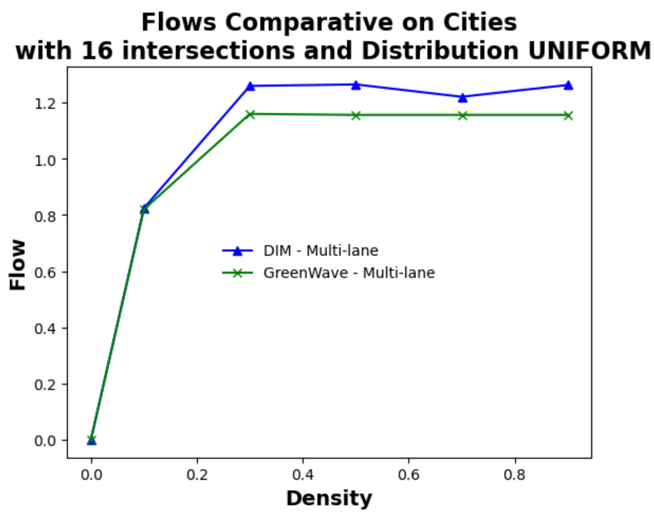


Figure 6.7: Flow results with “Uniform” density distribution: city with 16 intersections

In the case of velocity with this uniform density distribution, the “DIM model” once again shows a higher behavior than the “Green Wave” model in the city with 4 intersections (refer to Figure 6.8). Starting from 30% density in that city, our model shows a change due to the emerging behavior regarding the types of convoy sizes, ranging from large sizes for low densities to small sizes at high densities. In other words, our model shows an increase in overall velocity compared to the “Green Wave” model under high-density conditions. This can be explained due to the use of smaller convoys in our model, which results in reduced waiting times for vehicles following smaller queues as opposed to larger ones.

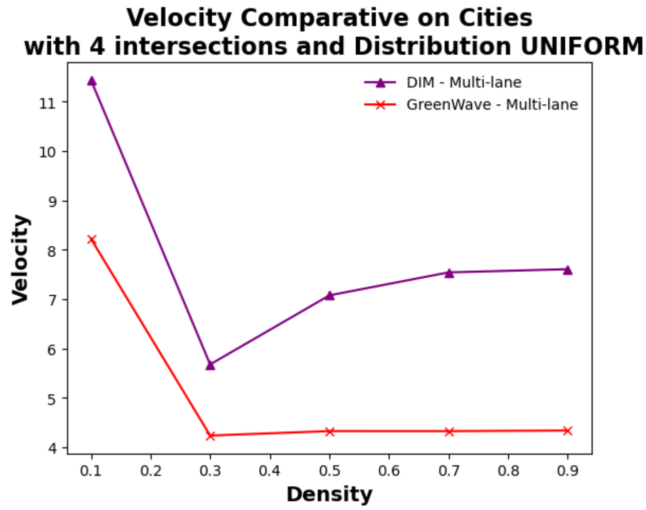


Figure 6.8: Velocity results with "Uniform" density distribution: city with 4 intersections

Similar observations can be made for velocity in the city with 16 intersections (refer to Figure 6.9). The "DIM model" demonstrates better behavior at 30% and 70% density (explained earlier for the results of the 4-intersection city), but there are two similar points at 50% and 90% densities.

The reason for this lies in our model, where a transition is observed, describing an emerging global behavior as the city enters a high-density state. Initially, if at least one lane is filled after an intersection, the vehicles before the intersection come to a halt until this space is cleared.

Simultaneously, there is an increased frequency of changes in the size of convoys. This condition is effectively managed from 50% to 70%. However, beyond 71%, the velocity experiences a decline once again.

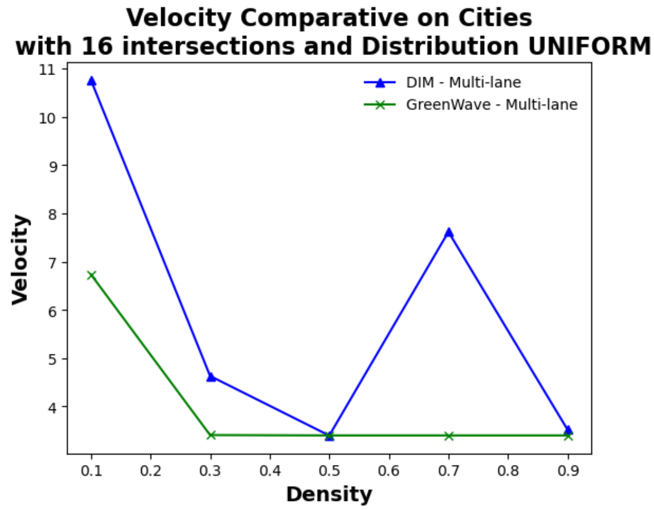


Figure 6.9: Velocity results with “Uniform” density distribution: city with 16 intersections

Finally, as can be observed in Figure 6.10, our model outperforms the “Green Wave” model in terms of waiting time, particularly evident in the city with 4 intersections, where it exhibits an average reduction of 50% in vehicle waiting. This improvement highlights our DIM model’s effective management of intersection crossings, achieved by forming smaller convoys, which is maintained from 30% to 90% densities.

In the case of the city with 16 intersections (See Figure 6.11), a similar trend to that of the city with 4 intersections is observed. Our model exhibits an initial average reduction of 50% in vehicle waiting time when the city’s vehicle density is at 30%, compared to the “Green Wave” model. However, as density increases, there is a slight increase in waiting time, albeit without significantly impacting overall performance. Specifically, our model maintains an average waiting time of 237 seconds from 30% to 90% vehicle density, while the “Green Wave” model shows an average waiting time of 362 seconds within the same density range. This represents an average global reduction in vehicle waiting time of 52%. It is important to note that the slight increase in waiting time in our model is attributed to the policy of halting vehicles before intersections when at least one lane is filled in the next street. Although this may lead to a slight increase in waiting time locally, it does not negatively affect the overall performance of the model.

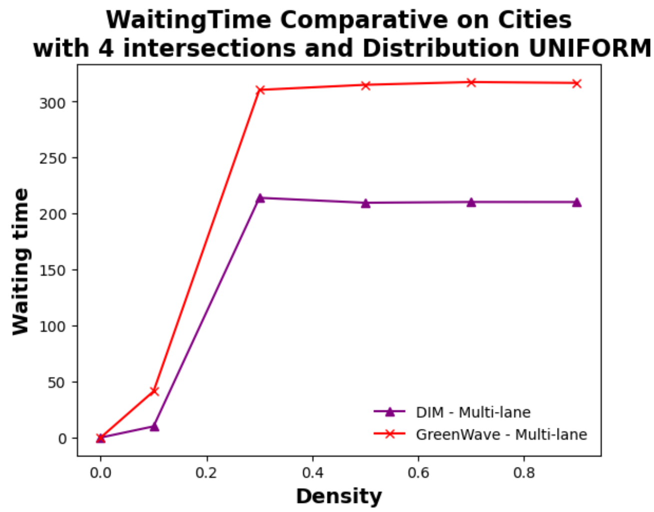


Figure 6.10: Waiting-Time results with "Uniform" density distribution: city with 4 intersections

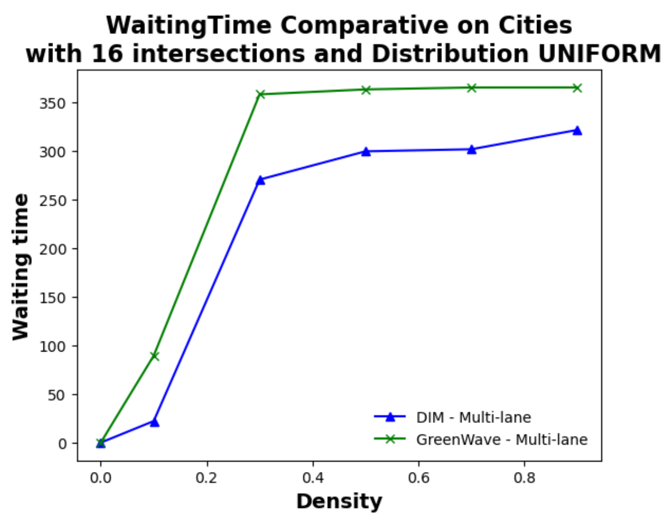


Figure 6.11: Waiting-Time results with "Uniform" density distribution: city with 16 intersections

6.3.3 Experiment applying the “Biased” density distribution.

Following we explore the “Biased” density distribution in the same two cities (with 4 and 16 intersections, respectively). The main purpose of this experiment is to observe how, as the lanes in the cities become congested, there is a transition from the formation of large convoys per lane to smaller ones, starting at a density of 30%. This transition occurs due to the rapid formation of queues (or jams) in each lane of the street when at least one lane is overloaded. The different results obtained in this experiment can be seen in Figures 6.12, 6.13, 6.14, 6.15, 6.16 and 6.17.

Figures 6.12 and 6.13 describe the flow versus density relationship in both types of cities. These figures illustrate a similar trend in our DIM model, which shows slight superiority over the Green Wave model in both types of cities between 10% and 30% density.

After reaching 30% density, our model exhibits a higher growth rate, particularly notable between 50% density and beyond, where it demonstrates a 9% increase in flow compared to the “Green Model” in the cities of 4 and 16intersections.

It is necessary to note that in our model, there is a little increase in the cities with 4 and 16 intersections within the density range of 10% to 30%. As explained earlier, although our model shows slight growth during this range, this increase can be attributed to the overload on one lane, influenced by the bias factor (ϕ).

This bias factor (ϕ) allows for the observation of rapidly forming convoys or queues on the overloaded lane even at low densities. In such cases of low densities, vehicles from all lanes advance towards the intersection until the threshold set by the last vehicle of the convoy detected by the bias factor (ϕ) is reached.

This results in two different behaviors: firstly, large convoys (formed per overloaded lane) tend to congest faster compared to other types of density distribution, leading to reduced flow; secondly, when a street is nearly filled, particularly in the overloaded lane, vehicles in the street behind the intersection are halted until the overloaded lane ahead, within a distance e, becomes free, even if other lanes are clear. This also contributes to reduced flow.

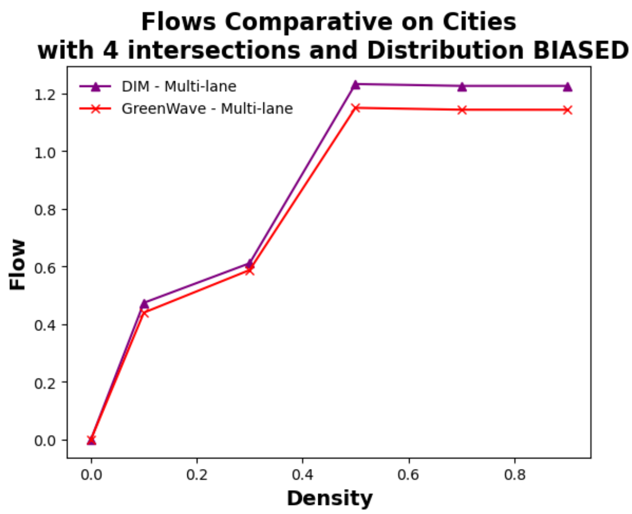


Figure 6.12: Flow results with “Biased” density distribution: city with 4 intersections

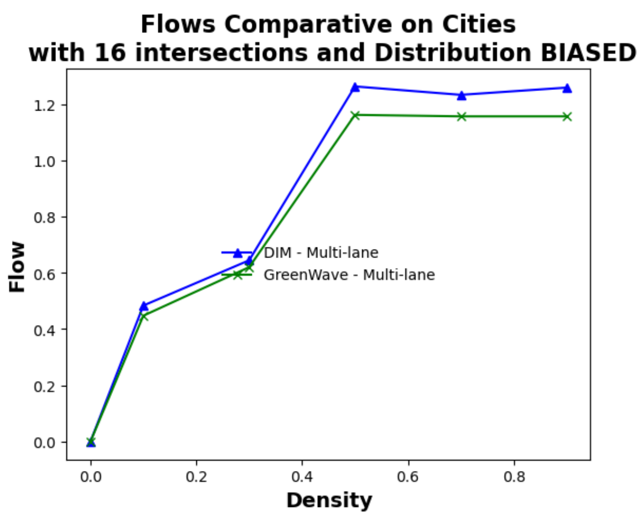


Figure 6.13: Flow results with “Biased” density distribution: city with 16 intersections

In terms of velocity, a different behavior is observed, where the “Biased” distribution density once again influences overall performance, considerable in comparison with the previously observed “Uniform” distribution density. In both the cities with 4 and 16 intersections, the velocity curve shows an increase from 10% to 30% density.

This increase is attributed to lane overloading, leading to the formation of queues that initially slow down velocity. In the case of the city with 4 intersections (as shown in Figure 6.14), our model demonstrates superior performance compared to the “Green Wave” model, with an average maximum velocity of 8.45 $m/s.$, in our model compared to 6.43 $m/s.$, in the “Green Wave” model.

This represents a 31% average improvement in our model at 30% density. Although both models experience a decrease in the performance for velocities beyond 50% densities due to street closures after the intersection, our model maintains its performance superiority. Beyond 50% density, both models stabilize in velocity, with our model consistently performing 50% better than the “Green Wave” model.

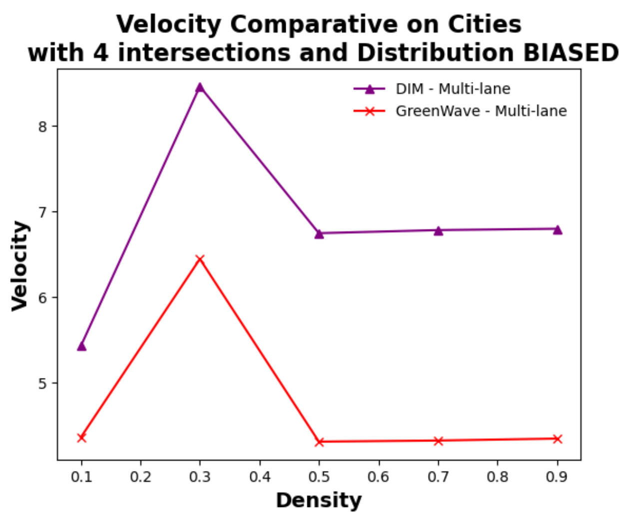


Figure 6.14: Velocity results with “Biased” density distribution: city with 4 intersections

In terms of velocity, focusing on the city with 16 intersections (Figure 6.15), our model consistently maintains a better performance, with an average 36% higher velocity compared to the “Green Wave” model. Similar to the previous simulation in the city with 4 intersections, both models experience degradation in velocity after 30% density until reaching 50% density.

However, in comparison to the city with 4 intersections, our model shows a higher increase in velocity from 50% to 70% density, reaching a velocity peak of 6.60 $m/s.$, while the velocity of the "Green Wave" model remains stable at 3.39 $m/s.$, from 50% density onwards, resulting in our model being 94% superior in velocity.

Beyond 70% density, our model experiences another decrease in performance, but it still maintains higher velocity compared to the centralized model. This behavior, characterized by two velocity peaks, is attributed to an emerging behavior where changes in convoy size and congestion in one lane affect our model, yet it continues to outperform the "Green Wave" model.

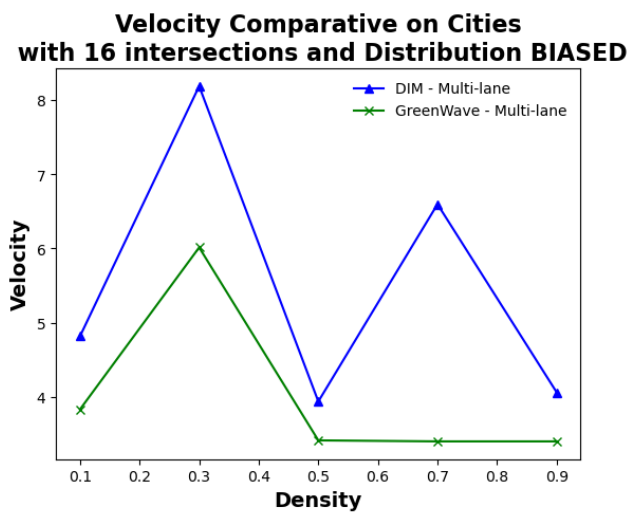


Figure 6.15: Velocity results with "Biased" density distribution: city with 16 intersections

In terms of waiting time with the "Biased" distribution density, our model outperforms the "Green Wave" model in the city with 4 intersections (refer to Figure 6.16). At 30% density, our model demonstrates a significantly lower average waiting time of 140 seconds for vehicles in the simulation, compared to an average waiting time of 259 seconds in the centralized model. This represents an 85% improvement over the centralized model. Although there is an increase in waiting time in our model after reaching 30% density until 50%, similar to the behavior observed at 10% density, it stabilizes thereafter and continues to outperform the "Green Wave" model. This behavior observed at 30% density in our model is attributed to changes in convoy sizes as discussed earlier.

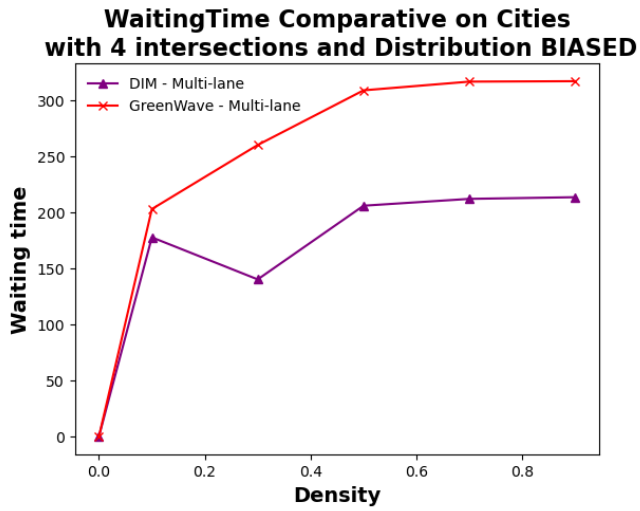


Figure 6.16: Waiting-Time results with "Biased" density distribution: city with 4 intersections

Analyzing the behavior of our model in the city with 16 intersections (Figure 6.17), we observe that our model maintains a slightly higher performance at 30% density, with vehicles experiencing an average waiting time of 212 seconds compared to 241 seconds in the "Green Wave" model. This represents a 14% reduction in the number of seconds vehicles spend in a halted state. However, our model experiences a slight increase in waiting time thereafter, attributed to congestion triggered by the closure of streets while the lane is being released in front of it to avoid blocking the intersection. Despite this, our model continues to outperform the "Green Wave" model.

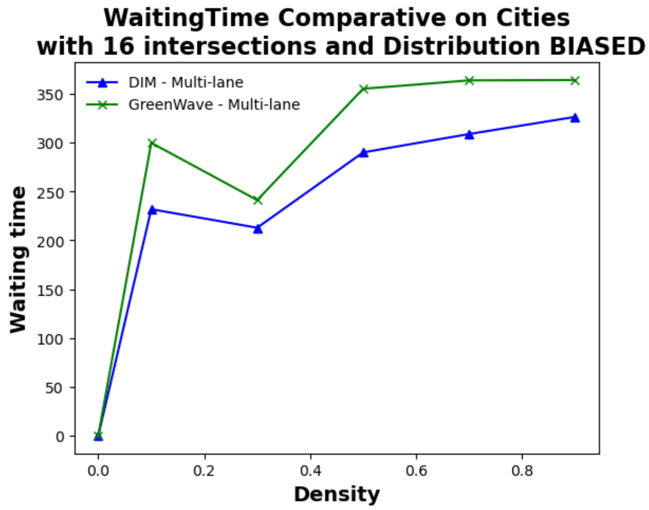


Figure 6.17: Waiting-Time results with “Biased” density distribution: city with 16 intersections

6.3.4 Experiment applying the “Random” density distribution.

Finally, we analyze the simulation behavior in both cities (4 and 16 intersections) utilizing the “Random” distribution density. Here, the distribution assigns a random percentage of vehicles to the first lane based on the density value, and then distributes the remaining density across subsequent lanes using a random function.

This process is repeated for each remaining lane. With this distribution, our goal is to observe how convoy sizes fluctuate and how traffic congestion affects performance as density increases, especially in the city with more intersections.

In the case of flow in the city with 4 intersections (Figure 6.18), both models exhibit similar values initially. However, beyond 50% density, our model shows a slight increase, improving the average flow by 7%.

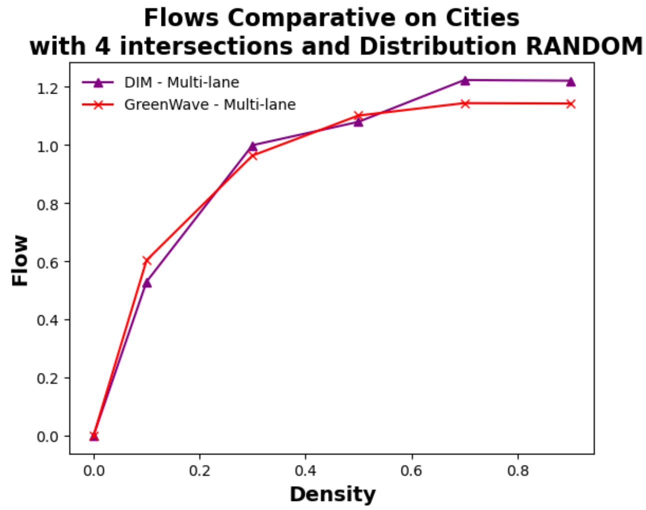


Figure 6.18: Flow results with “Random” density distribution: city with 4 intersections

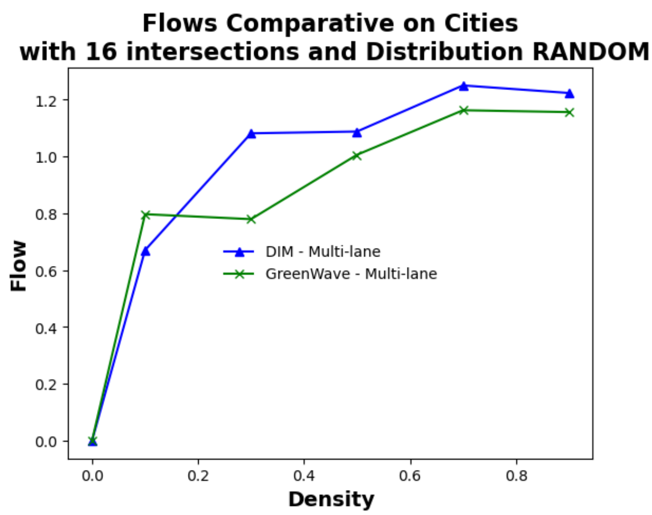


Figure 6.19: Flow results with “Random” density distribution: city with 16 intersections

Moving to the city with 16 intersections (See Figure 6.19), our model demonstrates notably better performance compared to the flow behavior in the city with 4 intersections. This improvement is particularly evident at 30% density, where our model outperforms the “Green Wave” model, showing a

40% increase in average flow. Beyond this point, our model maintains a growth trajectory similar to that of the "Green Wave" model, albeit slightly better with an average improvement of 7%.

In terms of velocity in the "Random" distribution density, two types of behavior are observed in both cities, each with its own nuances. In the city with 4 intersections (Figure 6.20), our model initially exhibits better performance. However, there is a degradation in velocity from approximately 20% to 30% density.

Beyond 30% density, our model demonstrates a steeper positive growth curve, surpassing the "Green Wave" model from around 35% density onwards. At higher congestion levels (90% density), our model consistently outperforms the "Green Wave" model by an average of 66%. It is important to note that the degradation observed in our model compared to the "Green Wave" model from 20% density is attributed to the type of density distribution employed, which initially manages convoy size changes in a less optimal manner.

However, as density increases, the distribution tends towards a more uniform pattern, leading to our model of superior performance in velocity over the "Green Wave" model from around 35% density.

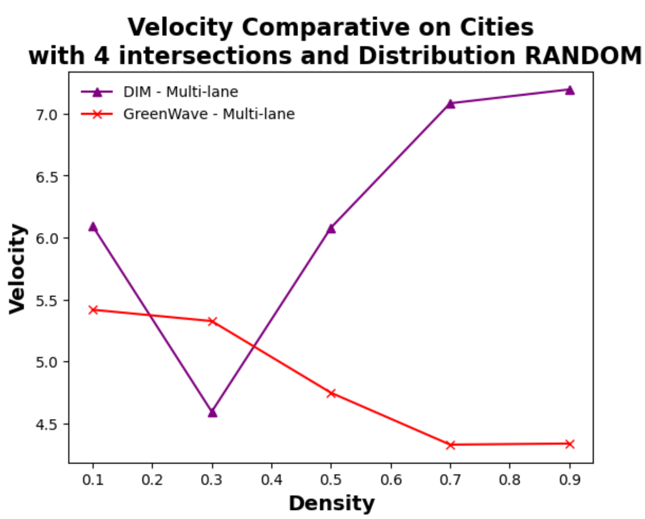


Figure 6.20: Velocity results with "Random" density distribution: city with 4 intersections

In the case of velocity in the city with 16 intersections (Figure 6.21), utilizing the “Random” distribution density, our model consistently outperforms the “Green Wave” model across all density levels. It’s important to note, however, that our model experiences two sections of degradation in velocity: from 10% to 30% and from 50% to 70% density.

This degradation is similar to what was observed in the city with 4 intersections for the first section, yet our model continues to outperform the “Green Wave” model in both sections. At higher densities, our model demonstrates significantly superior performance, with a 120% increase in velocity compared to the “Green Wave” model.

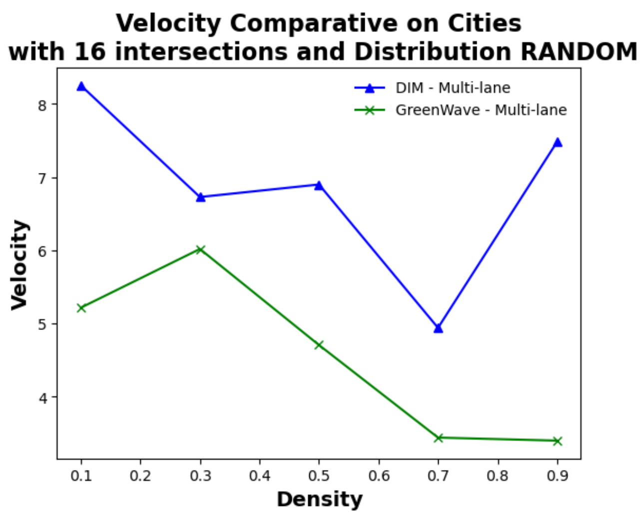


Figure 6.21: Velocity results with “Random” density distribution: city with 16 intersections

Finally, considering the waiting time with the “Random” density distribution, at 30% density, we observe an improvement in performance for both types of cities. Although our model exhibits slight superiority in the initial section (from 10% to 30%), there is a degradation at 30% density. However, from this point onward, our model demonstrates a substantial improvement.

In the case of the city with 4 intersections (see figure 6.22), there is a 17% reduction in vehicle waiting time at 50% density, and an average reduction of 50% at 70% and 90% densities. In other words, as convoy sizes begin to fluctuate, our model demonstrates better management of queues at intersections, particularly with smaller groups of vehicles.

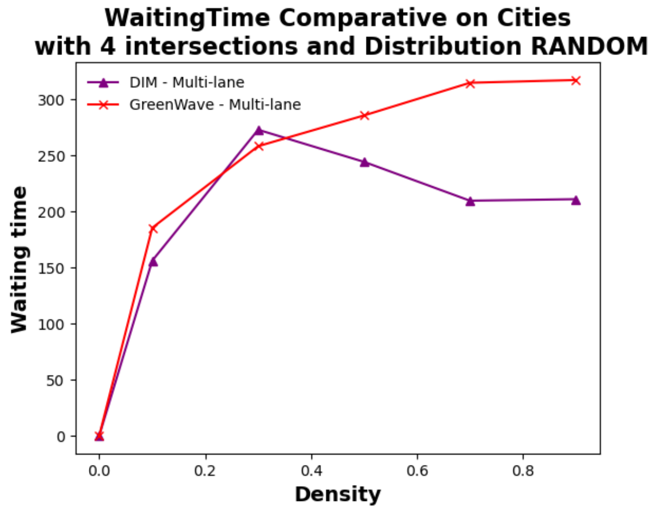


Figure 6.22: Results with “Random” density distribution. City with 4 intersections

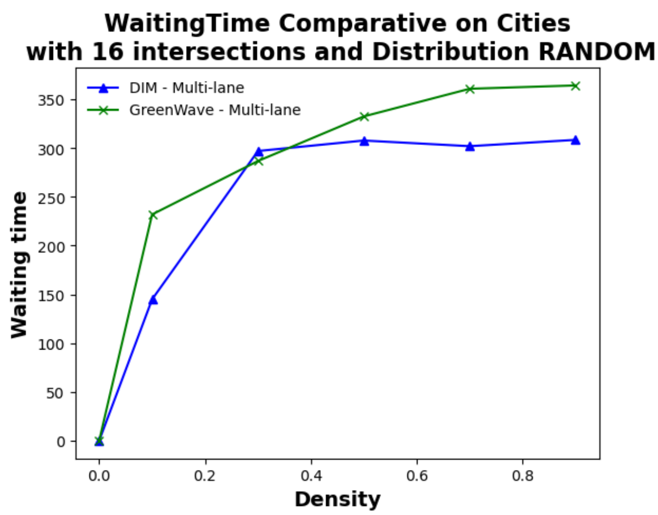


Figure 6.23: Results with “Random” density distribution. Cities with 16 intersections

Additionally, in the case of the city with 16 intersections (see Figure 6.23), our model shows a stable improvement from 30% density onwards. Despite high congestion, our model maintains consistent waiting times, even when streets are closed before their intersections due to a vehicle being stopped in front of the street after the intersection within a distance e, regardless of lane. This represents better queue management in our model compared to the “Green Wave” model, with an average reduction of 15% in waiting time beyond of 30% of density.

6.4 Conclusions

This chapter has introduced a new behavior in autonomous vehicles, characterized by a greater number of interactions, because each street in the proposed model includes three lanes. This extension introduces additional ways for vehicles to manage their commutes, facilitating a new emerging global behavior where vehicles choose different sizes of convoys to handle high levels of density.

To observe the new emerging global behavior, it was necessary to construct three types of density distribution. Through the experiments, it became apparent that the “Biased density distribution” and “Random density distribution” exhibited the most representative features of choosing different sizes of convoys. These distributions were instrumental in illustrating, through graphics, how congestion in any lane slightly impacted the flow performance in our model.

The proposed interaction feature called “Free to pass” ensures that autonomous vehicles can not make arbitrary decisions when they arrive late to a group of vehicles that are either beginning to cross an intersection or finishing crossing an intersection.

Finally, the emergent behavior in our multi-lane model, involving the transition of convoy sizes from large to small, significantly enhances queue management at high density levels. This improvement is evident across all density distributions and becomes apparent when the simulation reaches 30% density and beyond, indicating increased complexity.

Part IV

Conclusions and future work

Chapter 7

Conclusions and future work

In this chapter, we summarize the key contributions of this thesis on enhancing autonomous driving through complex interaction management. We showcase the development and impact of our distributed algorithm, particularly at traffic intersections, highlighting its potential to improve commuting flows with diverse routes and priorities. This conclusion encapsulates our achievements and outlines the significance of our work in the broader context of intelligent transportation systems and autonomous vehicle coordination.

Initially, we detail our goals and achievements, offering insight into our project's impact on autonomous and cooperative driving. We then analyze our algorithm's performance metrics, examining its effectiveness in simulations to affirm our strategy's validity and potential for intersection management.

Lastly, we explore into future research. The intention is to extend our model's applicability by addressing real-world complexities inherent in intersection traffic. By tackling these challenges head-on, our research aims to fortify the foundations of algorithms for autonomous and cooperative driving. This forward trajectory aligns with the evolving landscape of intelligent transportation systems.

7.1 Conclusions

Based on the defined objectives, the conducted research has successfully addressed several key aspects in the development of a coordination system with a distributed approach for managing entry and crossing at intersections for autonomous vehicles. The following conclusions can be drawn:

The analysis of Advanced Driver Assistance Systems (ADAS) and Automated Vehicles (AV) served as the foundational step in understanding the existing landscape of automated technologies in vehicles. Insights gained from this exploration were instrumental in shaping the subsequent stages of the research, ensuring alignment with current advancements in the field.

The research into existing strategies for vehicle crossing at intersections revealed crucial insights into both centralized and distributed algorithms. By identifying limitations and gaps in current approaches, the research aimed to push the boundaries of intersection management. This comprehensive understanding provided a solid basis for the development of innovative and effective solutions.

To validate the proposed algorithms, the creation of a robust simulation environment was imperative. This environment, integrating microscopic and macroscopic models, facilitated extensive testing and evaluation. The versatility of the simulation allowed for the exploration of diverse scenarios, ensuring the proposed coordination system's adaptability to varying traffic conditions.

As observed, the current state of the art emphasizes automated vehicles as a key component and the associated technology as the pathway toward achieving autonomous driving. However, realizing fully autonomous driving requires ongoing validation of the decision-making capabilities of automated vehicles as they interact with others of the same nature. This includes assessing the speed of responses during interactions and the overall performance of traffic, encompassing aspects such as flow, waiting times, emergency handling, and addressing failures.

Therefore, traffic intersections serve as ideal scenarios for validating the aforementioned challenges. Consequently, numerous challenges persist in the development of algorithms that effectively manage intersection crossings, particularly in handling complex interactions between automated vehicles. This entails adopting a distributed approach to enhance computational performance, increase robustness to failures, and concurrently, keeping certain issues open for improvement, particularly those related to non-cooperative decision-making.

The focal point of the research involved the design of algorithms to enable diverse autonomous vehicles to navigate intersections without reliance on a central server. This process included the development of roles for vehicle behaviors, establishment of messaging protocols, and the creation of resilient decision-making strategies. Consideration of physical failures further added a layer of complexity, ensuring the system's robustness in the face of unexpected challenges.

Recognizing the critical role of emergency vehicles in urban traffic scenarios, the research extended its focus to incorporate these vehicles into the coordination system. This enhancement aimed to evaluate the system's responsiveness and effectiveness in managing emergencies, thereby contributing to the overall safety and reliability of the proposed approach.

Extensive experiments conducted on two vehicular traffic simulators provided a comprehensive evaluation of the distributed system. The systematic progression from simpler scenarios to more complex ones, involving failures, emergency management and additional lanes, demonstrated the system's adaptability and efficiency. Comparative analyses with centralized systems highlighted the advantages of the distributed approach, showcasing its robust performance across diverse traffic conditions.

To begin with and building upon the framework proposed by Zapotecatl and Gershenson (Centralized strategy, self-organized), our algorithm was devised to cater to each autonomous vehicle's interactions individually. These interactions of the vehicles developed behaviors with the primary objectives of ensuring collision-free movement, maintaining high flow in traffic, minimizing waiting times, and preventing intersection blockages.

The interaction model was built upon an ideal exchange of messages, assuming no noise or data loss, facilitated by two systems for recognizing the vehicle's surroundings. This include a communication radius (encompassing downstream and upstream broadcasts, requests, etc.) and a perception radius (enabling vehicles to recognize one another and understand their dynamic flow).

In our initial testing to assess its performance, our model was compared with two existing proposals: the Zapotecatl and Gershenson model, and a traditional traffic light system known as "Green Wave." This comparison was conducted using Zapotecatl's simulator, which is based on cellular automata. The key performance metrics evaluated included flow, velocity, and waiting time, and the experiments were conducted in both small and large cities following a Manhattan-style layout. Within the Zapotecatl simulator, as the density increased, vehicles filled the streets behind intersections until there was no free space left, reaching a density of 100% in the city. In the first experiment, our model shows significant similarities to the Zapotecatl and Gershenson model, while surpassing traditional traffic control systems like Green Wave across different city sizes and numbers of intersections.

For the second experiment, also we utilized the Zapotecatl's simulator, based on cellular automata, to compare our model with the Zapotecatl and Gershenson model. The objective of these experiments was to evaluate the performance of both models in the face of communication failures, specifically the inability to manage intersection crossings. In the centralized approach, communication failures are simulated as failures in the traffic lights, allowing vehicles to cross the intersection without stopping. In our model, communication failures are represented as issues within the vehicles themselves, preventing a vehicle with communication failures from coordinating its crossing with other vehicles. As a result, our model demonstrates greater robustness than the centralized model against failures. Our proposal maintains a consistent vehicle flow even when 50% of vehicles experience communication failures. In contrast, the performance of the centralized model diminishes in the presence of communication failures, even at low levels of traffic density.

To conduct the third and fourth experiments, we utilized a new simulator called "SUMO" (Simulator Urban MObility), chosen for its broader scope and integration of microscopic and macroscopic models, enabling comprehensive testing and evaluation. These experiments incorporated emergency vehicle coordination, where our model was compared to the centralized "Green Wave" model in a city layout resembling Manhattan, with varying traffic densities from 0 to 1. In our model, emergency vehicles are given priority at intersections only when they are within the communication radius of N_v vehicles, ensuring a balanced approach within vehicle queues.

In the third experiment, a city with 4 intersections was employed, with emergency vehicles introduced at a prior probability of one vehicle per every 3600 vehicles. The results indicated that our model outperformed the “Green Wave” model. Notably, in terms of waiting time, our model exhibited an average 15% reduction in waiting time for both normal and emergency vehicles combined at 60% density. Additionally, our model showed a 35% improvement specifically for emergency vehicles in waiting time at the same density level compared to the “Green Wave” model.

In the fourth experiment, cities with 4 and 25 intersections were utilized, incorporating two different percentages (1% and 9%) of emergency vehicles. These percentages corresponded to a prior probability of 36 per every 3600 vehicles and 332 per every 3600 vehicles, respectively. The outcomes demonstrated the superior performance of our model over the “Green Wave” model. Furthermore, we assessed our model’s performance in testing queues and halted vehicles in cities with 4 and 16 intersections at high densities (0.7 and 0.9). Additionally, we varied the distance between intersections to 200, 500, and 700 meters. In these experiments, we maintained the percentage of emergency vehicles at 1%. Our findings revealed that at these densities and distances, our model exhibited an average reduction of 10% in halted vehicles compared to the “Green Wave” model. Moreover, unlike the “Green Wave” model, the distance between intersections did not influence the performance of our model. This can be attributed to the emergent coordination within our model, which adjusts dynamically depending on traffic density and vehicle interactions.

For the last experiment, we again utilized the SUMO simulator. This experiment involved cities with multi-lane streets (3 lanes per street). Two types of cities were simulated: one with 4 intersections and the other with 16 intersections, resembling a Manhattan layout, with varying traffic densities. Our model was compared to the centralized “Green Wave” model.

In our model, a novel behavior in autonomous vehicles was implemented, allowing for expanded interactions due to multi-lane streets. This enabled vehicles to adapt convoy sizes to handle density, observed through uniform, biased, and random density distributions. The “Free to pass” feature prevented arbitrary decisions during intersections.

Notably, as density increased beyond 30%, convoy size transitions improved queue management, benefiting from varied convoy sizes. Ultimately, our model outperformed the “Green Wave” model across all three global variables measurements in the three types of density distributions.

In summary, this section has presented the core contributions towards enhancing autonomous traffic management through the development of a distributed coordination system for autonomous vehicles. This encapsulates the significant strides made in understanding and implementing complex urban traffic systems for autonomous vehicles, setting the stage for future research and improvements in efficiency, safety, and adaptability of autonomous intersection management.

7.2 Future work

In this section, we propose future research directions stemming from this thesis on autonomous traffic management. These future studies could be ideally pursued as part of a postdoctoral investigation, providing an excellent opportunity to delve deeper into the thesis's area.

One crucial direction for further investigation involves delving into more complex interactions, particularly scenarios involving multiple lanes and the integration of emergency vehicles capable of lane-changing. Conducting comprehensive tests under varying conditions will be essential to evaluate the system's performance thoroughly, considering factors such as the presence of emergency vehicles. These experiments will continue to utilize the three distinct density distributions discussed in Chapter 6 to assess global performance comprehensively.

Additionally, there is a keen interest in exploring the integration of turns (both left and right) at intersections to replicate real-world driving scenarios more accurately. Another intriguing avenue for future work is the exploration of real-world implementations and the incorporation of our model into practical applications, bridging the gap between theoretical advancements and practical applicability.

Moreover, optimizing communication protocols will be a focal point to ensure efficient and secure data exchange between vehicles and infrastructure. Additionally, the implementation of bio-inspired algorithms like swarm intelligence holds promise for improving our proposal further.

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