UNIVERSITAT POLITÈCNICA DE VALÈNCIA

UNIVERSITAT POLITÈCNICA DE VALÈNCIA

DEPARTMENT OF COMPUTER ENGINEERING

Using Ontologies and Intelligent Systems for Traffic Accident Assistance in Vehicular Environments

Thesis submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Computer Science

Javier Barrachina Villalba

Ph.D. Advisors:
Dr. Piedad Garrido Picazo
Dr. Juan Carlos Cano Escribá

Valencia, July 2014

To my parents, my sister, and my girlfriend,
for their patience and support.

Acknowledgments

Since I was a child I had always wanted to get a university education when I grew up. At that time, I had different studies on my mind; I wanted to be anything from a lawyer to an architect (dreams and ideas of children). I was focusing my preferences towards engineering and at the end I decided to combine it with one of my passions: computers.

Just as I finished my Computer Science Degree, in 2011, one of my advisors, Dr. Piedad Garrido, offered me the chance to work with her as a researcher. Since finding a job was not easy at that moment due to the global economic recession, especially in my town, Teruel, I immediately took her up on the offer. At first, I worked with her and Dr. Francisco José Serón on issues related to Artificial Intelligence in Computer Graphics. After a while, Piedad and, Dr. Francisco José Martínez, encouraged me to continue my academic training. So, I began to study my Master's Degree in Artificial Intelligence, with the aim of carrying on with the development of this Thesis. In addition, I changed my scope in order to combine artificial intelligence with vehicular networks in my research. All this time they have given me the support and the motivation I have needed, as well as critiquing and correcting my work. Thus, I would like to give them my sincere thanks; without them, I would never have achieved this goal.

After having gone on this adventure, I had the opportunity to meet the people from the Grupo de Redes de Computadores (GRC) at the Universitat Politècnica de València: Dr. Carlos Tavares Calafate, Dr. Pietro Manzoni, and especially, Dr. Juan Carlos Cano, my other advisor. I wish to thank all them for giving me the chance to work together with them; their feedback and corrections have both helped me to improve my research world. It has been an enriching experience.

I will not forget my classmates of the Intelligent Networks and Information Technologies (iNiT) research group of the University of Zaragoza, Manolo, Fernando, Vicente, Jesús Ibáñez, Chon, Jesús Fuentes, and Julio, our hard work has made its existence possible. Besides, our conversations and discussions about any daily topic, as real experts, have served as release when we were under a lot of pressure. Also, I cannot miss out my other university peers, Ángel and Nava, who made the coffee breaks more enjoyable. Thank you!

I do not want to forget Dr. Severino Fernández, my Master's Thesis advisor whose proposals and corrections related to Evolutionary Algorithms were very useful for me.

I am also very thankful to the Fundación Antonio Gargallo, the Universitat

Politècnica de València, and the Diputación Provincial de Teruel for their economic support for the development of this work.

My loving thanks to my father Javier and my mother Mercedes for the sacrifices that they have made in order to give me the opportunity to have come so far, the upbringing that they have given me, the moral values that they have taught me, and their unconditional support, without you I wouldn't have been able to fulfil this dream. Thanks to my sister Alba, since she has always been even more thrilled than me when I have had successful moments. And I also want to thank the rest of my family for their support, especially little Aina, her happiness and innocence have reminded me how wonderful life is.

And of course, my warmest thanks to my wonderful girlfriend Vero, for her excitement and support in both good and bad moments, for helping me up when I fall, and for making me feel special every day.

Finally, I want to thank all my friends and colleagues who have contributed something along my life, especially Héctor, Tomás, Ana, Guillermo, Marc, and to everyone who I have not named which would mean that this text would be endless, but you know who you are.

Thanks to all of you!

Javier Barrachina Villalba
Valencia, July 2014

Abstract

Although security measures in transportation systems are becoming larger, the progressive increase in the number of vehicles traveling through the cities and highways around the world certainly increases the probability of an accident. In such situations, the response time of emergency services is crucial, as it is shown that the shorter the time is between an accident and hospital care of the injured, the greater are their chances of survival.

Vehicular networks allow communication among vehicles and the communication between vehicles and infrastructure, leading to a plethora of new applications and services in the vehicular environment. Focusing on applications related to road safety, vehicles could inform other vehicles and emergency services in case of accident.

When an accident occurs, it is necessary to develop an effective plan of action, which allows a fast rescue of the injured. Arrival time of emergency services to the area where the accident took place can be the difference between the injured survive or die. In this Thesis a system able to reduce the time of the emergency services arrival to the accident scene by redistributing traffic is proposed. The system combines traffic density information with road map topology complexity in order to reduce the emergency services arrival time. Results show that our system is able to reduce the arrival time up to 47.9 %.

On the other hand, one of the most important issues is to know what information related to the accident must be sent. Nowadays, vehicles have a variety of sensors that allow obtaining information about themselves (speed, location, states of security systems, number of passengers, etc.), and about their surroundings (weather information, road conditions, lightness, etc.). In this Thesis we propose an ontology to structure and encode this information, with the aim of allowing the interaction and communication among vehicles of different manufacturers, and between them and central systems.

Finally, in order to make that information generated by crashed vehicles to properly arrive to the emergency services, we propose to use the infrastructure to provide coverage to all vehicles in the scenario. Specifically, in this work we propose a road-side-units deployment scheme that allows automatically obtaining the smallest number of them and their optimal position, thereby reducing costs without losing services.

Resumen

A pesar de que las medidas de seguridad en los sistemas de transporte cada vez son mayores, el aumento progresivo del número de vehículos que circulan por las ciudades y carreteras en todo el mundo aumenta, sin duda, la probabilidad de que ocurra un accidente. En este tipo de situaciones, el tiempo de respuesta de los servicios de emergencia es crucial, ya que está demostrado que cuanto menor sea el tiempo transcurrido entre un accidente y la atención hospitalaria de los heridos, mayores son sus probabilidades de supervivencia.

Las redes vehiculares permiten la comunicación entre los vehículos, así como la comunicación entre los vehículos y la infraestructura, lo que da lugar a una plétora de nuevas aplicaciones y servicios en el entorno vehicular. Centrándonos en las aplicaciones relacionadas con la seguridad vial, mediante este tipo de comunicaciones, los vehículos podrían informar en caso de accidente al resto de vehículos y a los servicios de emergencia. Cuando ocurre un accidente, es necesario elaborar un plan de actuación eficaz, que permita el rápido rescate de los heridos. El tiempo de personación de los servicios de emergencia en el lugar del accidente puede suponer la diferencia entre que los heridos sobrevivan o fallezcan. En esta Tesis se propone un sistema capaz de reducir el tiempo de llegada de los servicios de emergencia al lugar del accidente redistribuyendo el tráfico. El sistema combina información de la densidad del tráfico con la complejidad de la topología del mapa para reducir el tiempo de llegada de los servicios de emergencia. Los resultados muestran que nuestro sistema permite reducir el tiempo de llegada en un 47.9%.

Por otro lado, uno de los aspectos importantes a determinar es saber qué información relacionada con el accidente se debe enviar. Actualmente los vehículos disponen de una serie de sensores que les permiten obtener información sobre ellos mismos (velocidad, posición, estado de los sistemas de seguridad, número de ocupantes del vehículo, etc.), y sobre su entorno (información meteorológica, estado de la calzada, luminosidad, etc.). En esta Tesis se propone una ontología para estructurar y codificar esta información, con el objetivo de permitir la interacción y comunicación entre vehículos de diferentes fabricantes y los sistemas centrales.

Finalmente, para que la información enviada por los vehículos accidentados pueda llegar correctamente a los servicios de emergencia, es necesario disponer de una infraestructura capaz de dar cobertura a todos los vehículos. En este trabajo se propone un mecanismo de despliegue de unidades de comunicación en carretera que permite calcular el número mínimo y la posición óptima de los nodos de infraestructura, reduciendo costes sin perder prestaciones.

Resum

A pesar que les mesures de seguretat en els sistemes de transport cada vegada són majors, l'augment progressiu del nombre de vehicles que circulen per les ciutats i carreteres a tot el món augmenta, sens dubte, la probabilitat que ocórrega un accident. En aquest tipus de situacions, el temps de resposta dels serveis d'emergència és crucial, ja que està demostrat que com menor siga el temps transcorregut entre un accident i l'atenció hospitalària dels ferits, majors són les seues probabilitats de supervivència.

Les xarxes vehiculars permeten la comunicació entre els vehicles, així com la comunicació entre els vehicles i la infraestructura, la qual cosa dóna lloc a una plètora de noves aplicacions i serveis en l'entorn vehicular. Centrant-nos en les aplicacions relacionades amb la seguretat vial, mitjanant aquests tipus de comunicacions, els vehicles podrien informar en cas d'accident a la resta de vehicles i als serveis d'emergència. Quan ocorre un accident, és necessari elaborar un pla d'actuació efica, que permeta el rescat ràpid dels ferits. El temps que tarden a personar-se els serveis d'emergència en el lloc de l'accident pot suposar la diferència entre que els ferits sobrevisquen o muiren. En aquesta Tesi es proposa un sistema capa de reduir el temps d'arribada dels serveis d'emergència al lloc de l'accident redistribuint el trànsit. El sistema combina informació de la densitat del trànsit amb la complexitat de la topologia del mapa per reduir el temps d'arribada dels serveis d'emergència. Els resultats mostren que el nostre sistema permet reduir el temps d'arribada en un 47.9 %.

D'altra banda, un dels aspectes importants a determinar és saber quina informació relacionada amb l'accident s'ha d'enviar. Actualment els vehicles disposen d'una sèrie de sensors que els permeten obtenir informació sobre ells mateixos (velocitat, posició, estat dels sistemes de seguretat, nombre d'ocupants del vehicle, etc.) i sobre el seu entorn (informació meteorològica, estat de la calada, lluminositat, etc.). En aquesta Tesi es proposa una ontologia per a estructurar i codificar aquesta informació, amb l'objectiu de permetre la interacció i comunicació entre vehicles de diferents fabricants i els sistemes centrals.

Finalment, perquè la informació enviada pels vehicles accidentats puga arribar correctament als serveis d'emergència, és necessari disposar d'una infraestructura capa de donar cobertura a tots els vehicles. En aquest treball es proposa un mecanisme de desplegament d'unitats de comunicació en carretera que permet calcular el nombre mínim i la posició òptima dels nodes d'infraestructura, reduint costos sense perdre prestacions.

Contents

List of Figures

List of Tables

List of Algorithms

Chapter 1

Introduction

1.1 Motivation

Currently, the number of vehicles on the roads drastically increases every year, and traffic accidents represent a serious drama in our society. Therefore, safety also acquires a special relevance when accounting for transportation systems. Governments are increasingly establishing restrictive regulations to improve safety on roads, so that current roads are designed to be safer. Moreover, the automotive industry adds new safety elements inside vehicles (e.g. airbags, stability control systems, antilock brake systems, etc.). However, the number of accidents still increases every year all over the world, being the number of fatalities also higher.

A close look at the accidents shows that many of the deaths occurred during the time between the accident and the arrival of medical assistance. The so called 'Golden hour' after a car crash is the time within which medical or surgical intervention by a specialized trauma team has the greatest chance of saving lives. If more than 60 minutes have elapsed by the time the patient arrives to the operating table, the chances of survival fall sharply. The arrival of medical help typically takes about 15 minutes, but initial access and treatment starts 25 minutes after the accident. Transportation of the injured to the hospital usually takes place 50 minutes later. Therefore, time is critical to the survival of the injured in a severe incident. Hence, any technology capable of providing a fast and efficient rescue operation after a traffic accident will increase the probability of survival of the injured, and will also reduce the injury severity [MTC+10].

In order to enable emergency services to reach the crash site in the shortest time possible, redistributing vehicular traffic in the accident area becomes necessary. This redistribution should benefit, as far as possible, all drivers. Therefore, we must take into account variables such as the number of junctions a vehicle will cross during its route (i.e., number of possible red lights or junctions without preference), the speed limits of the streets and avenues in which it is circulating, the vehicle density in a given area, etc. In particular, we want to reduce traffic density on the roads and junctions used by emergency vehicles, in order to improve the emergencies' response when an accident occurs.

In this scenario, it is clear that Intelligent Transportation Systems will play a leading role in our society, especially in scenarios such as warning drivers about vehicle accidents in real time, efficiently managing vehicle information required by governments and authorities, or even being able to offer drivers a variety of additional services.

Wireless technologies, through vehicular networks, enable peer-to-peer mobile communications among vehicles (V2V), as well as communications between vehicles and infrastructure (V2I), which allow avoiding collisions among vehicles. In addition, using these technologies, crashed vehicles are able to alert nearby vehicles, as well as notify emergency services when an accident occurs. The combination of V2V and V2I communications can propel our communication capabilities. Regarding traffic safety, by adding infrastructure to vehicular networks, two benefits are provided: (i) infrastructure can provide Internet access to vehicles, allowing them to communicate with the emergency services immediately, thereby reducing notification times in case of an accident, and (ii) infrastructure access points can rebroadcast messages delivered by vehicles in low vehicle density scenarios (allowing messages to reach more vehicles).

Vehicles are nowadays provided with a variety of new sensors capable of gathering information about themselves and from their surroundings. When an accident occurs, is very important that emergency services know as much information as possible. For this reason, collecting the information in advance by vehicles and send it to the emergency services is of utmost importance. The main problem is to treat this information in an effective way. To structure and to encode the information collected by sensors in the vehicle, enabling the interoperatibility among all the agents involved in modern Intelligent Transportation Systems is a crucial issue.

Evolutionary Algorithms imitate the principles of natural evolution as a method to solve parameter optimization problems. They have been successfully used to solve various types of optimization problems, since they provide an optimal solution without checking all the possible solutions, thereby reducing the execution time drastically. They have been widely used in the field of dynamic traffic distribution.

Global Positioning System (GPS) navigation devices are used more and more in vehicles by drivers. This technology calculates vehicles routes taking into account the shortest distance between two points, or the faster route considering the speed of the streets, but not contemplating the current traffic density. In addition, these systems do not consider special situations as accidents, traffic jams, or road works. As mentioned above, by using Vehicular Networks, vehicles are able to share real-time environment information in order to improve the navigation experience. In addition, combining real-time environment information and Evolutionary Algorithms optimal routes can be calculated, since the shortest route is not necessarily the fastest.

In this Thesis all these important issues are studied in order to propose a framework to improve traffic accident assistance to estimate the necessary infrastructure, as well as to achieve the ‘common understanding’ between all network elements and emergency services.

1.2 Objectives of the Thesis

The main objective of this Thesis is to improve traffic accident assistance automatically alerting the emergency services, providing them with information collected by the vehicles involved in the accident, and reducing their arrival time. To achieve this goal, we consider necessary to fulfill these partial aims:

- The first objective is to define an structure for encoding the information collected by vehicles. This objective can be achieved by defining an ontology, since it is a description of a small part of the real world, the types of items that appear in this world, the relations among them, the existing elements, and their restrictions.

- The second objective is to propose an algorithm that allows to calculate the needed number of infrastructure nodes in a vehicular network, making vehicles able to communicate with centralized systems in a reasonable time. This issue is critical since, using too many infrastructure nodes the network deployment cost increases, but, using an insufficient number of them, several vehicles could not communicate with centralized systems.

- The third objective of this work is to develop a system able to estimate the real-time traffic density by using vehicular networks. In particular, we need to estimate how the traffic is distributed within an area if we want obtain efficient vehicle routes.

- Finally, the fourth objective of this Thesis is to propose an approach to reduce the emergency services arrival time when a car accident occurs, in order to improve the chances of survival for passengers involved in it. This goal can be achieved by an evolutionary algorithm using the environment information sent through vehicular networks.

1.3 Organization of the Dissertation

This Thesis dissertation is organized as follows: Chapter 2 reviews how Vehicular Networks are being used in Intelligent Transportation Systems (ITS), emphasizing on how vehicular networks may improve the current emergency services response time in case of traffic accident. We also make an introduction to Vehicular Networks, showing their main characteristics and applications. In addition, this chapter contains an explanation of the Evolutionary Algorithms and their subsets, and an overview of the current state-of-the-art related to Intelligent Transportation Systems that rely on evolutionary computing.

Chapter 3 proposes the VEhicular ACcident ONtology (VEACON), a proposal designed to structure and encode the information collected by vehicles, in order to obtain a 'common understanding' between all network elements and the emergency services. Our proposed ontology is used in the rest of validation experiments of this Thesis to structure the information collected by vehicles.

In Chapter 4 we present a Density-based Road Side Unit deployment policy (D-RSU), specially designed to obtain an efficient RSU deployment with the lowest possible cost to alert emergency services in case of an accident.

Chapter 5 presents a novel solution to estimate the density of vehicles that has been especially designed for Vehicular Networks. This proposal allows improving proactive traffic congestion mitigation mechanisms to better redistribute vehicles' routes, while adapting them to the specific traffic conditions. The proposed estimation algorithm is used in our intelligent traffic routing approach to know how vehicles are distributed in the scenario.

In Chapter 6 we propose a novel infrastructure-based intelligent vehicle routing approach, specially designed to redistribute traffic in case of accident. We also present other similar approaches and compare them in order to demonstrate that vehicle density is a very important factor to reduce the computation time, increasing the system efficiency with the aim of: (i) reducing rescue time in case of an accident, and (ii) not penalize the travel time of other vehicles.

Finally, Chapter 7 presents a summary of the main results of this Thesis, along with some concluding remarks. In addition, we comment possible future research works that can derive from the work here presented.

Chapter 2

Background on Vehicular Networks and Evolutionary Algorithms

The population of the world is increasing everyday, with China and India being the two most densely populated countries. For this reason, road traffic has experienced a drastic increase in recent years. This situation implies that road traffic has been getting more and more congested. While careful city planning can help to alleviate transportation problems, such planning does not usually scale well over time with unexpected growth in population and road usage.

Modernization, migration, and globalization have also taken great tolls on road usage. Inadequacy in transportation infrastructures can cripple a nation's progress, social well-being, and economy. It can also make a country less appealing to foreign investors and can cause more pollution as vehicles spend a longer time waiting on congested roads. Increased delays can also result in road rage, which gives rise to more social problems, which are undesirable. With fuel price soaring and potential threats of fuel shortage, we are now faced with greater challenges in the field of transportation systems. In addition to this trend, technology has also impacted transportation, giving it a different outlook.

Intelligent Transportation Systems (ITS) emerge as the technology that can efficiently manage information on the road, being able to offer to drivers a variety of added services such as safe, efficient, and smart driving. Electronics technology impacted the construction of cars, embedding them with sensors and advanced electronics, making cars more intelligent, sensitive and safe to drive on. But, on the other hand, these ITS need communication support that allows to exchange information among all the component involved.

On the other hand, Evolutionary Algorithms are used in parameter optimization problems since they provide a sub-optimal solution without checking all the possible solutions, reducing the execution time drastically. In ITS, Evolutionary Algorithms are used for obtaining efficient routes.

All approaches presented in this Thesis are based in two different technologies:

(i) Vehicular Networks, and (ii) Evolutionary Algorithms. Vehicular Networks allow vehicles to communicate between them, and between them and the infrastructure. Since this work is focused on the improvement of the traffic accident assistance, we consider interesting to apply this kind of networks in our systems. In addition, as the emergency services travel time is a critical factor, we optimize their routes by using a system based on Evolutionary Algorithms.

This Chapter reviews the state of the art of both technologies, and presents different projects focusing on vehicular environments.

2.1 Vehicular Networks

Nowadays, wireless communication technologies are applied in different areas of daily life. Vehicles are being equipped with wireless communication devices, enabling them to communicate with other cars, and with centralized systems by using road-side infrastructure nodes. These communications offer new opportunities for developing new applications for vehicles. By using this technology, the automotive industry is able to improve transportation systems efficiently.

In vehicular environments, wireless technologies enable peer-to-peer mobile communications among vehicles (V2V), as well as communications between vehicles and infrastructures (V2I). For this reason, vehicular networks are considerably used in ITS. In order to allow V2I communications, vehicular networks are commonly equipped with Road Side Units (RSUs) consisting on static nodes that behave like the rest of mobile nodes, but, they usually have internet connection through cable.

The specific characteristics of vehicular networks favor the development of attractive and challenging services and applications. Vehicular networks can be used for different purposes, as to complement smart navigation systems sharing traffic information in real time, to alert emergency services and other nearby vehicles when an accident occurs, or even to share files related to entertainment as audio files, multimedia files, etc.

In this Section we present an explanation of vehicular networks, introducing their features, showing some applications that use this kind of networks, and finally presenting several testbeds applied in vehicular networks.

2.1.1 Features of Vehicular Networks

As mentioned above, vehicular networks are composed of vehicle-to-vehicle communications (V2V) and vehicle-to-infrastructure communications (V2I). For this reason, vehicles and RSUs are necessary to form a vehicular network. Figure 2.1 shows an example of a vehicular network. As shown, there are communications among vehicles, and between vehicles and the infrastructure. In addition, using the infrastructure, vehicles are able to access to Internet.

V2V communications have the following advantages: (i) allow short and medium range communications, (ii) present lower deployment costs, (iii) support short messages delivery, and (iv) minimize latency in the communication link. Nevertheless, V2V communications present the following shortcomings: (i) frequent topology

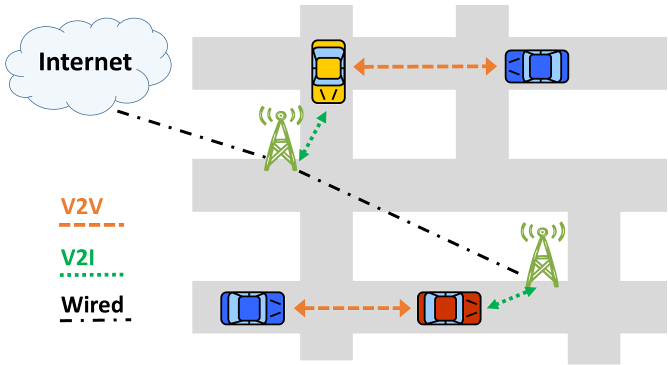


Figure 2.1: Example of Vehicular Network.

partitioning due to high mobility, (ii) problems in long range communications, (iii) problems using traditional routing protocols, and (iv) broadcast storm problems in high density scenarios [TNCS02].

Concerning V2I, current research efforts include: (i) information dissemination for Vehicular Ad Hoc Networks (VANETs), especially using advanced antennas [KRS+07], (ii) VANET/Cellular interoperability [SRS+08], and (iii) WiMAX penetration in vehicular scenarios [YOCH07]. The integration of Worldwide Interoperability for Microwave Access (WiMAX) and Wireless fidelity (WiFi) technologies seems to be a feasible option for better and cheaper wireless coverage extension in vehicular networks. WiFi, under the 802.11p standard, is a good candidate to be used in V2V communications. With the emergence of new applications (Internet access, infotainment, social networking, etc.), the use of fixed infrastructure will become an attractive option [WTP+07].

On the other hand, vehicular communications need the support of reliable link and channel access protocols. The IEEE 802.11p wireless access in vehicular environments (WAVE) [IEE10] is a standardization effort that provides a protocol suite to support vehicular communications in the 5.9 GHz licensed frequency band (5.85-5.925 GHz).

WAVE supports both V2I and V2V communications. Also, WAVE can enhance road safety and driving efficiency since it offers the required support to provide faster rescue operations, generate localized warnings of potential danger, and convey real-time accident warnings. WAVE complements satellite, WiMax, 3G, and other communications protocols by providing high data transfer rates (3-54 Mbps) in circumstances where the latency in the communication link is too high, and where isolating relatively small communication zones is important. Details about radio frequencies, modulation, link control protocols and media access can be found in [UDSAM09].

2.1.2 Applications using Vehicular Networks

The specific characteristics of Vehicular networks favor the development of attractive and challenging services and applications. These applications can be grouped

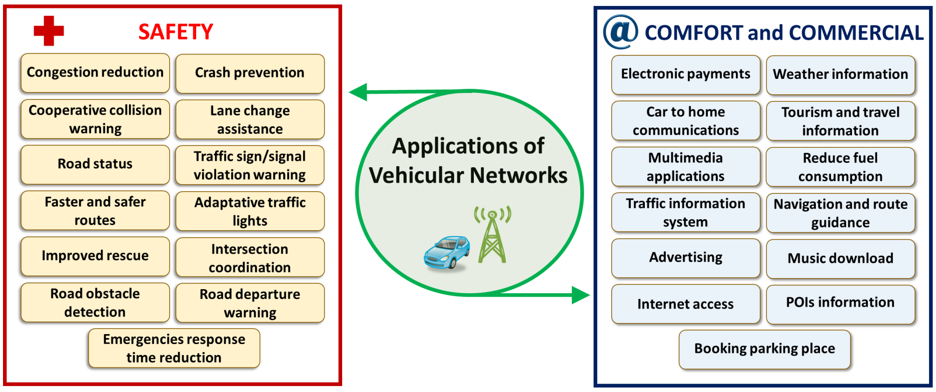


Figure 2.2: Applications of Vehicular Networks.

together into two main different categories: (i) Safety applications, and (ii) Comfort and Commercial applications (see Figure 2.2). In this Subsection we present different proposals related to both categories.

2.1.2.1 Safety applications

This kind of applications looks for increasing safety of passengers by exchanging relevant safety information via V2V and V2I communications, in which the information is either presented to the driver, or used to trigger active safety systems. These applications will only be possible if the penetration rate of VANET-enabled cars is high enough.

Next, we present several of the most novel proposals related to safety by using vehicular networks:

- Fazio et al. [FDRL13] proposed an application that uses the peculiarities of the VANETs to advise danger or emergency situations with V2V and V2I message exchange. The performance of the application was evaluated through many simulations executed in different scenarios, to provide general data independent from them.

- Bhargav and Singhal [BS13] provided a comprehensive approach towards developing an efficient emergency response system to manage rescue missions of vehicular accidents occurring at remote locations with the aid of Vehicular Ad-hoc Networks.

- Garcia et al. [GJA+13] presented a novel approach for pedestrian detection based on data fusion. The application is complemented by an efficient communication VANET protocol able to alert vehicles in the surroundings by a fast and reliable communication. Tests proved the viability of the detection system and the efficiency of the communication, even at long distances.

- Fogue et al. [FGM+11b] presented the e-NOTIFY system, which allowed fast detection of traffic accidents, and the submission of relevant information on the conditions of the accident using a combination of V2V and V2I communications.

- Martinez et al. [MCCM08a] presented a driver warning system in which damaged vehicles send warning messages and the rest of the vehicles make intelligent diffusion of these messages in order to spread warning messages.

- Kwatirayo et al. [KAL13] presented a case study based on a specific intersection in the city of Moncton with real traffic data, and proposed a new adaptive traffic light control algorithm based on VANETs. Their results showed a substantial improvement of traffic throughput and average waiting time in comparison with fixed optimal cycle's time currently used by the city of Moncton and with existing adaptive solutions. Using their approach, traffic jams were avoided, reducing the probability of rear-end crashes.

- Jiang and Yu [JY13] proposed a traffic jam early alert protocol which could propagate the alert information of traffic jam to drivers through VANETs as soon as possible. The early alert information could help drivers to avoid the jammed area. Simulations showed how their protocol improved packets successful delivery, as well as rapid disseminating information process. As the previous work, this system reduced the probability of rear-end crashes.

- Khekare and Sakhare [KS13] introduced a new scheme for a smart city framework able to transmit useful information about traffic conditions. This information will help drivers to take appropriate decisions. It consisted on a warning message module together with an Intelligent Traffic Light which provides information to the driver about current traffic conditions, reducing the probability of traffic jams generation.

2.1.2.2 Comfort and Commercial applications

These applications improve passenger comfort and traffic efficiency, optimize the route to a destination, and provide support for commercial transactions. Comfort and commercial applications must not interfere with safety applications [JK08].

Next, we present some works related to comfort and commercial applications which are based on vehicular networks:

- Guo et al. [GAS13] designed a system with extended Service Oriented Architecture (SOA) for VANET clients providing context-aware services in real-time. This design enabled the system to retrieve data from Internet flexibly, and also process them according to a defined logic appropriate for users. The presented approach can make drivers' journey more interesting and comfortable.

- Chen and Tsai [CT13] proposed a stored-value card to provide an added-value service of payment protocol in VANET. When the user wants to use the added-value service, the service provider verifies the request and sends it to the payment gateway. Then, the payment gateway forwards the transaction message to the Issuer and Acquirer to process it. Their scheme achieved protection against double-spending, unforgeability, non-repudiation, anonymity, and the recovery issue.

- Doolan and Muntean [DM13] introduced EcoTrec, an eco-friendly routing algorithm for vehicular traffic which considers road characteristics, such as surface conditions and gradients, as well as existing traffic conditions to improve the fuel savings of vehicles and reduce gas emissions. EcoTrec makes use of VANETs both for collecting data from distributed vehicles and to disseminate information supporting the routing algorithm. The algorithm calculates the fuel efficiency of various routes and then redirects the vehicle to the most efficient route.

- Chunxiao et al. [CWD+13] proposed an scheme which calculates the optimal speed by on-board units, and then the recommended speed is provided to drivers. Vehicles' current speed and space headway are obtained by Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communications. The drivers can change their speed to the recommended speed. At the recommended speed, vehicle travel efficiency can be improved: vehicles can arrive at destinations in a shorter travel time with fewer stop times, lower fuel consumption, and less CO2 emission. In particular, when approaching intersections, vehicles can pass through the intersections reducing the red light waiting time.

- Elbery et al. [EEC+13] proposed and described a general architecture of the social VANET system (S-VANET) that supports social interaction through vehicular networks. Also, they presented a carpooling recommendation system that works as S-VANET application. Their main objective was to recommend individuals to join their friends during trips or travels.

- Huang et al. [HWC+13] presented an adaptive seamless streaming dissemination system for vehicular networks. A series of simulations were conducted, with the experimental results verifying the effectiveness and feasibility of their proposed work.

- Xie et al. [XMM13] presented an Ad-hoc Streaming Adaptive Protocol (ASAP), an application-layer protocol based on User Datagram Protocol (UDP). ASAP may be readily applied to VANETs, and be used as an alternative to cellular networks for relieving the burden on data usage.

2.1.3 Validation of Vehicular Networks

New proposals focused on vehicular networks must be tested and validated. In particular, authors can validate them in two different ways: (i) using real-world scenarios, and/or (ii) using simulators. In this subsection we present several works regarding the two validation options. In addition, several simulation tools are presented.

2.1.3.1 Real-world Testbeds

There are some projects which tested vehicular network proposals in real-world scenarios. For instance, Moske et al. [MFHF04] presented a real-world ad hoc network testbed built using cars as mobile nodes. These cars were equipped with computing and communication devices. Specifically, authors reported on measurements and experiences with this testbed for static, 1-hop, and 3-hop scenarios as well as for mobile 3-hop scenarios. Beside the power, loss-rate, throughput, and delivery ratio measurements, they presented their methodology for conducting experiments with 'real-world' mobile ad hoc networks and discussed problems of beacon position-based routing due to radio fluctuations.

Neves et al. [NCMS11] developed a small-scale testbed for experimenting the IEEE 802.11p protocol [IEE10] in a real-world scenario. This testbed consisted on two on-board units (single computer), two wireless interfaces, two antennas, and a GPS. The units were placed inside two vehicles. Their experiments were focused on assessing vehicles intercommunication in two different scenarios: (i) vehicles circulating along the same street, and (ii) vehicles circulating in an intersection.

Weng et al. [WKPG13] presented a VANET testbed where multiple experimental configurations ran simultaneously on identical network conditions. Their testbeds consisted on two different platforms: (i) software, and (ii) hardware platforms. Software platform consist on Linux Gentoo distribution patched with Xen, an open source industry standard virtualization environment that allows several virtual machines to share hardware. As a hardware platform they used nodes which were common commercial laptops with an Intel Core 2 Duo CPU, 2GB of RAM and a 120GB hard drive. Each laptop was instrumented with a Ubiquiti SRC wireless card with Atheros 802.11 wifi chipsets (AR5004).

Ameixieira et al. [ACN+13] presented a real-world testbed for research and development in vehicular networking that had been successfully deployed in the sea port of Leixoes in Portugal. The testbed allowed for cloud-based code deployment, remote network control, and distributed data collection from moving container trucks, cranes, tow boats, patrol vessels, and roadside units, thereby enabling a wide range of experiments and performance analyses. After describing the testbed architecture and its various modes of operation, they gave examples of its use and offered insights on how to build effective testbeds for wireless networking with moving vehicles.

As shown, some authors propose different real-world testbeds focused on vehicular networks. However, in all presented works, authors only use a small number of mobile nodes (vehicles), since to equip mobile nodes is too expensive. For this reason, researches usually use simulators to validate their VANET-related proposals, making it possible to use a large number of mobile nodes and reducing the costs.

2.1.3.2 Simulated Approaches

Due to the difficulty of testing vehicular networks proposals, the majority of researchers use simulators. For instance, Slavik et al. [SMA12] showed how to design a statistical multi-hop wireless broadcast protocol using the distance method that adapts its decision threshold value to current network conditions by monitoring the rate of incoming messages. For validating their proposal, they used VanetMobiSim [HFBF06] to generate traffic patterns, and the distribution of JiST/SWANS [JiS04] for network simulations.

Koyamparambil et al. [KHS13] presented a cluster based MAC protocol suitable for traffic safety applications in VANETs. The goal was to define a protocol able to scale over the number of vehicles and deliver the messages within the deadline. To validate their work, they used highway scenarios generated by the SUMO traffic simulator. As a network simulator, they used ns-2.

There are other proposals which were validated using ns-2 simulator and tools based on SUMO. For instance, Fogue et al. [FMG+13] presented a proactive Cooperative Neighbor Position and Verification protocol that detects nodes advertising false locations so as to mitigate the impact of adversarial users. To validate their proposal, they used the ns-2 simulator [FV00], and C4R [FGM+12b], a realistic simulation framework which combines vehicular mobility over real roadmaps and ns-2 optimizations to obtain more accurate and meaningful results when simulating vehicular environments.

Cespedes et al. [CTS13] studied the secure and timely handover of IP services in an asymmetric VANET and propose a multihop-authenticated Proxy Mobile IP (MA-PMIP) scheme. They use OMNeT++ simulator to corroborate the analytical evaluation and security analysis presented in their work. Other authors used the same simulator in their works. For example, Balador et al. [BCCM13] proposed a new IEEE 802.11-based MAC protocol which controls the CW size based on a network density estimation. They validated their proposal by using Omnet++ as the network simulator and SUMO as the real vehicular traffic generator.

As previously commented, the majority of authors usually validate their proposals related to vehicular networks using simulators. This validation option is cheaper and easier to implement. For this reason, we consider more efficient to validate our proposals related to vehicular networks with simulators. Next, we present some of these tools, and we show in detail the simulators that we use in this Thesis.

2.1.3.3 Simulation Tools Used in this Thesis

There are several simulators used to validate proposals related to vehicular networks. Existing vehicular networks simulation software could be classified in three different categories: (i) vehicular mobility generators, (ii) network simulators, and (iii) VANET simulators. Figure 2.3 shows a summary of the most important tools.

Vehicular mobility generators generate realistic vehicular mobility traces to be use as an input for a network simulators, increasing the level of simulations realism. Examples of these simulators are SUMO (Simulation of Urban MObility) [KEB12], MOVE (MObility model generator for VEhicular networks) [MOV12], CityMob [MCCM08b], C4R (Citymob For Roadmaps) [FGM+12b], STRAW (STreet RAndom Waypoint) [STR08], FreeSim [MH07], Netstream [MKT08], and VanetMobiSim [HFBF06].

Network simulators perform detailed packet-level simulation source, destinations, data traffic transmission, reception, background load, route, links, and chan-

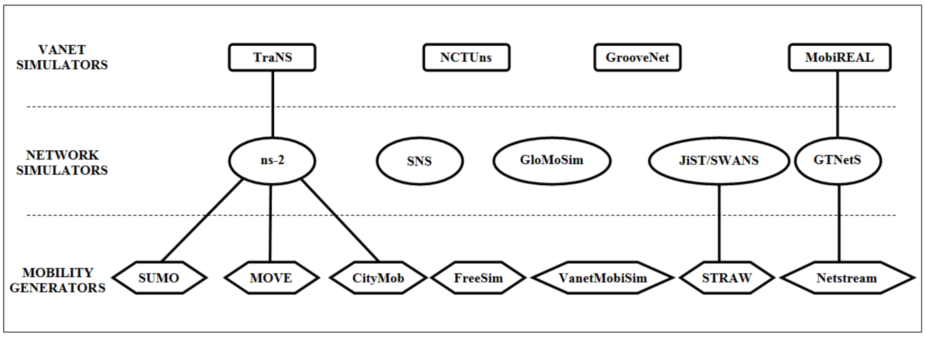


Figure 2.3: VANET Simulators, Network Simulators, and Mobility Generators [MTC+11a]

nels. Examples are ns-2 [FV00], GloMoSim (Global Mobile information systems Simulation library) [Mar01], SNS (Staged Network Simulator) [WS03], JiST/SWANS [JiS04], and GTNetS (The Georgia Tech Network Simulator) [GTN08].

VANET simulators provide both traffic flow simulation and network simulation. Examples of these simulators are TraNS (Traffic and Network Simulation environment) [PRL+07], NCTUns [Inc08], GrooveNet [MWR+06], and MobiREAL [Mob08].

In this Thesis, specifically we use ns-2 as a network simulator, and C4R as a vehicular mobility generator.

ns-2 is a discrete event simulator developed by the VINT project research group at the University of California at Berkeley. The simulator was extended by the Monarch research group at Carnegie Mellon University [The01] to include: (i) node mobility, (ii) a realistic physical layer with a radio propagation model, (iii) radio network interfaces, and (iv) the IEEE 802.11 Medium Access Control (MAC) protocol using the distributed coordination function (DCF). However, the ns-2 distribution code had some significant shortcomings both in the overall architecture and the modeling details of the IEEE 802.11 MAC and PHY modules. In [CSEJ+07], authors presented a completely revised architecture and design for these two modules. The resulting PHY is a full featured generic module capable of supporting any single channel frame based communications. The key features include cumulative signal to interference plus noise ratio (SINR) computation, preamble and physical layer convergence procedure (PLCP) header processing and capture, and frame body capture. The MAC layer accurately models the basic IEEE 802.11 carrier sense multiple access with collision avoidance (CSMA/CA) mechanism, as required for credible simulation studies. We improved the simulator by including the IEEE 802.11p and IEEE 802.11p standards in PHY and MAC layers, which defines enhancements to 802.11 required to support ITS applications [IEE10]. In terms of the physical layer, the data rate used for packet broadcasting is 6 Mbit/s, as this is the maximum rate for broadcasting in 802.11p.

C4R is a mobility pattern generator for vehicular networks, which allows simulating vehicular traffic in different locations using real maps. C4R has been im-

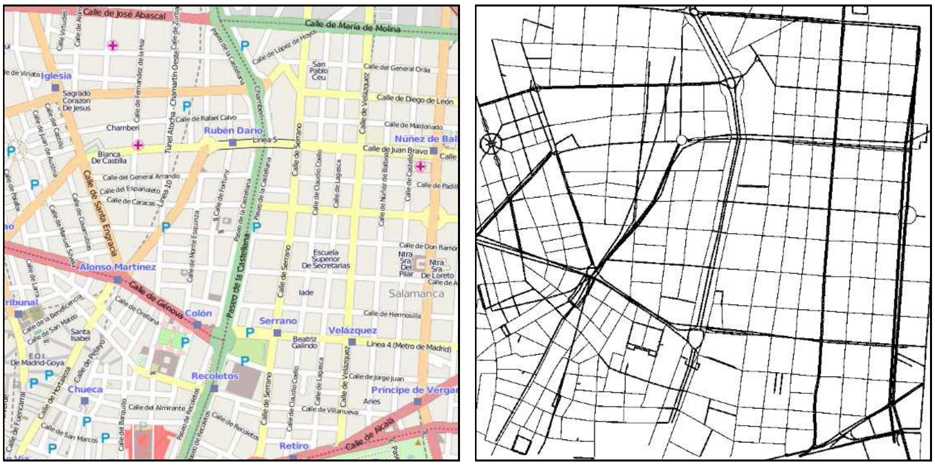


Figure 2.4: Scenario used in our simulations, fragment of the city of Madrid (Spain): (a) street map, (b) street graph.

plemented using the Java programming language, and it is distributed under the GNU/GPL license. It relies on both the OpenStreetMap tool [Ope14] to get the real roadmaps, and SUMO [KEB12] to generate the vehicles and their movements within these scenarios.

OpenStreetMap is a collaborative project to create a free editable map of the world, which is being built largely from scratch, and released with an open content license.

SUMO is an open source, highly portable, microscopic road traffic simulation package designed to handle large road networks. Its main features include collision free vehicle movement, different vehicle types, single-vehicle routing, multi-lane streets with lane changing, junction-based right-of-way rules, hierarchy of junction types, openGL graphical user interface (GUI), and dynamic routing. SUMO can manage large environments, i.e., 10 000 streets. Thus, by combining SUMO and OpenStreetMaps, we can simulate traffic in different locations of the globe. Figure 2.4 shows an example of a real map obtained from OpenStreetMaps, and its graph in SUMO. However, since SUMO is a pure traffic generator, its generated traces cannot be directly used by the available network simulators, which is a serious shortcoming.

The functionality provided by C4R is twofold: it constrains vehicle movements to the streets defined in the roadmap, and it limits their mobility according to the vehicular congestion and traffic rules. C4R has the following features [FGM+12b]:

- Ease of use (users can generate several mobility traces from scratch in just few minutes).
- Highly portable system (MAC, Windows and Linux compatibility).

- It is possible to work with real maps from all over the world.
- Users can easily change the number of simulated vehicles.
- C4R distinguishes among different types of vehicles (cars, trucks, taxis, etc.).
- Vehicle routes can be defined either by the user or randomly.
- Attraction and repulsion points in the roadmap can be defined graphically or by providing the coordinates manually.
- Vehicles movements are defined according to the selected mobility model (Krauss [KWG97], Krauss modified [KEB12], Wagner [Wag06], Kerner [Ker98], Intelligent driver model (IDM) [THH00], and the Downtown model [MCCM08b]).
- It is possible to visualize simulations.
- C4R allows users to obtain multiple ns-2 compatible mobility traces at once.
- All the necessary steps in the trace creation process can be taken using a user-friendly wizard, making the use of C4R very simple.

C4R can be tuned by the user in order to adapt the different possibilities to the user needs. Some of the most important parameters available in C4R are:

- Attraction rate: users can assign different rates to the attraction/repulsion areas.
- Downtown rate: users can define the probability for a vehicle to be within an attraction/repulsion area, and the probability of traveling to/from this area.
- Departure: users can deploy different vehicles at different time instants.
- Maximum simulation time: user can define the total duration of the simulation.
- Number of traces: users can define their required number of traces.
- Acceleration: users can define the maximum acceleration of the vehicles.
- Deceleration: users can define the maximum deceleration of the vehicles.
- Sigma: users can indicate the drivers imperfection.
- Tau: users can define the drivers reaction time.
- k: users can define the vehicle density measured in vehicles per kilometer.
- Phi: users can define the flow rate measured in vehicles per time interval.
- Headway: users can set the desired time headway to the vehicle in front.

Table 2.1: Common parameter values for the simulations

Parameter	**Value**
channel bandwidth	$6Mbps$
simulated area	$2000m \times 2000m$
packets sent by vehicles	1 *per second*
warning message priority	$AC3$
normal message priority	$AC1$
mobility generator	$C4R$ [FGM+12b]
radio propagation model	RAV [MFT+13]
maximum transmission range	$400m$

- MinGap: users can express the minimum net distance that is kept even at a complete stand-still in a traffic jam.

For all simulations included in this Thesis, we use the common parameters presented in Table 2.1. As shown, In terms of the physical layer, the data rate used for message broadcasting is 6 Mbit/s, as this is the maximum rate for broadcasting in 802.11p. The MAC layer was also extended to include four different priorities for channel access. Our simulations use different real scenarios of 4 km^2, obtained from OpenStreetMaps. Vehicles can operate in two different modes: (a) warning, and (b) normal. Vehicles in warning mode inform other vehicles about their status by sending warning messages periodically (every second). Normal mode vehicles enable the diffusion of these warning packets and, every second they also send beacons with information such as their positions, speed, etc. These periodic messages have lower priority than warning messages and are not propagated by other vehicles. Therefore, application messages are categorized into four different Access Categories (ACs), where AC0 has the lowest and AC3 the highest priority. As shown, we use AC1 for normal messages, and AC3 for warning messages.

Regarding the radio propagation model, the network simulator was also modified to make use of our *Real Attenuation and Visibility* (RAV) scheme [MFC+10], which proved to increase the level of realism in VANET simulations since it accounts for the effect of obstacles (e.g., buildings) in radio signal propagation when simulating urban scenarios. We consider as a maximum transmission range $400m$.

2.1.4 Summary

Road traffic is experiencing a drastic increase in recent years. Enhancing transportation safety and efficiency has emerged as a major objective for the automotive industry in the last decade. Overall, it is accepted that increased road safety can be achieved by exchanging relevant safety information among vehicles (V2V) and between vehicles and the infrastructure (V2I). We consider that the combination of V2V and V2I communications can propel our communication capabilities even further, increasing the traffic safety while traveling on the road.

To validate proposals based on vehicular networks, authors use two different options: (i) real-world testbeds, and (ii) simulations. Since vehicular networks are not extended in the real world, and the cost of equipped nodes is high, in this Thesis we validated all the proposals using simulations. Specifically, we use C4R and ns-2 modified to include the IEEE 802.11p, since ns-2 has become one of the most widely used network simulators for wireless communications researchers, and C4R provides a graphical user interface, obtains realistic maps from OpenStreetMaps, and generates input traces of ns-2.

2.2 Evolutionary Algorithms

Evolutionary computing is a computer science research area based on the process of natural evolution. It has been used in the academic environment for several years. In 1948, Turing proposed a "genetic or evolutionary search", and in 1962, Bremermann performed experiments based on 'optimization through evolution and recombination' [Fog98]. From that moment, several scientists started to develop different branches of this idea, which were finally unified during the 90's.

Evolutionary algorithms are based on Darwinian theories of evolution to explain the origin of species [Dar59]. The selection is inevitable in an environment that can only accommodate a limited number of individuals. Natural selection favors those individuals competing for resources in a more effective way. This selection based on competition and the phenotypic variations (i.e., physical or behavioral features which affect the interaction of the individual with the environment) are the essence of the evolution process. A favorable modification of these features produces a propagation of them to the offspring, since it increments the reproduction probability. A microscopic view of natural evolution is obtained by molecular genetics. Each individual is considered as a dual entity formed by: (i) external phenotypic properties, and (ii) its internal chromosome or genotype (gene set). The genotype of an individual encodes its phenotype, and genes are the inheritance functional units.

In computer science, these algorithms are used to solve optimization, modelling, and simulation problems [ES03]. They consist on applying natural selection to an individual population in order to obtain individuals better adapted to the environment. Before a determined number of generations, these algorithms have obtained the best solution for a particular problem (i.e., the best adapted individual).

In this section we present: (i) a definition of the evolutionary algorithms, (ii) a candidate classification of the evolutionary algorithms subsets, (iii) the performance of the evolutionary algorithms, and (iv) several Intelligent Transportation Systems proposals which applies Artificial Intelligence.

2.2.1 Definition of Evolutionary Algorithms

Evolutionary algorithms consist on an individual population which generates descendants, and the best individuals are selected to obtain the next generation. In each generation, some of the best candidates are chosen to generate a new offspring by applying recombination and mutation operators, giving rise to new individuals who will return to compete in the environment.

Algorithm 1 Evolutionary Algorithm Scheme

```
BEGIN
    Initialize Population
    Evaluation
    REPEAT UNTIL ( Finish Condition ) DO
        Parents Selection
        Recombination
        Mutation
        Evaluation
        Survivor Selection
    END LOOP
END
```

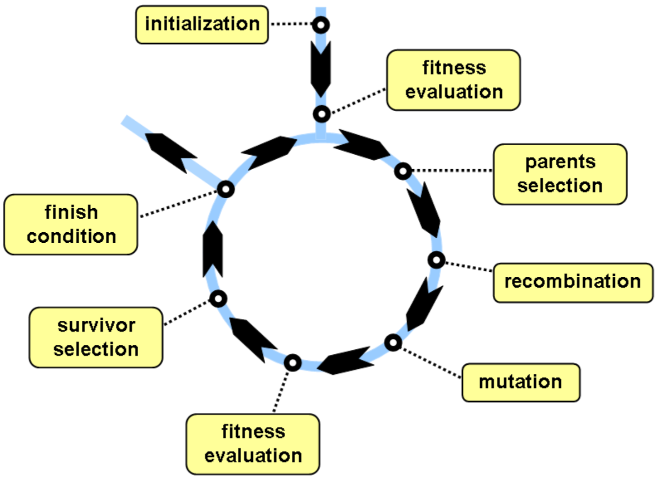


Figure 2.5: Methodology of Evolutionary Algorithms.

All evolutionary algorithms have the same methodology, presented in Algorithm 2 and Figure 2.5. As shown, this scheme belongs to the category search algorithms for generation-and-test.

The recombination or crossover operator is usually the most important in this type of algorithms. It is based on a combination of two (or more) genotypes called parents to generate new genotypes, the offspring. Parents are selected from existing individuals based on their level of adaptation or fitness, in order to obtain descendants which have inherited good genes from their parents. Applying iteratively this operator the probability of appearing the best chromosome genes in the population increases, leading to a convergence towards the best solutions.

Mutation operator is responsible for random changes in the characteristics of chromosomes and is typically performed at the gene level. Usually, the mutation rate (probability of changing a gene) is very small and depends on the length of the

Table 2.2: Main features of the evolutionary algorithms

Algorithm	Encoding	Main Application
Genetic Algorithms	binary	discrete optimization
Evolution Strategies	discrete or continuous	global optimization
Genetic Programming	tree structures	computer programs evolution
Evolutionary Programming	tree structures of a finite automaton	computer programs evolution

genotype, hence, the new produced genotypes after mutation will not be very different from the originals. The role of the mutation in the evolutionary algorithms is also very important, since recombination typically implies that the population of individuals converges making individual chromosomes very similar. However, there may be a state space region which has not been properly scanned, and therefore, the mutation is used to reintroduce genetic diversity in the population and avoid local optimal.

The parents selection is done by giving priority to the best adapted individuals using a particular algorithm, which can be proportional to their fitness value, ordering the individuals according to their adaptation degree, etc.

The evaluation function (degree of adaptation or fitness) represents a heuristic estimate of the quality of the solution. The survivors for the next generation are selected by using this function.

2.2.2 Classification of Evolutionary Algorithms

Evolutionary algorithms allow automating the resolution of problems in a several number of applications in different areas. They can be classified into two ways: (i) according to the branches defined in evolutionary computation, and (ii) depending on the feature that is wanted to determine (i.e., system inputs, system outputs, or the internal model which connects them). Next, we detail them.

2.2.2.1 According to Evolutionary Computation

This classification is based on the representation of a possible solution, i.e., data structure that encodes the solution. According to this, the most important categories are: (i) Genetic Algorithms (GA), (ii) Evolution Strategies (ES), (iii) Genetic Programming (GP), and (iv) Evolutionary Programming (EP). The use of each category depends on the kind of problem. One specific problem can be solved in a more efficient way using the category which better adapts its representation. Table 2.2 shows the main features of the categories. Following we present them in detail.

A) Genetic Algorithms

Genetic Algorithms are heuristic searches that mimic the process of natural evolution. They are used to solve discrete optimization and search problems. They randomly select parents (based on a performance function as roulette, tournament, etc.), who are replaced by the offspring in each generation keeping only the best father in the population. This algorithms use binary codification to represent the possible solutions. The parameterization of their mutation is fixed. Genetic algorithms find application in computational science, engineering, economics, manufacturing, mathematics, physics, and other fields. This kind of algorithms is the most popular of evolutionary algorithms.

B) Evolution Strategies

Evolution Strategies are optimization techniques based on ideas of adaptation and evolution. This strategies are usually used in global optimization problems of continuous variables, but they can also be used in problems with discrete parameters. They select parents randomly. The survivors selection consists on deterministically choosing the μ best individuals, after creating λ descendants and calculating their fitness. In this type of evolutionary algorithm, there are two kinds of survivor selection: (i) selection (μ, λ) where only the individuals of the offspring are considered to generate the next generation, and (ii) ($\mu + \lambda$) where survivors are selected from the union of parents and descendants. There is a strong emphasis on mutation for creating offspring, including the mutation parameters into the chromosome, and they are changed during a run of the algorithm, achieving faster results (self-adaptation). Mutation is implemented by adding some random noise drawn from a Gaussian distribution.

C) Genetic Programming

Genetic Programming is inspired by biological evolution to find computer programs that perform a user-defined task. Genetic programming is a specialization of genetic algorithms where each individual is a computer program. It is a machine learning technique used to optimize a population of computer programs according to a fitness landscape. Individuals are traditionally represented in memory as tree structures, since trees can be easily evaluated in a recursive manner. Every tree node has an operator function and every terminal node has an operand, making mathematical expressions easy to evolve and evaluate.

D) Evolutionary Programming

Evolutionary Programming is similar to Genetic Programming, but the structure of the program to be optimized is fixed, while its numerical parameters are allowed to evolve. In evolutionary programming, individuals are a set of three elements whose values represent states of a finite automaton. Each set consists on: (i) the value of the current state, (ii) one symbol of the used alphabet, and (iii) the value of the new state. These values are used, as in a finite automaton, as follows: taking the value of the current state, we take the value of the current symbol and, if it is the symbol of our set, we move to the new state.

2.2.2.2 Depending on the Feature to Determine

This classification is based on the system component that is unknown. Hence, we can classify Evolutionary Algorithms in three sets: (i) optimization, (ii) modeling or system identification, and (iii) simulation problems. Following we present them in detail.

A) Optimization Problems

In an optimization problem, the model and the desired output (or a description of the desired output) are known, and the task is to find the entry that allows to obtain that output.

B) Modeling or System Identification Problems

In a problem of modeling or system identification, a number of inputs and outputs interconnected are known, and it tries to find a model of the system that provides the correct output for each input. This tool can then be used to make predictions about unknown input values.

C) Simulation Problems

In a simulation problem, the system model and some entries are known, and it tries to calculate the outputs for these inputs. These systems generated by simulation have the advantage of being cheaper than testing with real prototypes.

2.2.3 Evolutionary Algorithms Performance

Generally, the performance of an evolutionary algorithm is divided into two stages: (i) a first scan in which new individuals occupying unexplored regions of the search space are found, and (ii) a second operation in which the solutions tend to be concentrated in the proximity to known solutions with good fitness values. An appropriate algorithm must achieve a balance between the two stages, since if it spends too much time to scan, the search is inefficient, and if it spends too much time on exploitation it can lead to non-global optimal solutions. The effect by which diversity of the population is lost too quickly and becomes stuck in a local optimum is called premature convergence, and should be avoided by a suitable mechanism of mutation.

Another effect of evolutionary algorithms can be seen in the evolution of the fitness value in the population as the generations pass [ES03]. Figure 2.6 represents the typical profile of the adaptation degree of the best individual in one of these algorithms. As shown, the most remarkable improvement occurs during the first generations, while in the course of time individuals tend to stagnate at optimal and much improvement is not seen.

Another significant effect is seen when deciding what strategy to follow to get an initial population. Perhaps the effort to employ some heuristics to improve the value of initial adjustment of individuals is not really effective to reduce the time needed to locate the global optimum dramatically. As shown in Figure 2.7, the extra effort to generate a population more adequate than a simple random only

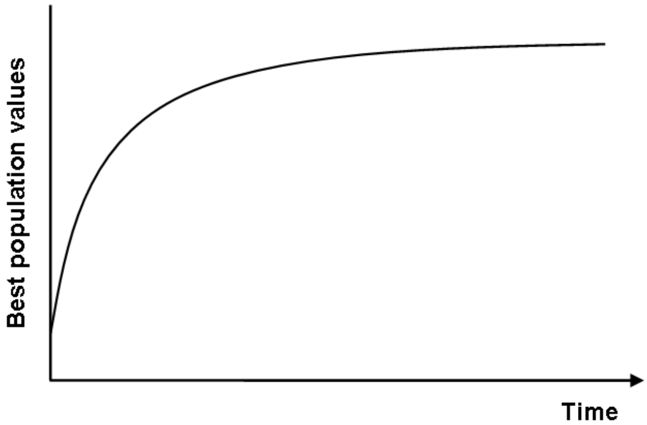


Figure 2.6: Typical progress of an evolutionary algorithm in terms of developing the best fitness value of the population through time.

allows slightly reduce the number of generations required, as the version totally random gets reach the level for heuristic version in short time ('k' value in the Figure).

Also related to the shape of the graph of evolution, we can determine which time period may be suitable for finding the optimum. The greatest advance in the adaptation degree of the population occurs during the first generations (see Figure 2.8), since evolutionary algorithms performance does not improve much after several executions. Thereby, this kind of algorithms can be suitable for solutions with remarkable quality level in applications that requiring obtain it as quickly as possible, since add additional time does not provide great improvements in the solution.

2.2.4 Artificial Intelligence Applied to Intelligent Transportation Systems

Artificial Intelligence has been widely used in Intelligent Transportation Systems. It is used to develop applications which make driving experience more safe and efficient. We can find approaches focused on controlling traffic lights, as the multiagent system based on neuronal networks presented by Srinivasan et al. [SCC06] in which authors proposed a system to develop distributed unsupervised traffic responsive signal control models, as well as approaches focused on automatic pedestrian detection, for instance, the classifier for pedestrian detection presented by Cao et al. [CXCQ09].

However, most of the studies of this scope are used to solve vehicles routing problems. Kanoh and Hara [KH08] formulated the routing problem as a dynamic multi-objective problem and showed how it can be solved using a Genetic Algorithm. In their work, there was three objective functions to simultaneously optimize that problem: route length, travel time that changes rapidly with time, and

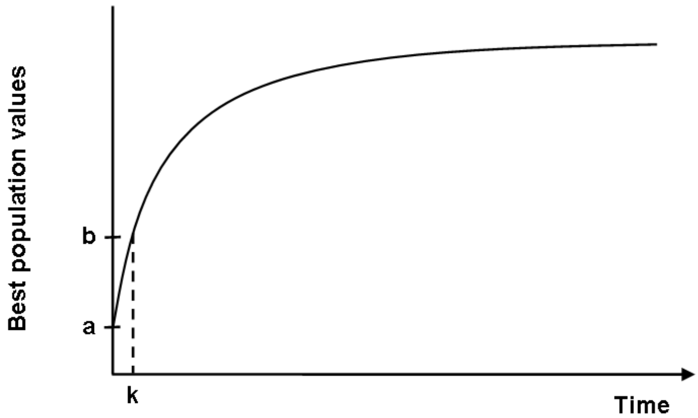


Figure 2.7: Illustration of the effect of using a heuristic to initialize the initial population. The level 'a' represents the best fitness of a population initialized randomly, and the level 'b' belongs to a heuristic initialization.

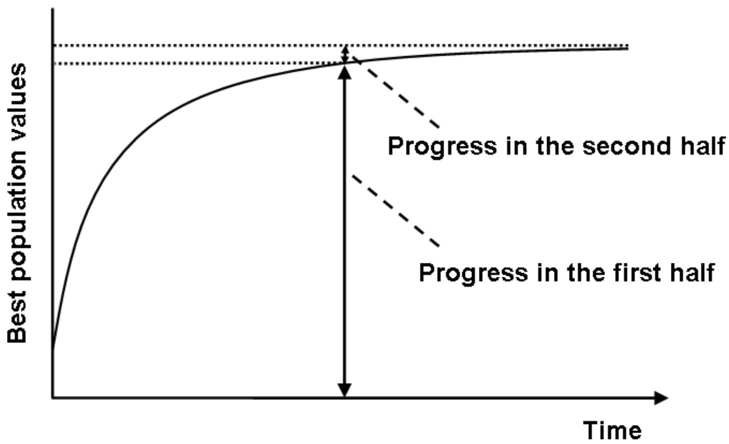


Figure 2.8: Example of common evolutionary algorithm performance.

ease of driving. They combined their genetic algorithm with Dijkstra algorithm to obtain the best routes and, finally, driver can choose one of them. Wang et al. [WTL07] presented an approach to search for best routes in dynamic network. They proposed a dynamic route evaluation model for modeling the responses of vehicles to changing traffic information, a modified Dijkstra's double bucket algorithm for finding the real-time shortest paths, and an improved evolutionary algorithm for searching the best vehicle routes in dynamic network.

Kanoh and Tsukahara [KT10] proposed a solution to the vehicle routing problem with time windows using an evolution strategy adopting viral infection. The proposed method preserves the schema as a virus and uses it by the infection operation in successive generations. The main advantage of their system was that the gather function is computed at decision without needing a training stage as required by the neural network gathers.

Tan et al. [TCG07] presented a multiobjective evolutionary algorithm that incorporates two vehicle routing problem with stochastic demand specific heuristics for local exploitation and a route simulation method to evaluate the fitness of solutions, in order to solve such a multiobjective and multi-modal combinatorial optimization problem. Their developed algorithm is further validated on a few VRPSD instances adapted from Solomons vehicle routing problem with time windows benchmark problems.

Since Evolutionary Algorithms are focused on optimization problems, in this work we use them to propose a system that allows emergency services to reduce their arrival time to the accident location, optimizing their vehicles route depending on the traffic density.

2.2.5 Summary

Evolutionary computing is a computer science research area based on the process of natural evolution. Evolutionary Algorithms allows to obtain suboptimal solutions in a reasonable time. However, they are rather used in vehicular environments to obtain efficient vehicle routes. In this Thesis, we apply this technology to efficiently manage traffic when an accident occurs. Specifically we implements an evolution strategy since this variant of evolutionary algorithms is typically used for conditions parameter optimization, and mutation parameters are changed during a run of the algorithm, achieving faster results.

Chapter 3

VEACON: a Vehicular Accident Ontology Designed to Improve Safety on the Roads

Vehicles are nowadays provided with a variety of new sensors capable of gathering information about themselves and from their surroundings. In a near future, these vehicles will also be capable of sharing all the harvested information, with the surrounding environment and among nearby vehicles over smart wireless links. They will also be able to connect with emergency services in case of accidents. Hence, distributed applications based on Vehicular Networks (VNs) will need to agree on a 'common understanding' of context for interoperability, and, therefore, it is necessary to create a standard structure which enables data interoperability among all the different entities involved in transportation systems. In this chapter, we focus on traffic safety applications; specifically, we present the VEhicular ACcident ONtology (VEACON) designed to improve traffic safety. Our ontology combines the information collected when an accident occurs, and the data available in the General Estimates System (GES) accidents database. We assess the reliability of our proposal using both realistic crash tests, held in the facilities of Applus+ IDIADA in Tarragona, Spain, and vehicular network simulations, based on the ns-2 simulation tool. Experimental results highlight that both nearby vehicles and infrastructure elements (RSUs) are correctly notified about an accident in just a few seconds, increasing the emergency services notification effectiveness. Our VEACON Ontology will be used in all the schemes proposed along the Thesis.

3.1 Introduction

In this chapter we focus on safety applications. Specifically, our aim is to improve traffic safety by using an ontology-based approach in Vehicular Networks.

To that end, we propose the *VEhicular ACcident ONtology* (VEACON), a novel lightweight ontology proposed to provide sharing and reusing knowledge about traffic accidents. VEACON allows to efficiently structure and encode the information collected by sensors in the vehicle, enabling the interoperatibility among all the agents involved in modern ITS (i.e., vehicles, RSUs, emergency services, and authorities).

Nowadays, vehicular networking technologies allow a vehicle to alert emergency services in case of an accident. Although there are many solutions that rely on Vehicular Networks for that purpose, there are fewer solutions based on semantics to send accident information to the emergency services. In this chapter, we explore the use of an ontology framework for sending critical information captured by vehicles involved in road accidents. This information will not only be sent to the emergency services, but also it will be shared among nearby vehicles. Hence, this warning information will be used for different proposes such as: (a) preventing new accidents (avoiding that other vehicles collide with the vehicles already involved in the accident), (b) helping to allocate resources for a rescue, and (c) maintaining statistics on road accidents, which allows fast database searches and the creation of prediction models to estimate the severity of future accidents.

This chapter is organized as follows: Section 3.2 reviews the related work regarding to the use of ontologies applied on ITS. Section 3.3 presents VEACON, our proposed ontology. In Section 3.4, we assess the feasibility of our proposal by doing some real experiments as well as carrying out some simulation tests. Finally, Section 3.5 concludes this chapter.

3.2 Related Work

For the proper operation of traffic safety systems, we must consider two different factors: (i) vehicles must be able to communicate among them in order to share information, and (ii) the shared information should be understood by all the entities involved in transportation systems. The first factor has been widely studied by the wireless networking research community [MTC$^+$10, BGL11, ARBOGZMP11, DPRK11]. However, the second factor has not yet been studied to the same extent.

Regarding the use of semantics in vehicular environments, some authors have worked on the integration of transportation systems information and semantics. Zhai et al. [ZZSS08] presented an ontology for structuring data traffic. Zhai et al. [ZWL08] introduced a knowledge navigation system with urban traffic information based on the XML Topic Maps technology, enabling intelligent information retrieval through association between topics. These different works highlight the importance of using ontologies in ITS, however they do not provide any ontology specially designed for ITS safety.

Regarding ITS safety, Eigner and Lutz [EL08] showed the need for ontological context models for VNs safety environments, and how all the components of the system would be able to understand one another through these models. They considered that vehicles should incorporate a variety of sensors to get data from the vehicles themselves, as well as from their surroundings. In addition, information obtained by these sensors could be shared with other vehicles using

VNs. The authors showed that vehicular applications can benefit from the inherent characteristics of ontological models such as distributed composition, partial validation, richness and quality of information, as well as a certain level of formality. Additionally, authors proved that calculations on the model are still fast enough to fulfill real-time requirements imposed by the active safety systems of vehicles. However, they did not build a specific ontology. More recently, Kannan et al. [KTK10] proposed an ontology modelling approach for assisting vehicle drivers through warning messages during time critical situation. Authors focused on generating the alert messages based on the context aware parameters such as driving situations, vehicle dynamics, driver activity, and the environment.

Although the above presented works proposed ontological models for warning messages using Vehicular Networks, none of them enriched their proposal with historical information to estimate the severity of accidents using real crash tests.

3.3 VEACON: Our Ontology for Vehicular Networks

From the point of view of Communications and Information Technologies for Vehicular Networks, ITS applications will rely on efficient vehicular communications and smart exchange of information among all the entities involved, i.e., vehicles, RSUs, emergency services, management authorities, and police. When a traffic accident occurs, a crucial issue is to collect as much information as possible, since vehicles should rapidly warn nearby vehicles and the emergency services to obtain a quick and efficient response from them. However, the information usually collected in accidents is neither structured nor does it present relationships between their basic elements. We propose to organize this information by using an approach based on the Semantic Web, where the information can be obtained through various techniques such as ontologies, classifications, taxonomies, thesauri, or topic maps [Gar04].

Our system gets the information from warning messages exchanged among vehicles and emergency services. This information should be, on the one hand, concise enough to avoid irrelevant information, but, on the other hand, it should not ignore any information that might be useful for the emergency services to determine the most suitable set of resources. Thus, the delivered information should include: data about the conditions under which the accident occurred, data about the occupants of the vehicle, as well as a description of the security systems included within the vehicle. When an accident occurs, all these data will be sent to the emergency services, providing a more detailed view of the conditions of the accident before their arrival.

In this work, we use an ontology based technique to group all these information sources, while allowing to make inferences over the collected data. An ontology formally represents knowledge about the entities within a domain, so we can elaborate estimations about the entities involved. In our case, we can estimate the different factors of the accident (impact severity, passenger injuries, and so on). Basically, an ontology consists of three parts: classes and instances of real-world

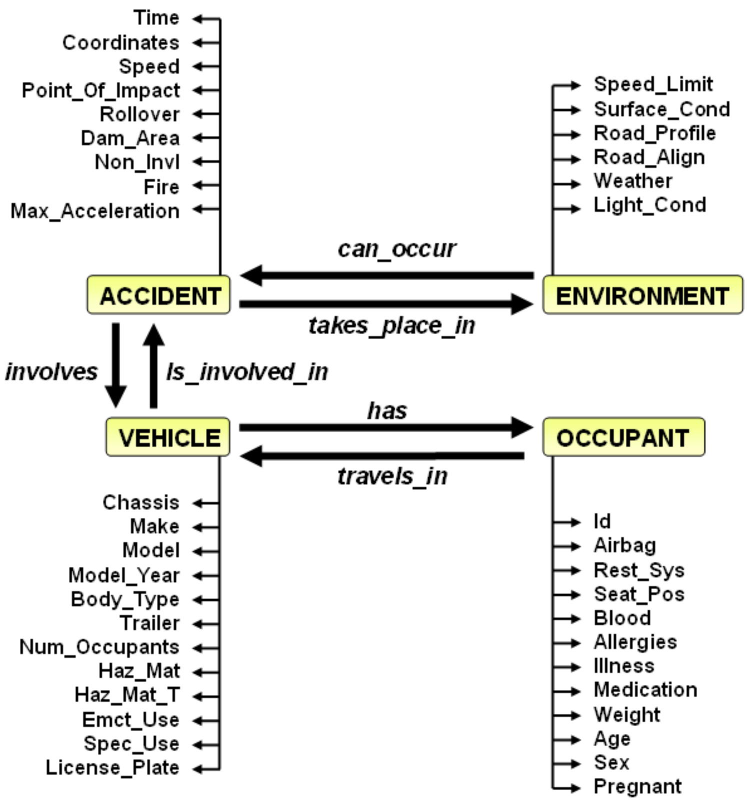


Figure 3.1: VEACON ontology components.

items, relations among these items, and rules for modeling knowledge and complex behaviors (creation, restraint, and response).

Specifically, we propose the Vehicle Accident Ontology (VEACON), a novel lightweight ontology proposed with the aim of sharing and reusing knowledge about the vehicles involved in road accidents. VEACON meets our requirements since it: (i) promotes interoperability between different knowledge sources, (ii) provides an infrastructure or cooperative system, (iii) facilitates the information sharing, and (iv) enables domain knowledge reuse. These features cannot be provided by a simple rule based system. VEACON consists of a set of classes representing the categories of the entities of interest in the ITS domain, the attributes which define properties of those classes, and the relationships between those entities.

Figure 3.1 shows the basic VEACON ontology structure, which groups the available information into four different areas: Vehicle, Accident, Occupant and Environment. As for the languages, we decided to use the Ontology Web Language (OWL) [The04] to create XML-based messages, since it is a flexible and expressive language which provides a basic syntax to describe the relationships between entities. Listing 3.1 shows an example of a VEACON-compliant warning message.

```
<?xml version="1.0"?>
<rdf:RDF xmlns="http://www.owl-ontologies.com/VehicleCrash.owl#" ...>
  <owl:Class rdf:ID="Occupant"/> ...
  <owl:ObjectProperty rdf:ID="takes_place_in">
    <rdfs:domain rdf:resource="#Accident"/>
    <owl:inverseOf>
      <owl:ObjectProperty rdf:ID="can_ocurr"/>
    </owl:inverseOf>
    <rdfs:range rdf:resource="#Environment"/>
  </owl:ObjectProperty> ...
  <Occupant rdf:ID="Occupant_2">
    <illness>No</illness>
    <pregnant rdf:datatype="http://www.w3.org/2001/XMLSchema#boolean">
        true</pregnant>
    <blood>A+</blood>
    <weight rdf:datatype="http://www.w3.org/2001/XMLSchema#float">56.4</weight>...
  </Occupant>
</rdf:RDF>
```

Listing 3.1: Example of a VEACON OWL-based warning message.

Due to privacy requirements of the collected data, especially the medical information of the passengers, all the messages generated with the VEACON ontology are encrypted using the Advanced Encryption Standard (AES) [DR02] before being sent by the vehicles.

3.3.1 Getting Information into our Ontology

Nowadays, vehicles incorporate a series of sensors to obtain information about different areas. Examples of them are crash sensors [Bre91], occupant position sensors [BCJD98], rain sensors [Pet99], or seat belt tension sensors [HS00]. Therefore, it is possible to get key information from these sensors when an accident occurs.

Furthermore, we consider that future vehicles will get additional information from the environment and its occupants, since vehicles will be provided with sensors capable of knowing if there are pedestrians or cyclists involved in an accident, and also information regarding the health of the occupants such as blood group or heart problems will be available. Currently, there are some approaches addressing these issues; for example, the Ford Motor Company [For11] is designing seats that can monitor the driver's heartbeat in real time. For personal information and health data of the occupants, we consider that occupants could have this information previously stored in their smartphones. Hence, our system would automatically collect this data when passengers enter into the vehicle by using wireless technologies such as Near Field Communication (NFC) or Bluetooth.

To allow estimating the severity of the accidents, our proposal also uses the General Estimates System (GES), an historical database maintained by the National Highway Traffic Safety Administration (NHTSA) [Nat11], which contains information related to previous traffic accidents, obtained from a sample of Police Accident Reports (PARs) collected all over the USA roads. To protect individual privacy, no personal information such as names, addresses or specific crash location is coded. We used data from thousands of real accident situations to develop an accident detection algorithm which was able to correctly predict the event of an accident in all the experiments [FGM+11b, FGM+12a]. The thresholds used to differentiate between accident and non-accident situations were selected in order to minimize the error in the prediction. Even if the initial prediction was wrong,

Table 3.1: Vehicle dataset.

Field	Description
Chassis	Vehicle chassis number
Make	Manufacturer of the vehicle
Model	Vehicle model
Model_Year	Vehicle model year
Body_Type	Vehicle body type
Trailer	If vehicle is towing trailing units
Num_occupants	Number of vehicle occupants
Haz_Mat	If vehicle is carrying hazardous materials
Haz_Mat_T	Hazardous materials type
Emcy_use	If vehicle is on an emergency run
Spec_use	Vehicle special use category applied
License_Plate	Vehicle plate number

Table 3.2: Accident dataset.

Field	Description
Time	Time when crash occurred
Coordinates	Crash point coordinates
Speed	Vehicle speed at the crash moment
Point_Of_Impact	Point of impact for the crashed vehicle
Rollover	If vehicle has overturned
Dam_Area	Dam area for the crashed vehicle
Non_Invl	Number of non-motorists involved in the crash
Fire	If vehicle is in fire
Max_Acceleration	Vehicle maximum deceleration during the crash

our ontology includes additional information (speed before the impact, light condition, etc.) that can be subsequently compared to the GES historical accident data, thus accurately determining the severity of the impact and its consequences on the passengers. Therefore, for every collision, two filters must be passed before considering it effectively a potentially dangerous accident.

3.3.2 VEACON Fields

For our proposed ontology, we selected a number of existing fields in the GES database, and we have also added others that we consider necessary. The selection was specifically made considering the data that can be significant when an accident occurs.

We have grouped the information into four areas: (i) Vehicle, which contains the characteristics of the vehicle and data for identification; (ii) Accident, which collects the location and time of the crash, the characteristics of the collision,

Table 3.3: Occupant dataset.

Field	**Description**
Id	Occupant identifier
Airbag	Airbag availability/function in the seat position of the occupant
Rest_Sys	Restraints that are being used by the occupant immediately prior to the crash
Seat_Pos	Occupant seating position
Blood	Occupant blood type
Allergies	Occupant allergies
Illness	Occupant illness
Medication	If occupant needs specific medication or treatment
Weight	Occupant weight
Age	Occupant age
Sex	Occupant gender
Pregnant	If occupant is pregnant

and the caused damages; (iii) Occupant, which collects occupants' personal and medical information, their location within the vehicle, and the safety systems deployed; and (iv) Environment, which contains information about road, weather and lighting conditions.

Concerning to the Vehicle dataset, the fields used are those indicated in Table 3.1. For this dataset, we used available fields from the GES database, and added two new fields: *License_Plate* and *Chassis*. We believe that they are necessary since they provide a unique identifier (Chassis), and allow the emergency services to quickly recognize vehicles at the scene of accident (License_Plate).

With respect to Accident, the fields used are those indicated in Table 3.2. For this dataset, we used fields from the Accident and Vehicle dataset from the GES database, and added two new fields: *Coordinates* and *Max_Acceleration*. We consider that they are necessary to locate the crash site (Coordinates), and to obtain a measure of the impact severity (Max_Acceleration). Note that, if using the appropriate technology, the system can also determine the value of the *Non_Invl* field, which indicates whether people outside the vehicle (pedestrian or cyclist) were involved in the crash. This information could be very useful for emergency services to decide the rescue resources required.

In the set of data related to Occupants, the fields used are those indicated in Table 3.3. For this dataset, we used basic fields from the GES database, and also added nine new fields: *Blood*, *Allergies*, *Illness*, *Medication*, *Pregnant*, *Weight*, *Age*, *Sex* and *Id*. The first eight fields could be previously stored on the mobile phone of each passenger. Then, in case of an accident, emergency services will receive all this individualized medical information, thereby allowing emergency services to identify each person.

Finally, Table 3.4 shows the different fields related to Environment. For this dataset, we used fields from the Accident dataset available in the GES database.

Table 3.4: Environment dataset.

Field	Description
Speed_Limit	Roadway legal speed limit
Surface_Cond	Roadway surface condition
Road_Profile	Roadway profile
Road_Align	Roadway alignment
Weather	Atmospheric conditions at the time of the accident
Light_Cond	Light conditions at the time of the accident

3.3.3 Qualitative Comparison with other Similar Existing Ontologies

Table 3.5 presents a summary of the VEACON comparison we made with respect to other existing ITS ontologies, such as the ontologies proposed by Eigner and Lutz [EL08] and Kannan et al. [KTK10]. We have structured the comparison in eight different categories: (a) the source of their attributes, (b) if they used any historical database, (c) if they support accident severity prediction, (d) the tagging language used, (e) the software frameworks used, (f) if data is grouped into classes, (g) if they present the relationships, and (h) the method selected for the evaluation.

As shown, VEACON is the only ontology that uses historical data for its design, enabling the prediction of accidents severity, which in our opinion makes the difference, since nowadays traffic accidents cause millions of people killed or severely injured. Moreover, in contrast to VEACON, the rest of studied ontologies have not been evaluated under real testbed crash environments, and using vehicular simulations.

3.4 Validation of Our VEACON Ontology

To verify that our ontology works correctly in Vehicular Networks, we performed two different kinds of experiments: (i) real crash tests involving V2I communications, where we verify that messages using our ontology proposal are correctly sent to the emergency services in case of an accident, and (ii) vehicular network simulations, to study how VEACON messages would be propagated to the rest of vehicles in terms of V2I and V2V communications, in realistic urban environments.

3.4.1 Real Crash Tests

To prove the feasibility of our ontology, we performed several crash experiments in the facilities of Applus+ IDIADA [App11] Passive Security Department sited in Santa Oliva (Tarragona, Spain). This laboratory is one of the most sophisticated crash test laboratories in the world, and is an official center for approval under the EuroNCAP: European New Car Assessment Programme [Eur11]. Due to the cost of using real vehicles in the collision experiments, tests were performed using

Table 3.5: ITS ontologies comparison.

Description	**VEACON**	**Eigner and Lutz [EL08]**	**Kannan et al. [KTK10]**
Where does it select attributes?	GES database enriched	At their own discretion	At their own discretion
There is historical data to compare accidents?	Yes, the GES database	No	No, it is designed to support a Driver Assistance System
Does predict it the damage from accident?	Yes, using historical data	No, it is only designed to prevent accidents	This ontology is not specific for traffic accidents
Tagging language	OWL	OWL	OWL
Software used	Protégé	Not specified	Protégé
Does it present the ontology relationships?	Yes	No	Only partially
System Evaluation	Crash tests and network simulations	Simulations using the Virtual Traffic Simulator (VISSIM)	Ad-hoc simulator
Map Topology for Validation	Real roadmaps	Synthetic roadmaps	Synthetic single, 2-way, and 4-way roads

a platform (known as “sled”) which is able to reproduce different kind of vehicles and impact severities in traffic accidents.

Validation experiments consisted in front, side, and rear-end collision tests with different severities. The classification of the severity of the collision is dictated by the EuroNCAP and RCAR tests [RCA11]. In our experiments, the OBU installed in the sled collected all the information provided by the sensors, built the warning message according to our VEACON ontology, and then, when the accident is detected, it wirelessly sends our ontology-based alert information to warn about the accident. An external computer acted as a Road Side Unit (RSU) in charge of receiving the warning messages broadcasted by vehicles, and forwarding them to a suitable Public Safety Answering Point (PSAP) or 112 Service Center.

The results obtained in the real crash tests were very promising. The OBU is in charge of determining the severity of the impact. Interpreting acceleration values is not trivial since the received pulses have a very limited duration, and also because both their amplitude and duration should be considered in the classification.

The experiments performed in real crash tests proved that our system was able to collect all the information provided by in-vehicle sensors, to build the VEACON-compliant message, and to communicate with the RSU in every tested situation without message loss. Moreover, the OBU was able to accurately determine the impact severity by using the integral approach in all cases, generating an adequate warning message, and sending it to the nearest RSU. Warning mes-

Table 3.6: NS-2 Tcl file for the IEEE 802.11p.

```
#Configuration for 802.11p PHY layer

Phy/WirelessPhy set CPThresh_   10.0
Phy/WirelessPhy set CSThresh_   1.559e-11
Phy/WirelessPhy set RXThresh_   3.652e-10
Phy/WirelessPhy set Rb_         2*e6
Phy/WirelessPhy set Pt_         3.57382      ;# Maximum tx range = 400 meters
Phy/WirelessPhy set freq_       5.9e9        ;# 5.9 GHz
Phy/WirelessPhy set L_          1.0
Phy/WirelessPhy set bandwidth_  54e6

#Configuration for 802.11p MAC layer (based on 802.11e MAC layer)

Mac/802_11p set CWMin_              15
Mac/802_11p set CWMax_              1023
Mac/802_11p set SlotTime_           0.000009        ;# 9 us
Mac/802_11p set SIFS_               0.000016        ;# 16 us
Mac/802_11p set PreambleLength_     96              ;# 96 bit
Mac/802_11p set PLCPHeaderLength_   40              ;# 40 bits
Mac/802_11p set PLCPDataRate_       6.0e6           ;# 6 Mbps
Mac/802_11p set RTSThreshold_       3000            ;# 3 Kbytes
Mac/802_11p set ShortRetryLimit_    7               ;# retransmissions
Mac/802_11p set LongRetryLimit_     4               ;# retransmissions
Mac/802_11p set basicRate_          6e6             ;# 6 Mbps
Mac/802_11p set dataRate_           6e6
```

sages were broadcasted and successfully received by the RSU, and the contained information was correctly extracted and interpreted. Consequently, we conclude that the VEACON ontology can be successfully used to notify accident situations in real environments.

3.4.2 Network Simulation Tests

To study how VEACON messages propagate in a vehicular network scenario, simulations were done using the ns-2 simulator and C4R, as presented in the previous chapter.

Table 3.6 shows the main parameters used for the configuration of the ns-2 simulator in order to model the performance of the 802.11p standard.

The purpose of the 802.11p standard is to provide the minimum set of specifications required to ensure interoperability between wireless devices attempting to communicate in potentially rapid changing communication environments. For our simulations, we chose the IEEE 802.11p because it is expected to be widely adopted by the industry.

We want to evaluate whether or not our proposal ontology could affect to the dissemination of warning messages in Vehicular Networks.

We tested our proposed ontology by evaluating the performance of a Warning Message Dissemination mechanism where each vehicle periodically broadcasts information about itself, or about an accident. These messages are built according to our VEACON ontology.

Table 3.7: Main features of the selected maps.

Selected city map	New York (USA)	San Francisco (USA)	Rome (Italy)
Streets/km^2	175	428	695
Junctions/km^2	125	205	298
Avg. street length	$122.55m$	$72.71m$	$45.89m$
Avg. lanes/street	1.57	1.17	1.06

Table 3.8: Simulation parameters.

Parameter	**Value**
number of vehicles	50, 100, 200, 400, *and* 600
simulated cities	*New York*, *San Francisco*, *and Rome*
number of collided vehicles	2
warning packet size	13 *and* $18KB$
mobility models	Krauss and Downtown
MAC/PHY	802.11p

Our simulations have been carried out in three different scenarios of 4 km^2, obtained from real maps from New York (USA), San Francisco (USA), and Rome (Italy). As shown in Figure 3.2, the New York map presents the longest streets, mostly arranged in a Manhattan-grid style, while the city of Rome represents the opposite situation, with short streets in a highly irregular layout. The city of San Francisco shows an intermediate layout, with a medium density of streets in a less irregular arrangement compared to Rome. Table 3.7 includes the main features of the selected cities.

We simulated a frontal impact scenario where two vehicles are involved. The first vehicle is a family car with two occupants, and expressing all the information required, according to VEACON, it requires a message of 13 KBytes. The second vehicle is a minivan with eight occupants, which required up to 18 KBytes to code the data for all passengers. Each simulation run lasted for 450 seconds. In order to achieve a stable state, we collect data only after the first 60 seconds. All results represent an average of over 90 executions with different scenarios (maximum error of 10% with a degree of confidence of 90%). Table 3.8 shows the parameters used in the simulations.

In order to determine the feasibility of VEACON in different situations, we present the results obtained when considering both V2I and V2V communications. According to previous works [MTC$^+$11b, FGM$^+$11a], we consider that some factors, such as the density of vehicles, the density of Road Side Units (RSUs), or the map topology, should have a significant impact on the performance of our ontology-based scheme. Therefore, we performed different experiments by varying these factors, and studied their effect on the following metrics: (i) the notification time (i.e., the period elapsed between the time when a warning-mode vehicle requests for help, and the time when any RSU receives the warning message, deliv-

(a) (b)

(c)

Figure 3.2: Scenarios used in our simulations: (a) fragment of the city of New York (USA), (b) fragment of the city of San Francisco (USA), and (b) fragment of the city of Rome (Italy).

ering it to the next Public Safety Answering Point (PSAP) or 112 Service Center), (ii) the reachability (i.e., the percentage of times that warning messages reach any RSU), (iii) the warning notification time (i.e., the time required by nearby vehicles to receive a warning message sent by a collided vehicle), and (iv) the percentage of vehicles receiving the warning messages. These metrics are crucial when assessing the usefulness of our studied system, since a warning message delivered too late is useless when facing dangerous situations.

3.4.2.1 V2I Communications Results

Regarding V2I communications, Table 3.9 shows the minimum notification time and the reachability (i.e., the percentage of times that warning messages reach any RSU), when varying the number of vehicles, the number of RSUs, and the simulated roadmap. Note that RSUs are uniformly distributed in the scenario to maximize the coverage area.

As shown, when the vehicle density is very low, the system yields poorer performance in terms of warning notification time and reachability. On the contrary, in high density scenarios, the warning messages are correctly notified (i.e., they already reach one RSU at least) in almost every simulation, and the warning notification time is also reduced. When 600 vehicles are simulated, notification requires more time in Rome, since the topology is more complex than New York or San Francisco. Moreover, results show that in lower density scenarios and complex roadmaps like Rome, the reachability is extremely lower compared to New York, where the longer streets, mostly arranged in a Manhattan-grid style, favors the wireless signal propagation. As expected, results reflect that increasing the density of vehicles highly increases the chances for warning messages to reach any RSU, i.e., the emergency services notification effectiveness.

Regarding the number of RSUs deployed in the scenario, the results reflect that it also affects the warning notification time and the reachability. When increasing the number of RSUs, the probability that the warning messages created according to our VEACON ontology are correctly notified increases, while the system required less time to notify the emergency services. Results show that in low density scenarios, the number of RSUs is crucial, since the chance of multihop communication between the vehicles and the infrastructure decreases significantly. However, in high density scenarios, the required number of RSUs deployed decreases without losing performance.

In addition, the simulated roadmap affects both the warning notification time and the percentage of times that warning messages reach any RSU. Our results demonstrate that highly complex roadmaps (such as Rome) tend to show higher notification times, and lower percentage of successful RSU notifications. We think that results demonstrate that V2I communications can play an important role to correctly and quickly notify accidents to the emergency services, as well as favor the dissemination of warning messages among the nearby vehicles, especially in complex topology scenarios.

Table 3.9: V2I simulation results.

		New York		*San Francisco*		*Rome*	
Vehicles	**RSUs**	**Notif. time (s)**	**Reach. (%)**	**Notif. time (s)**	**Reach. (%)**	**Notif. time (s)**	**Reach. (%)**
50	1	18.239	40.0	22.650	20.0	14.473	10.0
	2	16.644	65.0	20.220	42.5	13.642	15.0
	4	12.961	75.0	18.752	55.0	17.882	20.0
	8	10.097	90.0	15.463	62.5	13.443	35.0
	16	8.319	92.5	12.140	62.5	12.200	35.0
100	1	15.439	80.0	14.635	45.0	11.152	27.5
	2	10.887	95.0	13.921	65.0	10.449	37.5
	4	8.817	100.0	11.020	75.0	13.286	45.0
	8	8.464	100.0	9.472	75.0	13.045	50.0
	16	4.440	100.0	6.694	95.0	10.079	55.0
200	1	4.870	85.0	7.645	95.0	15.438	20.0
	2	2.622	95.0	5.985	90.0	15.306	30.0
	4	3.237	100.0	4.850	95.0	15.716	72.5
	8	2.490	100.0	3.901	95.0	11.424	82.5
	16	2.233	100.0	3.368	95.0	8.298	90.0
400	1	1.869	100.0	3.848	85.0	16.383	67.5
	2	1.676	100.0	3.459	100.0	12.941	72.5
	4	1.611	100.0	3.126	100.0	10.279	72.5
	8	1.396	100.0	3.005	100.0	8.915	80.0
	16	1.306	100.0	2.782	100.0	6.458	90.0
600	1	2.719	100.0	3.479	100.0	7.852	65.0
	2	2.021	100.0	1.865	100.0	6.477	80.0
	4	1.799	100.0	1.715	100.0	4.977	80.0
	8	1.321	100.0	1.644	100.0	4.070	90.0
	16	1.064	100.0	1.667	100.0	2.936	100.0

3.4.2.2 V2V Communications Results

Regarding V2V communications, Figure 3.3 shows the obtained results when varying the scenario topology and the vehicle density.

As shown, both factors have a high impact on the performance. The selected map has a great influence on the percentage of vehicles receiving warning messages and on the warning notification time, especially when the vehicle density is low. When only 50 vehicles are simulated, warning messages reach only 10.27% of the vehicles in Rome, 30.17% of the vehicles in San Francisco, and 42.73% of the vehicles in New York, where the long and regular streets allow easy propagation of the wireless signal. The system requires 1 second to reach 4.23%, 9.10%, and 15.63% of the total number vehicles, in Rome, San Francisco, and New York, respectively. For higher vehicle densities, the differences detected when using different maps are reduced, although they are still evident. The percentage of informed vehicles increases (e.g., when 600 vehicles are simulated, warning messages reach 94.93% of the vehicles in the New York scenario, 95.80% of the vehicles in the San Francisco scenario, and 84.08% of the vehicles in Rome).

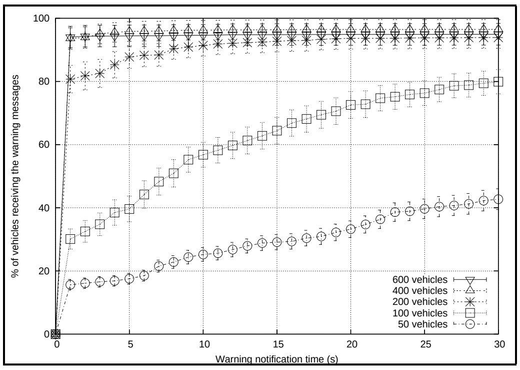
Additionally, depending on the roadmap topology, the system needs less time to inform the same percentage of vehicles (e.g., when 100 vehicles are simulated, the system requires less than 1 second to reach 30% of the vehicles in New York, and 6 seconds to reach the same percentage of the vehicles in San Francisco, while in Rome this percentage of informed vehicles can never be achieved at such low vehicle densities). According to results, when simulating 200 vehicles and when only 10 seconds have elapsed from the time of the accident, our system allows to inform 91.4% of the vehicles in New York, 77.09% of the vehicles in San Francisco, and 18.53% of the vehicles in Rome.

We consider that simulated results confirm the feasibility of our system, since the warning messages created according to our proposed ontology are correctly disseminated by the nearby vehicles in reasonable times.

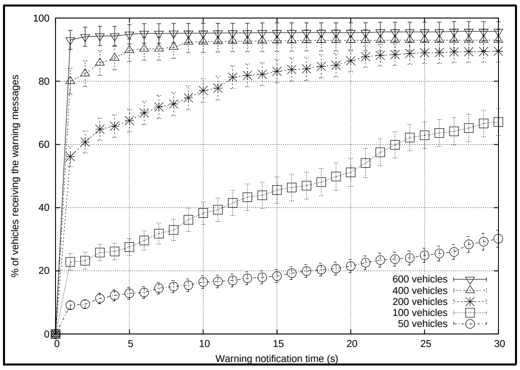
3.5 Summary

In this chapter we presented VEACON, our Vehicle Accident Ontology for Vehicular Networks. VEACON allows to efficiently structure and encode the information collected by in-vehicle sensors, enabling the interoperatibility among all the agents involved in modern ITS (vehicles, RSUs, emergency services, authorities, etc.). VEACON combines the information sensed from the accident with the available data in the GES database to offer rich and structured information to the parties involved in traffic accidents management. VEACON provides an ontology based approach for improved understanding between vehicular applications.

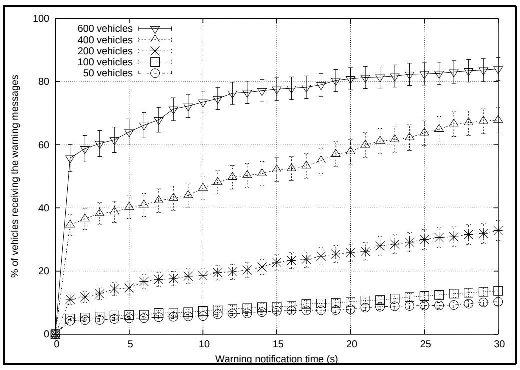
To verify that VEACON messages are correctly transmitted using VANETs, we performed simulations which demonstrated the feasibility of our system in terms of V2I and V2V communications. Experimental results highlight that both nearby vehicles and infrastructure Road Side Units (RSUs) are correctly notified about an accident in just a few seconds, increasing the emergency services notification effectiveness, and thereby validating the proposed approach.



(a)



(b)



(c)

Figure 3.3: Warning notification time when varying the density of the vehicles and the simulated roadmap: (a) New York, (b) San Francisco, and (c) Rome.

Chapter 4

Road Side Unit Deployment: A Density-Based Approach

In this chapter, we propose an approach for RSU deployment in urban scenarios and compare it with other alternative deployment policies to obtain an efficient system to alert emergency services in case of an accident. Specifically, we propose the Density-based Road Side Unit deployment policy (D-RSU).

Our aim is to reduce the deployment cost by minimizing the required number of RSUs, as well as to reduce the warning notification time (i.e., the time required to notify emergency services and other vehicles). In particular, we tested these deployment policies by simulating a urban scenario where vehicles want to alert both the emergency services and the nearby vehicles. The obtained results show how D-RSU is able to reduce the required number of RSUs, as well as the accident notification time.

This chapter is organized as follows: Section 4.1 reviews the related work regarding vehicular networks using infrastructure. In Section 4.2 we present three different RSU deployment policies (i.e., Minimum Cost, Uniform Mesh, and D-RSU). Section 4.3 introduces the simulation environment to assess our D-RSU proposal. Section 4.4 shows the obtained results. Finally, Section 4.5 concludes this chapter.

4.1 Related Work

Vehicular networks have been studied for several years but, although there are many studies regarding V2V communications, only a few focused on V2I communications, too.

Regarding V2I communications, Wu et al. [WGLL12] proposed a novel mechanism, called Distributed Sorting Mechanism (DSM), to improve the efficiency of communication between vehicles and RSUs. In their work, every vehicle can individually calculate its own priority of communication, in order to reduce the time required to compete and obtain the channel. Authors also consider that vehicles moving away from the coverage of communication can appropriately adjust their priorities. However, the specific deployment strategy of the RSUs in a specific area is an issue than remains untackled, and only the communication process towards a single RSU is addressed.

Mershad et al. [MAG12] studied how to exploit RSUs to route data packets between any source and destination in vehicular networks, developing an approach called Roadside Units as Message Routers in VANETs (ROAMER). They evaluated the RSU backbone routing performance via simulation, and compared their scheme to existing solutions, proving the feasibility and efficiency of their scheme in terms of query delay, packet delivery ratio, and overall traffic overhead. Nonetheless, in this work RSUs are deployed using a fixed infrastructure density depending on the coverage area, without exploiting road layout or vehicle density.

Furthermore, other authors studied how to place RSUs. Lochert et al. [LSW+08] proposed a genetic algorithm which was able to identify good positions for static RSUs in order to cope with the highly partitioned nature of a vehicular network in an early deployment stage for the city of Brunswick. They defended a tailored toolchain to optimize the placement with respect to an application-centric objective function. However, for all their simulations, they only used a reduced average equipment density of 0.25 equipped vehicles per radio range.

Kchiche and Kamoun [KK10] provided an analysis of the infrastructure deployment problem. Authors considered that the use of RSUs becomes essential for communications among vehicles in low density scenarios. They proved that centrality and equidistance are key factors for optimizing end-to-end delays and ensuring stable performances. However, their simulations were made using only a density of 200 vehicles in a total route-length of about 75 km. In addition, the potential RSU locations are determined by the user, and the proposed algorithm is only able to choose among the predefined positions, i.e., it requires additional knowledge from the user for all the possible scenarios, which is not feasible.

Lee and Kim [LK10] proposed a roadside unit placement scheme for vehicular networks, aiming at improving connectivity and reducing the disconnection interval for the given number of roadside units, the transmission range, and the overlap ratio on the road network of Jeju island. Performance measurement results obtained using the real-life movement history data in Jeju city showed that about 72.5% of connectivity can be achieved when deploying 1,000 RSUs, being the transmission range 300 m, while the disconnection time is mostly kept below 10 seconds. The policy followed to deploy the RSUs is based on the minimization of the overlapped coverage area, but the presence of obstacles and blind spots is not considered. Therefore, the results might not be valid for urban environments.

To the best of our knowledge, few proposals studied the RSU deployment problem, optimizing the placement of RSUs to maximize performance and reduce the deployment cost. Furthermore, these proposals have been tested in very simple scenarios with very specific traffic densities. Crucial factors such as the vehicle density, the presence of obstacles blocking the radio signal, or non-uniform RSU placement have not been considered, reducing the utility of the obtained results.

4.2 RSUs Deployment Policies

Roadside Units are usually expensive to install. Therefore, authorities limit their number, especially in suburbs and areas of sparse population, making RSUs a precious resource in vehicular environments. Moreover, given the current economic situation, authorities and transport agencies tend to reduce the infrastructure investments related to transportation systems.

Therefore, the selected deployment policy is of utmost importance when adding infrastructure for vehicular networks. Authorities could place RSUs in a homogeneous way (uniformly) trying to maximize the coverage area, or following a non uniform deployment approach (e.g., grouping RSUs in specific parts of an area) trying to reduce the deployment cost.

Similarly to the traffic lights or the traffic luminous panels, before deploying RSUs, authorities should make a preliminary study which involves gathering important data (regarding the economic impact, or the number of potential users) to decide where and how to deploy the infrastructure stations. We consider that Governments should also pay particular attention to accounting for the expected density of vehicles in order to optimize the infrastructure deployments, thereby reducing the economic cost, without reducing the time required by vehicles to get access to RSUs in case of emergency.

In the following subsections we propose in detail three different RSUs deployment policies: (i) the Downtown-based (D-RSU) (ii) the Minimum Cost, and (iii) the Uniform Mesh.

4.2.1 D-RSU Deployment Policy

In vehicular scenarios, traffic is not uniformly distributed; there are zones that usually have a higher vehicle density. For example, in the cities, these zones are usually located in the downtown area, business areas, or industrial areas, where the higher density of vehicles makes them move more slowly than in the outskirts, but it also increases the number of potential nodes of a vehicular network based on V2V communications.

In the D-RSU deployment polity, RSUs are placed using an inverse proportion to the expected density (i.e., more resources must be deployed in areas where less number of vehicles are usually expected, and authorities must deploy less RSUs in areas which are characterized by a high density of vehicles). For example, if authorities have in mind to deploy a total number of 100 RSUs in a city, and they consider that the expected traffic density in an specific area of this city is about 60% of the vehicles, according to the D-RSU deployment policy, they should install 40% of RSUs there, and the rest of the RSUs should be deployed in the rest of the area.

This deployment policy allows vehicles located in less dense areas to have a better Internet access capabilities thanks to the higher density of deployed RSUs. In contrast, we consider that areas which support a high density of vehicles do not require a high number of RSU, since V2V communications can complement the infrastructure (i.e., high reliable V2V scenarios do not require a great infrastructure

Figure 4.1: Example of 8 RSUs deployed following the D-RSU deployment policy.

without reducing performance). Figure 4.1 shows an example of this deployment policy.

This deployment policy has a high economical cost, because authorities have to provide Internet access in all the places where the RSUs are positioned.

Following, we present other two deployment policies in order to compare them with our proposed D-RSU.

4.2.2 Minimum Cost Deployment Policy

In the Minimum Cost deployment policy, we consider that authorities only account for reducing the economic cost of the infrastructure deployment, without considering whether RSUs will be placed to maximize the coverage area, or not. This policy consists on distributing RSUs with the minimum possible cost. In real environments, this policy would place RSUs in locations that already have Internet access, or where their installation is easy, regardless of their position in the map. Figure 4.2 shows an example of this deployment policy.

The total cost of this policy is the lowest, since authorities can place RSUs in sites where there are already Internet access (e.g., nearby government buildings, traffic luminous panels, etc.). However, this deployment policy can provoke that some areas remain isolated, without infrastructure coverage.

Figure 4.2: Example of 8 RSUs deployed following the Minimum Cost deployment policy.

4.2.3 Uniform Mesh Deployment Policy

The Uniform Mesh deployment policy consists on distributing RSUs uniformly on the map, regardless of the expected average traffic density, or the roadmap topology.

The advantage of this deployment policy is that it achieves a more uniform coverage area since the distance between RSUs is basically the same, preventing RSUs to be positioned too closely, or too sparsely. An example of this deployment policy is shown in Figure 4.3.

The Uniform Mesh policy tends to reduce the probability of having shadow areas in the map, where vehicles can remain isolated (without the possibility of alerting emergency services in case of an accident).

Similar to the D-RSU deployment policy, Uniform Mesh has a higher economical cost than the Minimum Cost deployment policy, since authorities need to provide Internet access in all the places where the RSUs are positioned.

4.3 Simulation Environment

Simulations were done using the ns-2 simulator and C4R, as presented in Chapter 2. We assume that all the nodes of our network have two different interfaces: (i) an IEEE 802.11n interface tuned at the frequency of 2.4 GHz for V2I communications, and (ii) an IEEE 802.11p interface tuned at the frequency of 5 GHz for V2V communications. This assumption is reasonable due to the low price of this type

Figure 4.3: Example of 8 RSUs deployed following the Uniform Mesh deployment policy.

Table 4.1: Main features of the selected map

Selected city map	Madrid (Spain)
Total streets	1387
Total junctions	715
Avg. street length	83.08m
Avg. lanes/street	1.27

Table 4.2: Parameter values for the simulations

Parameter	**Value**
density of vehicles (veh./km^2)	25, 50, 75, 100, 125, and 150
number of RSUs	$1, 2, 4, 8$, and 16
simulated city	Madrid
number of crashed vehicles	2
downtown size	$1000m \times 1000m$
downtown probability	0.7
warning message size	13 and 18KB
mobility models	Krauss [KWG97] and Downtown [MCCM08b]
MAC/PHY	802.11p and 802.11n
broadcast storm reduction scheme	eMDR [FGM+12d]

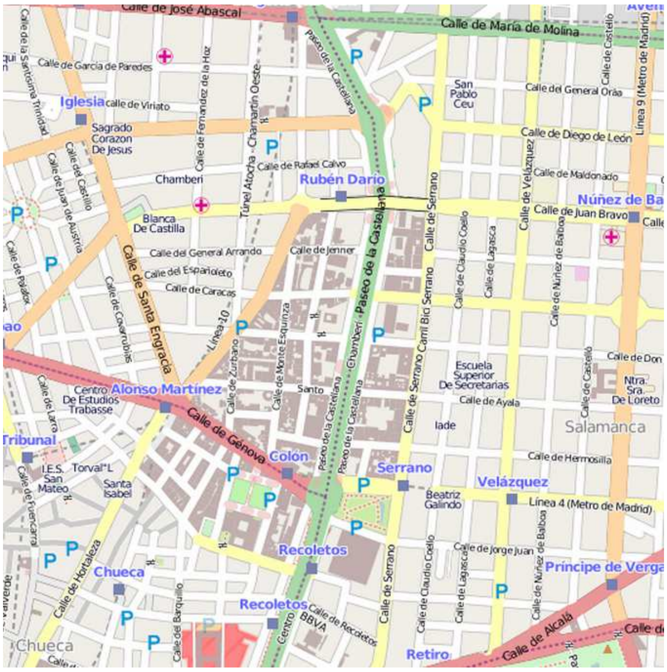


Figure 4.4: Fragment of the city of Madrid (Spain) used in our simulations.

of devices with respect to the total price of a vehicle.

RSUs mainly provide Internet access to vehicles, but they also enable the diffusion of the warning messages.

In order to validate our proposal, we used the tools and parameters presented in Section 2.1.3.3. Our simulations use a scenario of 4 km^2, obtained from the city of Madrid (Spain). We selected this scenario based on the results obtained after evaluating several maps from different parts of the world [FGM$^+$12c], achieving a classification of road topologies depending on their street and junction densities. The city of Madrid presents a representative road layout, close to the average values found in our classification, and thus it is a good example of a typical metropolitan area. Figure 4.4 shows the topology of the map, and Table 4.1 includes the main features of the selected city.

Since our proposal is focused on the use of an infrastructure to notify emergency services when an accident occurs, the warning messages exchanged between vehicles and RSUs are built according the Vehicular Accident Ontology (VEACON) [BGF$^+$12c], specially designed for sharing and reusing knowledge about the vehicles involved in road accidents, and which was presented in Chapter 3.

In particular, we simulated several front impact scenarios with two cars involved. The first vehicle is a family car with two occupants, and expressing all the information required produces a message of 13 KBytes. The second car is a minivan with eight occupants, which required up to 18 KBytes to code the data for all passengers. Each simulation run lasted for 300 seconds. All results represent an average of 20 executions with different scenarios (maximum error of 10% with a degree of confidence of 90%). Table 4.2 shows the parameters used in the performed simulations.

4.4 Simulations Results

In this section, we first study the required number of RSUs per square kilometer to have a feasible warning notification system, where crashed vehicles can properly alert the emergency services, as soon as possible. Then, we also show the impact of the RSUs deployment policy in the obtained results when varying the number of RSUs, and the density of vehicles in the scenario. Our aim is to determine which policy fits better in the studied conditions.

In our simulations, we measure notification times (the minimum, the maximum, and the average time that a warning message requires to reach an RSU), and the percentage of accidents that have been successfully notified (i.e., that have already reached an RSU, thereby considering that emergency services have been correctly notified).

4.4.1 Study of Required Number of RSUs

Table 4.3 shows the obtained results for the Uniform Mesh deployment policy when varying the number of RSUs deployed (1, 2, 4, 8, and 16), and the density of vehicles (25, 50, 75, 100, and 125) in the selected scenario.

As shown, when the density becomes very small (i.e., 25 vehicles/km^2, which is clearly infrequent in urban scenarios), and there are eight or less RSUs (two or less RSUs per square kilometer), about 5-25% of the total accidents are not correctly notified to the emergency services (i.e., no warning message effectively reaches an RSU). However, when increasing the density of vehicles ($\geq$50 vehicles/km^2), all the accidents are correctly notified, making it possible to provide precise information about the incident to reduce the response time of emergency services, thereby improving the assistance to people injured.

Regarding the average notification time, it ranges from 0.946 seconds (100 vehicles/km^2 and 16 RSUs) to 13.974 seconds (25 vehicles/km^2 and 1 RSU). As expected, the system requires less time to reach an RSU when increasing the number of RSUs, although we observe that in high density situations (125 vehicles/km^2), specifically when 8 and 16 RSUs are deployed, the system requires more time to reach an RSU than in scenarios where 100 vehicles/km^2 are simulated. This could be explained due to redundancy, contention, and packet collisions caused by simultaneous forwarding (usually known as the broadcast storm problem [TNCS02]).

Since we are interested in safety issues, it is extremely important to be sure that all the accidents will be correctly notified to the emergency services. Hence, according to the obtained results, we consider that authorities must deploy at least four RSUs per square kilometer (16 RSUs in our example).

Table 4.3: Simulation results for the Uniform Mesh Deployment Policy when varying the density of vehicles and RSUs

Vehicles/km^2	**RSUs**	**Min. notif. time (s)**	**Max. notif. time (s)**	**Avg. notif. time (s)**	**Accident notif. (%)**
25	1	0.476	31.003	13.974	75
	2	0.563	30.422	12.389	85
	4	0.676	26.701	9.650	85
	8	0.273	11.257	3.222	95
	16	0.230	15.753	2.935	100
50	1	0.827	33.125	9.937	100
	2	0.476	33.919	8.209	100
	4	0.363	12.958	3.471	100
	8	0.125	10.949	2.640	100
	16	0.333	21.281	1.922	100
75	1	0.777	9.546	4.683	100
	2	0.543	13.053	4.453	100
	4	0.852	6.782	3.000	100
	8	0.272	10.111	1.931	100
	16	0.241	10.460	1.328	100
100	1	0.999	11.594	3.551	100
	2	0.564	11.833	2.983	100
	4	0.550	11.604	3.078	100
	8	0.265	1.762	1.081	100
	16	0.295	1.712	0.946	100
125	1	0.598	9.277	3.503	100
	2	0.567	7.489	2.984	100
	4	0.273	7.478	2.793	100
	8	0.360	6.112	1.581	100
	16	0.272	5.751	1.433	100

4.4.2 Performance of the Different RSUs Deployment Policies

Table 4.4 shows the obtained results for the studied deployment policies, when varying the density of vehicles (25, 50, 75, 100, 125 and 150), and the number of RSUs deployed (8 and 16) in the studied scenario. For each deployment policy, we show the minimum, the maximum, and the average notification times (i.e., the time required for a warning message to reach an RSU), as well as the percentage of successfully accident notifications via the infrastructure.

As shown in Table 4.4, the warning notification system works well in all the different scenarios, since all the accidents are correctly notified to the emergency services (i.e., at least a warning message reaches an RSU). Only when the density becomes very small (25 vehicles/km^2), some accidents (only 5% of the amount total) are not reported to the emergency services.

Regarding the average notification time, Figures 4.5 and 4.6 graphically depict that, in small density scenarios ($\leq$50 vehicles/km^2), the Uniform Mesh deployment policy yields better results than the other policies. When simulating 16 RSUs, it reduces the average notification time compared to the Minimum Cost and the D-RSU (up to 44.58% and 37.41%, respectively). The Uniform Mesh policy works better in small densities, since RSUs are uniformly deployed in the map, increasing the probability that isolated vehicles have a nearby RSU. However, in higher density scenarios ($\geq$75 vehicles/km^2), our D-RSU deployment policy yields better performance results, since it requires less time to inform emergency services when an accident occurs. It reduces the average notification time up to 54.16% and 51.99%, compared to the Minimum Cost and to the Uniform Mesh, respectively.

These results suggest us that using the Minimum Cost approach is not a good idea, since accidents must be correctly notified in the minimum possible time.

Finally, Figure 4.7 shows a comparison between the D-RSU with only 8 RSUs, and the Uniform Mesh with 16 RSUs. As shown, in high density scenarios (when more than 100 vehicles per km^2 are simulated), D-RSU achieves better notification times even if half of RSUs have been deployed. This shows that using D-RSU allows to severely reduce the overall cost of deploying the infrastructure, without losing performance.

4.4.3 Our Proposed Deployment Algorithm

Figure 4.8 shows the average notification time for different vehicular densities when using our D-RSU and the Uniform Mesh deployment policies. We highlighted the trade-off point which remarks the specific densities when the D-RSU outperforms the Uniform Mesh policy.

As shown in Figure 4.8a, in scenarios where vehicle density is lower than 70 vehicles per km^2, the Uniform Mesh deployment policy yields the best performance. Instead, if density is higher than 70 vehicles per km^2, the D-RSU deployment policy is the best approach. In addition, if traffic density exceeds 90 vehicles per km^2, the D-RSU deployment policy is also the best approach, even when reducing the number of required RSUs to a half (see Figure 4.8b). Based on these results, we propose the RSU deployment algorithm showed in Algorithm 2.

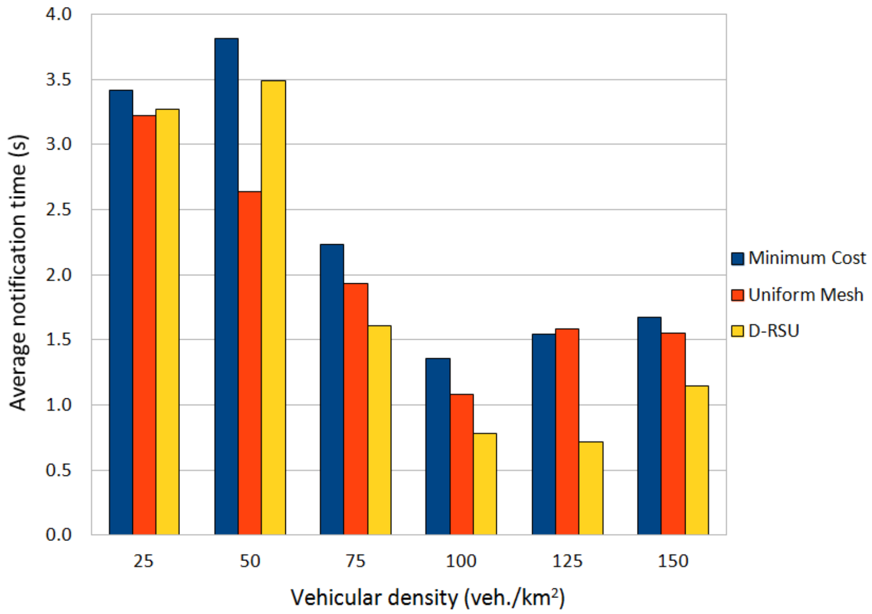


Figure 4.5: Comparison of the average notification time for the studied deployment policies when using 8 RSUs.

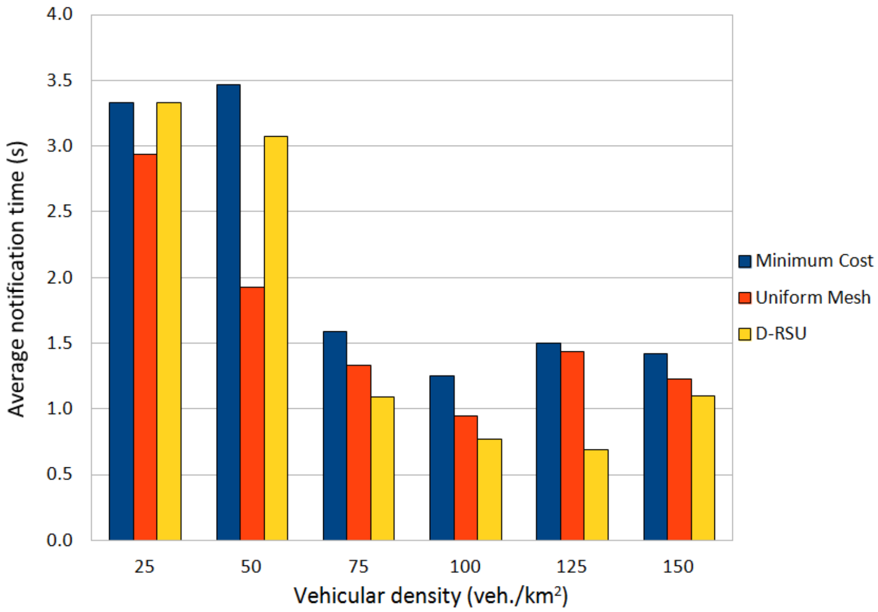


Figure 4.6: Comparison of the average notification time for the studied deployment policies when using 16 RSUs.

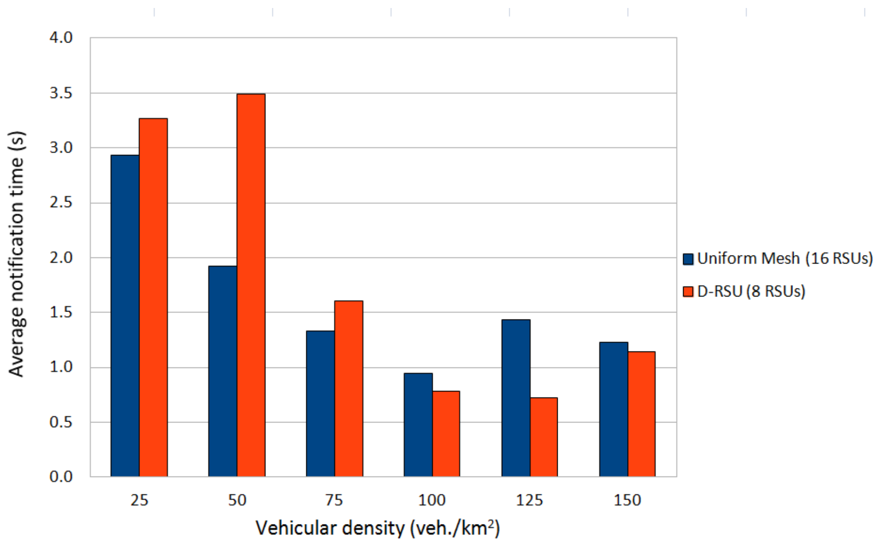


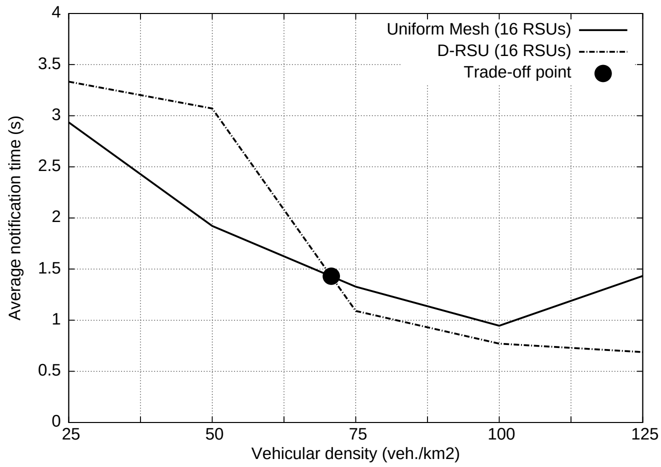
Figure 4.7: Comparison between the Uniform Mesh using 16 RSUs and D-RSU using 8 RSUs.

4.5 Summary

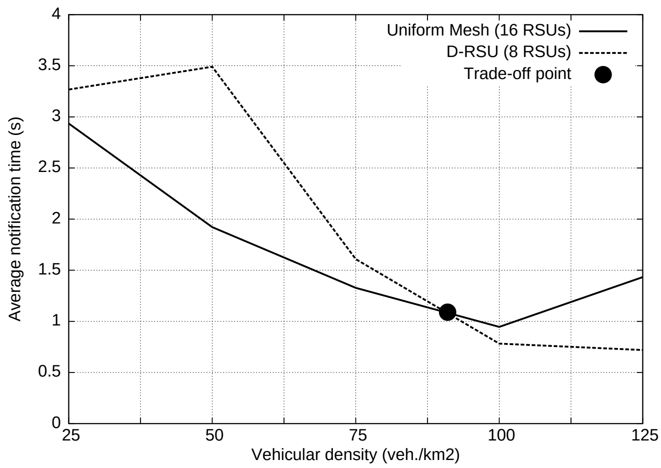
In this chapter we presented D-RSU, a density-based approach for Road Side Unit deployment in urban scenarios. D-RSU takes into account that the density of vehicles is not uniformly distributed in vehicular scenarios. D-RSU consists on placing RSUs according an inverse proportion to the expected density. This distribution allows that vehicles driving in less dense areas have better Internet access by increasing the number of nearby available RSUs, whereas in areas with high density of vehicles, V2V communications can complement the infrastructure to provide a reliable warning notification system without reducing its performance.

To assess our proposal, we compared D-RSU with two other deployment policies: the Minimum Cost, and the Uniform Mesh. Simulations showed that the Uniform Mesh deployment policy is more adequate for areas in which less than 70 vehicles per km^2 are expected. However, when the traffic density expected is greater or equal to 70 vehicles per km^2, D-RSU is the best deployment policy. In addition, if there are more than 90 vehicles per km^2, D-RSU obtains better results than the other approaches in terms of warning notification time, while reducing the required number of RSUs to half.

According to the obtained results, we proposed an RSU deployment algorithm which decides the optimum deployment policy based on the expected vehicle density.



(a)



(b)

Figure 4.8: Best deployment policy when the vehicular density is greater or equal than: (a) 70 vehicles per km^2, and (b) 90 vehicles per km^2.

Algorithm 2 Pseudocode of the RSU Deployment Algorithm

INPUT:
vehicleDensity: density of vehicles in the selected area
map: road topology of the selected area
downtownCoordinates: coordinates (latitude, longitude) of the subareas with high vehicle density
downtownPercentage: percentage of vehicles present in each downtown area

OUTPUT:
numRSU: number of RSUs to be deployed in the selected map area

numRSU = 4 * areaKm^2(*map*); // 4 RSUs/km^2
if *(vehicleDensity* **is** < 70 *vehicles/km^2)* **then**
  use UniformMesh(*map*, *numRSU*);
else
  if *(vehicleDensity* **is** < 90 *vehicles/km^2)* **then**
    use D-RSU(*map*, *numRSU*, *downtownCoordinates*, *downtownPercentage*);
  else
    numRSU = *numRSU* / 2;
    use D-RSU(*map*, *numRSU*, *downtownCoordinates*, *downtownPercentage*);

Table 4.4: Simulation results for the three different deployment policies when varying the density of vehicles and RSUs

Vehicles/km^2		**25**		**50**		**75**		**100**		**125**		**150**	
RSUs		**8**	**16**	**8**	**16**	**8**	**16**	**8**	**16**	**8**	**16**	**8**	**16**
Minimum Cost	**Min. notif. time (s)**	0.394	0.293	0.228	0.211	0.460	0.520	0.308	0.456	0.390	0.360	0.306	0.356
	Max. notif. time (s)	11.366	11.238	21.479	21.155	6.150	6.093	2.917	3.449	6.111	6.628	5.717	4.116
	Avg. notif. time (s)	3.417	3.333	3.816	3.468	2.234	1.590	1.359	1.248	1.543	1.501	1.672	1.421
	Accident notif. (%)	95	95	100	100	100	100	100	100	100	100	100	100
Uniform Mesh	**Min. notif. time (s)**	0.273	0.230	0.125	0.333	0.272	0.241	0.265	0.295	0.360	0.272	0.302	0.228
	Max. notif. time (s)	11.257	15.753	10.949	21.281	10.111	10.460	1.762	1.712	6.112	5.751	6.207	3.736
	Avg. notif. time (s)	3.222	2.935	2.640	1.922	1.931	1.328	1.081	0.946	1.581	1.433	1.551	1.227
	Accident notif.(%)	95	100	100	100	100	100	100	100	100	100	100	100
D-RSU	**Min. notif. time (s)**	0.234	0.268	0.238	0.197	0.400	0.471	0.480	0.372	0.381	0.190	0.385	0.251
	Max. notif. time (s)	11.161	11.040	17.400	20.516	6.282	6.263	1.832	2.061	1.723	1.800	3.459	3.339
	Avg. notif. time (s)	3.268	3.333	3.491	3.071	1.609	1.091	0.783	0.771	0.720	0.688	1.145	1.100
	Accident notif. (%)	95	95	100	100	100	100	100	100	100	100	100	100

Chapter 5

A V2I-based Real-Time Traffic Density Estimation System

Road traffic is experiencing a drastic increase in recent years, thereby increasing the everyday traffic congestion problems, especially in metropolitan areas. Governments are making efforts to alleviate the increasing traffic pressure, being vehicular density one of the main metrics used for assessing the road traffic conditions. However, vehicle density is highly variable in time and space, making it difficult to be estimated accurately.

Since the main goal of this Thesis is to improve traffic accident assistance by reducing the emergency services arrival time, we consider that to know traffic density information in real-time is necessary to make a suitable traffic redistribution.

In this chapter, we present a novel solution to accurately estimate the density of vehicles in urban scenarios. Our proposal, that has been specially designed for Vehicular Networks, allows Intelligent Transportation Systems to continuously estimate vehicular density by accounting for the number of beacons received per Road Side Unit (RSU), and also considering the roadmap topology where the RSUs are located. Simulation results reveal that, unlike previous proposals solely based on the number of beacons received, our approach accurately estimates the vehicular density, and therefore our approach can be integrated within automatic traffic controlling systems to predict traffic jams, and thus introduce countermeasures.

5.1 Introduction

Traditionally, vehicle density has been one of the main metrics used for assessing road traffic conditions. A high vehicle density usually indicates congested traffic; however, the density of vehicles in a city highly varies depending on the area and the time during the day. Thus, knowing the density of a vehicular environment is important since it allows estimating the level of traffic congestion while improving

ITS services by using the wireless channel more efficiently [SHG09].

Currently, most of the vehicle density estimation approaches are designed to use very specific infrastructure-based traffic information systems, which require the deployment of vehicle detection devices such as inductive loop detectors, or traffic surveillance cameras [TC07, BS08, THKH11]. However, these approaches are limited since they can only be aware of traffic density in *a priori* selected areas (i.e., the streets and junctions in which these devices are already located), making it difficult to estimate the vehicular density along a whole city. In addition, some of these approaches are not able to perform accurate estimations in real time (e.g., using cameras involves hard image processing and analysis).

Other existing works propose estimating the traffic density using V2V communications [SCB11, SFG+13]. These proposals allow vehicles to gain information about density in their neighborhood, but they are unable to offer traffic information for the rest of the scenario. Hence, these vehicles are unable to obtain the best route avoiding traffic jams. This problem could be solved by adding some infrastructure elements, since this solution allows using the traffic information obtained by the infrastructure nodes, with the aim of reducing traffic jams.

The main objective of this chapter is to propose a mechanism which allows estimating the density of vehicles in a specific area by using infrastructure-based Vehicular Networks. In particular, we estimate the density by taking into account the number of beacons received by the RSUs, and the characteristics of the roadmap topology. Unlike previous proposals, our approach allows ITS to continuously estimate the vehicular density in a given area.

The rest of this chapter is organized as follows: Section 5.2 reviews previous approaches related to our work, focusing on infrastructure-based solutions to estimate traffic density, and density-aware systems to avoid traffic jams. Section 5.3 details our proposal for V2I-based real-time vehicular density estimation, assessing its goodness. Additionally, we discuss the obtained results and measure the estimated error. In Section 5.4 we validate our proposal by simulating three particular scenarios, showing that it performs quite well and is able to accurately estimate the vehicular density. In Section 5.5 we compare our proposal with two beacon-based approaches, where the estimated vehicular density is based only on the number of beacons received. Finally, Section 5.6 concludes this chapter.

5.2 Related Work

In this section we review previous works related to our proposal. In particular, we focus on infrastructure-based solutions to estimate traffic density.

Despite the importance of determining vehicular density to reduce traffic congestion, so far only a few studies have explored the density estimation process.

Tyagi et al. [TKK12] considered the problem of vehicular traffic density estimation, using the information available in the cumulative acoustic signal acquired from a roadside-installed single microphone. This cumulative signal comprises several noise signals such as tire noise, engine noise, engine-idling noise, occasional honks, and air turbulence noise of multiple vehicles. The occurrence and mixture weightings of these noise signals are determined by the prevalent traffic density conditions on the road segment. Based on these learned distributions, they used a Bayes' classifier to classify the acoustic signal segments spanning a duration of 5-30 s. Using a discriminative classifier, such as a *Support Vector Machine* (SVM), results in further classification accuracy compared to a Bayes' classifier.

Tan and Chen [TC07] proposed a novel approach based on video analysis which combines an unsupervised clustering scheme called AutoClass with *Hidden Markov Models* (HMMs) to determine the traffic density state in a *Region Of Interest* (ROI) of a road. Firstly, low-level features were extracted from the ROI of each frame. Secondly, an unsupervised clustering algorithm called AutoClass was applied to the low-level features to obtain a set of clusters for each pre-defined traffic density state. Finally, four HMM models were constructed for each traffic state, respectively, with each cluster corresponding to a state in the HMM; the structure of the HMM is determined based on the cluster information.

Shirani et al. [SHG09] presented the Velocity Aware Density Estimation (VADE). In VADE, a car estimates the density of neighboring vehicles by tracking its own velocity and acceleration pattern. An opportunistic forwarding procedure, based on VADE estimation, was also proposed. In this procedure, data forwarding is done when the probability of having a neighbor is high, which dramatically reduces the probability of messages being dropped.

Maslekar et al. [MBML11] claimed that clustering has demonstrated to be an effective concept to implement the estimation of vehicular density in the surroundings. However, due to high mobility, a stable cluster within a vehicular framework is difficult to implement. In this work, they proposed a direction based clustering algorithm with a clusterhead switching mechanism. This mechanism aims at overcoming the influence of overtaking within the clusters.

Other authors use the Kalman filtering technique for the estimation of traffic density. For example, Balcilar and Sonmez [BS08] estimate traffic density based on images retrieved from traffic monitoring cameras operated by the Traffic Control Office of Istanbul Metropolitan Municipality. To this end, they use a Kalman filter-based background estimation which can efficiently adapt itself to environmental factors such as light changes. However, this approach requires the density estimation procedures to be applied to the road areas manually marked beforehand. More recently, Anand et al. [AVS11] proposed a method that also uses the Kalman filtering technique for estimating traffic density. In particular, they propose using the flow values measured from video sequences and the travel time obtained from vehicles equipped with a Global Positioning System (GPS). They also report density estimations using flow and Space Mean Speed (SMS) obtained from location based data, using the Extended Kalman filter technique.

All these previous works established the importance of vehicular density awareness for neighboring areas, but none of them has deepened in the analysis of the accuracy of the method used to estimate this density, or the impact that topology has on the obtained results. Moreover, the vehicular density estimation does not always take place in real time, and the majority of them require specialized infrastructure devices. In addition, neither method can obtain the traffic density for a specific sub-area, being only focused on the scenario as a whole.

5.3 Real-Time Vehicular Density Estimation

In this work we propose a technique that is able to accurately estimate the density of vehicles based on two parameters: (i) the number of beacons received by RSUs, and (ii) the roadmap topology. In order to find the best possible approach, we perform nearly 2000 simulations. Experiments involve a wide variety of controlled urban scenarios, where the actual density is known. According to the obtained results, and using a regression analysis, we propose a density estimation function capable of estimating in real time the vehicular density in urban environments. In this section we start by presenting a discussion about the most important features of urban roadmaps. Then, we present the main parameters and the selected methodology. Finally, based on the obtained results, we detail our proposed density estimation function, assessing its accuracy.

5.3.1 Features of the Cities Studied

The roadmaps used during the experiments to obtain our density estimation approach were selected in order to have different profile scenarios (i.e., with different topology characteristics).

The first step before starting the simulations was to obtain the main features for each roadmap (i.e., the number of streets, the number of junctions, the average segment size, and the number of lanes per street). As for the number of streets, we realized that different alternatives could be selected to obtain the number of streets of a given roadmap. Basically, there are three alternatives: (i) the number of streets obtained in SUMO [KEB12], where each segment between two junctions is considered a street, (ii) the number of streets obtained in *OpenStreetMap* (OSM) [Ope14], where each street has a different "name", and (iii) the number of streets according to the *Real Attenuation and Visibility* (RAV) [MFT+13] radio propagation model, where vehicles can only exchange information if they are in line-of-sight (i.e., visibility means that there are no obstacles blocking the wireless signal between the vehicles).

Figure 5.1 shows a small portion of New York City to depict the different criteria when counting the number of streets. For example, Thames Street is considered only one street in OSM, whereas the SUMO and RAV models consider that there are two different streets instead. However, if we observe Cedar Street, the RAV visibility model and the OSM approaches consider a single street (as expected), whereas it is represented by three different streets according to SUMO, since it has three different segments. Finally, according to both the OSM and SUMO approaches, Trinity Place and Church Street are represented as two different streets, whereas the RAV model considers that only one street exists.

Table 5.1 shows the the number of streets for the selected cities according to the three different criteria. As shown, the differences between these approaches are significant (e.g., New York has 700, 827, or 257 streets when considering SUMO segments, OSM streets, or the RAV visibility approach, respectively, whereas Sydney has 1668, 315, or 872 streets, depending on the selected criterion). Therefore, it is important to decide which one to use in order to obtain accurate results. By analyzing experimental results, we realized that the RAV approach better corre-

Figure 5.1: Different criteria when counting the number of streets.

Table 5.1: Number of Streets obtained depending on the approach used.

City	SUMO	OSM	RAV
New York	700	827	257
Minnesota	1592	105	459
Madrid	1387	1029	628
San Francisco	1710	606	725
Amsterdam	3022	796	1494
Sydney	1668	315	872
Liverpool	3141	1042	1758
Valencia	5154	1050	2829
Rome	2780	1484	1655

lated with the real features of cities. In fact, a street must not be considered as a graph lane between two junctions (SUMO) or different lanes with the same name (OSM), since this consideration does not take into account the visibility between vehicles. In terms of communication links, we can not consider that two vehicles are circulating in the same street if there is no wireless communication between them.

Table 5.2 shows the main features of each map for the cities under study. Specifically, we obtained the number of streets according to the RAV model, the number of junctions directly extracted from the graph (junctions are the intersection point between segments), the average segment size (segments are graph lines which link two junctions), and the number of lanes per street. We also added a column labeled as *SJ Ratio*, which represents the result of dividing the number of streets between the number of junctions, thereby indicating the roadmap complexity. As shown, the first city (New York) presents a SJ ratio of 0.5130, which

Table 5.2: Map features

Map	Streets	Junctions	avg. segment size (m.)	lanes/street	SJ Ratio
New York	257	500	122.5480	1.5730	0.5140
Minnesota	459	591	102.0652	1.0144	0.7766
Madrid	628	715	83.0820	1.2696	0.8783
San Francisco	725	818	72.7065	1.1749	0.8863
Amsterdam	1494	1449	44.8973	1.1145	1.0311
Sydney	872	814	72.1813	1.2014	1.0713
Liverpool	1758	1502	49.9620	1.2295	1.1704
Valencia	2829	2233	33.3653	1.0854	1.2669
Rome	1655	1193	45.8853	1.0590	1.3873

Table 5.3: Parameters used for the simulations

Parameter	Value
roadmaps	New York, Minnesota, Madrid, San Francisco, Amsterdam, Sydney, Liverpool, Valencia, and Rome
number of vehicles	$100, 200, 300...1000$
number of collided vehicles	2
warning message size	13 and 18KB
beacon message size	$512B$
number of RSUs	9
RSU deployment policy	Uniform Mesh
MAC/PHY	802.11p
mobility model	Krauss
channel bandwidth	$6Mbps$

indicates that it has a simple topology, whereas the last cities in the table present a greater SJ value, which indicates a more complex topology. As shown in Section 5.3.3, this aggregated factor correlates well with the obtained results.

The roadmap topology where the vehicles are located not only constrains vehicles movements, but it has also a great influence on the V2V and V2I communication capabilities [FGM+12c]. Thus, a wide set of maps with different complexities are going to be used in order to tune and validate our traffic density estimation system.

5.3.2 Simulation Environment

All the simulations performed in this chapter were done using the ns-2 simulator and C4R, as presented in Chapter 2.

To prove how maps affect the performance of vehicular communications, we selected nine street maps, each one representing a square area of 4 km^2. Figure 5.2 shows the topology of the maps used in the simulations.

In order to deploy RSUs in the maps, we used the Uniform Mesh deployment policy [BGF+12b], presented in Chapter 4. Table 5.3 shows the parameters used for the simulations.

To estimate our traffic density function, we consider a Warning Message Dissemination mechanism, where each vehicle periodically broadcasts information about itself or about abnormal situations (traffic jams, icy roads, etc.).

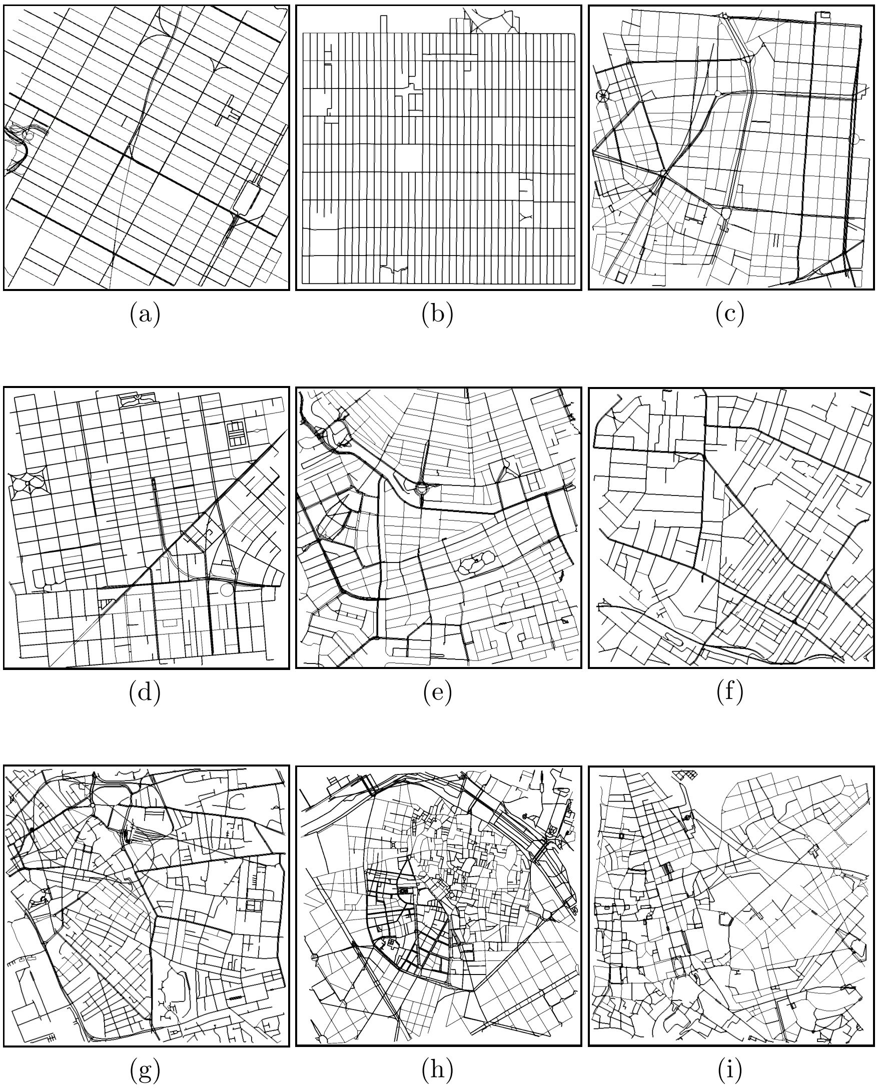


Figure 5.2: Scenarios used in our simulations. Fragments of the cities of: (a) New York (USA), (b) Minnesota (USA), (c) Madrid (Spain), (d) San Francisco (USA), (e) Amsterdam (Netherlands), (f) Sydney (Australia), (g) Liverpool (England), (h) Valencia (Spain), and (i) Rome (Italy).

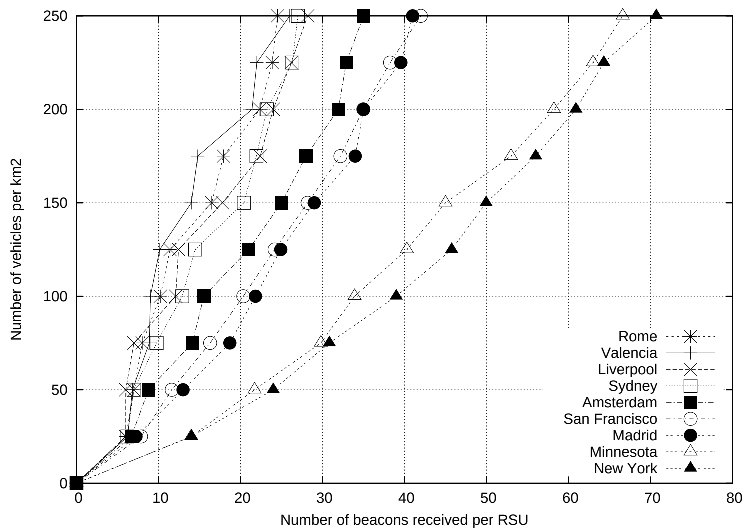


Figure 5.3: Number of beacons received when varying the vehicular density and the roadmap.

We simulated a frontal impact scenario where two vehicles are involved. The warning messages exchanged between vehicles and RSUs are built according the *Vehicular Accident Ontology* (VEACON) [BGF+12c], presented in Chapter 3, which provides a standard structure which enables data interoperability among all the different entities involved in transportation systems.

All the results represent an average of over 20 runs with different scenarios (maximum error of 10% with a degree of confidence of 90%).

5.3.3 Density Estimation Function

After performing the topological analysis of the selected city maps, we obtained the average number of beacons received by each RSU, taking into account that each vehicle sends one beacon per second, and that these messages, unlike warning messages, are not disseminated by the rest of the vehicles.

Figure 5.3 shows the obtained results for the different cities studied. As shown, the performance in New York and Minnesota in terms of number of beacons received highly differs from the rest of the cities. This occurs because both New York and Minnesota have a low SJ ratio (i.e., they present regular roadmaps).

As expected, complex roadmaps (maps which have a higher SJ Ratio) present a number of beacons received lower than regular roadmaps for a similar vehicular density, since the effect that buildings have over the signal propagation is higher in complex maps. Figure 5.3 also shows that the vehicular density not only depends on the number of beacons received, but also on the SJ ratio (according to data shown in Table 5.2). Therefore, the characteristics of the roadmap will be very

Table 5.4: Coefficients of our Proposed Density Estimation Equation

Coeff.	**Value**
a	2.30376E+02
b	1.90696E+01
c	-4.29461E+02
d	3.18810E+01
f	1.87953E+02
g	-6.81259E+01

Table 5.5: Density Estimation Error of our Proposed Equation

Error	**Absolute**	**Relative**
Minimum	-5.399E+01	-1.225E+00
Maximum	4.837E+01	1.697E+00
Mean	2.848E-13	3.041E-02
Std. Error of Mean	2.422E+00	3.543E-02
Median	2.371E-01	1.583E-03

useful in order to accurately estimate the vehicular density in a given scenario.

After observing the direct relationship between the topology of the maps, the number of beacons received, and the density of vehicles, we proceed to obtain a function to estimate, with the minimum possible error, each of the curves shown in Figure 5.3. To this end, we performed a regression analysis that allowed us to find an equation offering the best fit to the data obtained through simulation. Specifically, we used the *ZunZun* application [Zun12] which provides different equations for regression analysis. We select Equation 5.1 as the density estimation function, since it obtained the smallest relative error. This proposed function is able to estimate the number of vehicles per km^2 in urban scenarios, according to the number of beacons received per RSU, and the SJ ratio (i.e., streets/junctions) of the selected roadmap.

$$f(x,y) = a + b \cdot ln(x) + \frac{c}{y} + d \cdot ln(x)^2 + \frac{f}{y^2} + \frac{g \cdot ln(x)}{y} \tag{5.1}$$

In this equation, $f(x,y)$ is the number of vehicles per km^2, x is the average number of beacons received by each RSU, and y is the SJ ratio obtained from the roadmap. The values of the coefficients $(a, b, c, d, f, \ and\ g)$ are listed in Table 5.4. Figure 5.4 shows the 3-dimensional representation of the proposed equation.

To determine the accuracy of our proposal, we proceed to measure the estimated error. Table 5.5 shows the different errors when comparing our density estimation function with the values actually obtained by simulation. Note that the average relative error is of only 3.04%, which we consider accurate enough to validate our proposed approach.

In this work, we also tested other possible functions that can be used in our vehicular density estimation approach. Equation 5.2 presents one of the alternative equations we obtained. However, in terms of accuracy, the average relative error is of 8.45%, while the first function presents a lower value (3.04%). Additionally, the Sum of Squared Errors (SSE) for the absolute error relative to this function is

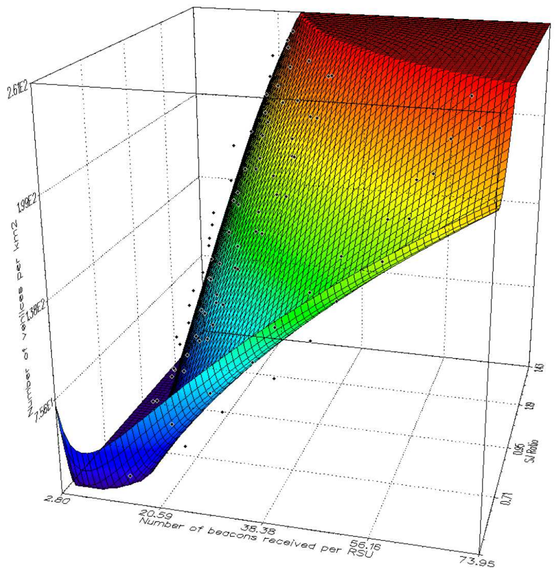


Figure 5.4: 3D representation of our density estimation function.

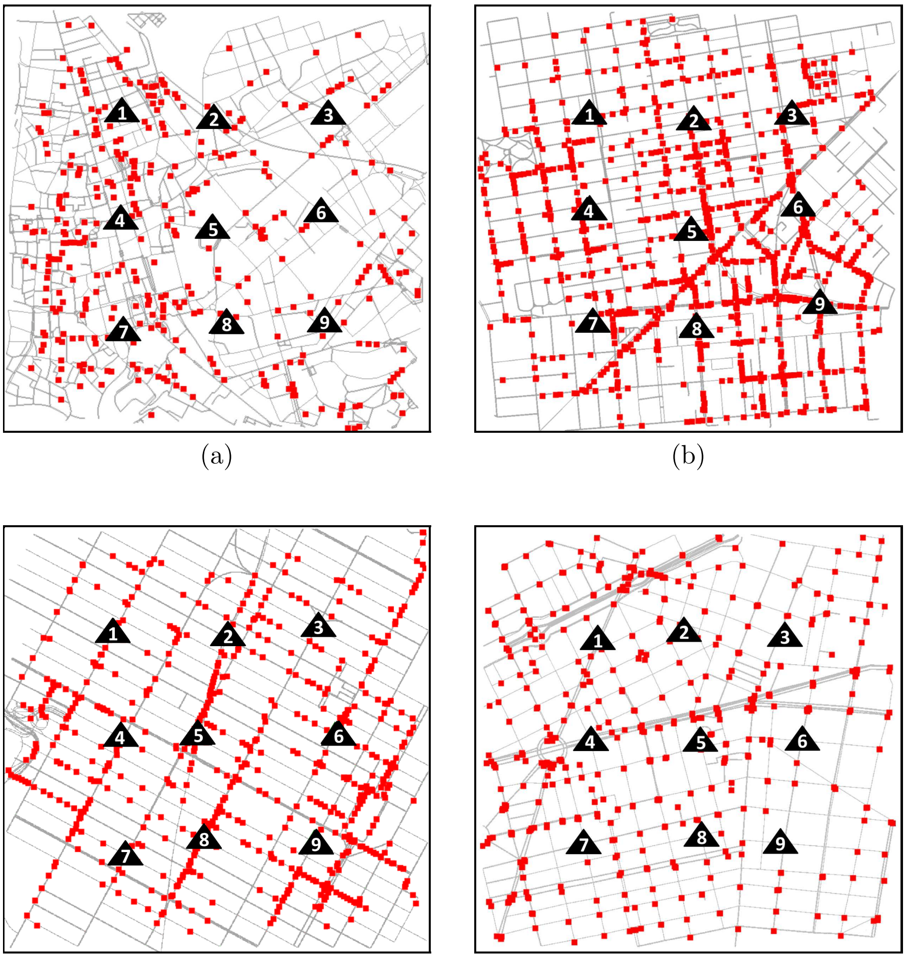
of 5.834E+04, while the first approach presents a lower value (4.700E+04). Thus, we considered adequate to use the first equation in our approach.

$$f(x, y) = a \cdot (dx + f)^b \cdot (gy + h)^c \tag{5.2}$$

5.4 Validation of our Proposal

To assess our proposed density estimation function, we chose four particular cases. Specifically, we simulated: (i) a density of 100 vehicles per km^2 in Rome, the city with the highest SJ Ratio (ii) a density of 250 vehicles per km^2 in San Francisco, a city with an intermediate SJ Ratio, (iii) a density of 200 vehicles per km^2 in New York, the city with the lowest SJ Ratio, and (iv) a density of 200 vehicles per km^2 in Mexico D.F., a city that was not used to obtain our density estimation function, and which has a SJ Ratio of 0.7722.

Figure 5.5 shows the RSU deployment strategy and the vehicles' location at the end of the simulation for the studied scenarios, whereas Table 5.6 shows the obtained results. We observe that the average number of beacons received per RSU is of 8.78, 52.67, 68.78, and 47.56 in Rome, San Francisco, New York, and Mexico D. F., respectively. These values are highly affected by the vehicular density, as well as the roadmap topology. Note that, although the vehicular density simulated in New York is lower than the one simulated in San Francisco, more beacons are received per RSU. This is caused by the lower SJ Ratio, since the roadmap topology of New York is simpler than San Francisco, thus allowing a better wireless signal propagation, as well as the reception of more messages by the RSUs.



(a) (b) (c) (d)

Figure 5.5: RSUs deployment and vehicles location at the end of the simulation in the cities of: (a) Rome, (b) San Francisco, (c) New York, and (d) Mexico D.F. Solid squares represent the vehicles, and the triangles represent the RSUs.

According to our proposal (i.e., applying the function shown in Equation 5.1), our system estimates a density of 103.68, 256.95, 196.87, and 196.91 vehicles, respectively (see Equations 5.3, 5.4, 5.5, and 5.6). Therefore, our vehicular density estimation approach accurately resembles the actual density, presenting an error of 3.68, 6.95, 3.13, and 3.09 vehicles, which only represents the 3.68%, the 2.78%, the 1.57%, and the 1.55% of the total vehicles. Results also indicate that our proposed density estimation function allows properly calculating the estimated traffic density in cities which were not used to tune our estimation function (e.g., Mexico D. F.).

$$f(x,y) = a + b \cdot ln(8.78) + \frac{c}{1.3873} + d \cdot ln(8.78)^2 + \frac{f}{1.3873^2} + g \cdot \frac{ln(8.78)}{1.3873} = 103.68 \tag{5.3}$$

$$f(x,y) = a + b \cdot ln(52.67) + \frac{c}{0.8863} + d \cdot ln(52.67)^2 + \frac{f}{0.8863^2} + g \cdot \frac{ln(52.67)}{0.8863} = 256.95 \tag{5.4}$$

$$f(x,y) = a + b \cdot ln(68.78) + \frac{c}{0.5140} + d \cdot ln(68.78)^2 + \frac{f}{0.5140^2} + g \cdot \frac{ln(68.78)}{0.5140} = 196.87 \tag{5.5}$$

$$f(x,y) = a + b \cdot ln(47.56) + \frac{c}{0.7722} + d \cdot ln(47.56)^2 + \frac{f}{0.7722^2} + g \cdot \frac{ln(47.56)}{0.7722} = 196.91 \tag{5.6}$$

Moreover, by using our system, we demonstrated that we are able to estimate the vehicular density in more specific areas. For example, using the data included in Table 5.6, our system can identify areas where the traffic is more congested (i.e., areas where the RSUs receive a higher percentage of beacons). For example, in the case of San Francisco, RSUs 2, 6, and 9 received a higher number of beacons compared to RSUs 1 and 7. According to these results, an automatic traffic control system could take advantage from V2I communication capabilities, adapting the vehicles' routes in order to redirect vehicles traveling in more congested areas to those areas where the RSUs receive a lower number of messages (i.e., less congested), thus avoiding traffic jams.

5.5 Comparing our proposal with previous Beacon-based Approaches

Other vehicular density estimation proposals (e.g., [MBML11], and [SCB11]) take only into account the number of beacons received, while omitting any data related to the map topology where the vehicles are located at. In order to assess the importance of the topology, we compared our proposal with a beacon-based approach, where the vehicular density is estimated only by using the number of beacons received. To make a fair comparison, we followed the same methodology in both approaches (i.e., we also made a regression analysis to obtain an equation capable of estimating the vehicular density, but in this case the estimation is solely based on the number of beacons received).

We tested several density estimation functions which are solely based on the number of beacons received, trying to obtain the lowest value for the Sum of

Table 5.6: Beacons received when simulating 100 vehicles/km^2 in Rome, 250 vehicles/km^2 San Francisco, 200 vehicles/km^2 in New York, and 200 vehicles/km^2 Mexico D. F.

RSU number	**Rome**		**San Francisco**		**New York**		**Mexico D. F.**	
	Received beacons	**% of rec. beacons**	**Received beacons**	**% of rec. beacons**	**Received beacons**	**% of rec. beacons**	**Received beacons**	**% of rec. beacons**
1	10	12.66	38	8.02	65	10.50	54	12.62
2	11	13.92	69	14.56	68	10.99	46	10.75
3	6	7.59	32	6.75	50	8.08	43	10.05
4	14	17.72	50	10.55	68	10.99	68	15.89
5	6	7.59	46	9.7	84	13.57	48	11.21
6	6	7.59	72	15.19	72	11.63	38	8.88
7	10	12.66	31	6.56	58	9.37	48	11.21
8	10	12.66	66	13.92	92	14.86	46	10.75
9	6	7.59	70	14.77	62	10.02	37	8.64
Total	**79**	**100**	**474**	**100**	**619**	**100**	**428**	**100**
Average	**8.78**	-	**52.67**	-	**68.78**	-	**47.56**	-

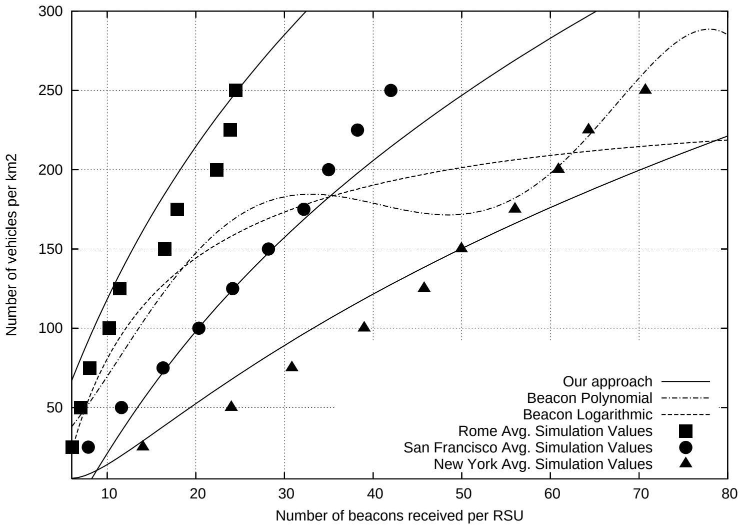


Figure 5.6: Comparison between our approach with respect to simulated and estimated results for beacon based density estimation function.

Squared Errors (SSE). In particular, we obtained the quintic polynomial function shown in Equation 5.7, and the logarithmic function shown in Equation 5.8.

$$f(x) = a + bx + cx^2 + dx^3 + fx^4 + gx^5 \tag{5.7}$$

$$f(x) = a + b \cdot ln(dx) + c \cdot ln(dx)^2 \tag{5.8}$$

Figure 5.6 shows a comparison of the estimated values with the simulation results obtained for the cities of Rome, San Francisco, and New York. The results confirm that our function provides more accurate results, presenting a low value for the Sum of Squared Errors (i.e., 4.700E+04), whereas the beacons-based functions present a Sum of Squared Errors value of 1.899E+05 (for the polynomial) and 2.016E+05 (for the logarithmic), i.e., one order of magnitude higher than our proposal.

As shown, our approach achieves a very good fit in the three cities studied, since it adjusts the estimation made by accounting not only for the number of beacons received, but also for the features of the maps where the vehicles are located. On the contrary, those approaches that only take into account the number of beacons received are prone to provide inaccurate estimations. Specifically, they overestimate the number of vehicles in high density complex environments, despite being able to correctly estimate lower densities in complex maps, and higher densities in simple maps. Therefore, the advantages of using our vehicular density estimation proposal are clear in terms of accuracy.

5.6 Summary

This chapter proposes a method that allows estimating vehicular density in urban environments at any given time by using V2I communications. Our proposal allows improving proactive traffic congestion mitigation mechanisms to better redistribute vehicles' routes, while adapting them to the specific traffic conditions.

Our vehicular density estimation algorithm takes into account not only the number of beacons received by the RSUs, but also the topology of the map where the vehicles are located. We demonstrated how our approach is able to accurately predict the vehicular density. Results showed that it allows estimating the vehicular density for any given city with high accuracy, thereby allowing governments to improve their traffic control mechanisms. Finally, we compared our proposal with respect to two different approaches that are solely based on beacons, proving the high efficiency of our approach when tested in a wide variety of vehicular scenarios.

In Chapter 6 we will use our density estimation function to propose an intelligent vehicle routing approach which will provide necessary information for avoiding emergency vehicles driving on congested areas.

Chapter 6

Reducing Emergency Services Arrival Time by Using Vehicular Communications and Evolution Strategies

Nowadays, traffic jams in urban areas have become a problem that keeps growing every year since the number of vehicles in our cities is continuously increasing. One of the most common causes producing traffic jams are vehicle accidents. Moreover, the arrival time of the emergency services could be raised due to traffic congestion. Intelligent Transportation Systems (ITS) have a key role in order to reduce or mitigate this problem.

In Chapter 5 we proposed a scheme to accurately estimate the traffic density in a certain area, which represents a key parameter to perform efficient traffic redirection, aimed at reducing the emergency services arrival time, and avoiding traffic jams when an accident occurs. In this chapter, we propose four different approaches addressing the traffic congestion problem, comparing them to obtain the best solution. In particular, we propose two approaches based on the Dijkstra algorithm, and two approaches based on Evolution Strategies to reduce the emergency services arrival time. Notice that, when an accident occurs, time is a critical issue, and the strategies here proposed contribute to find the optimal solution within a short time period.

6.1 Introduction

Traffic accidents represent a big problem for drivers and a serious burden for the economy of all the countries. A close look at traffic accidents shows that many of the casualties and serious medical conditions take place during the time elapsed between the accident occurrence and the arrival of the medical assistance. The so called 'Golden Hour' [FGM+13] after a car crash is the time within which medical or surgical intervention by a specialized trauma team has the greatest chance of saving lives. If more than 60 minutes have elapsed by the time the injured arrives to the operating table, the chances of survival fall sharply. Therefore, time is critical for the survival of the injured in a severe crash incident, and any technology capable of providing a fast and efficient rescue operation after a traffic accident takes place will increase the probability of survival of the injured, and reduce the injury severity.

Additionally, urban traffic congestion affects most cities around the world. This scenario is getting even worse since the number of vehicles circulating in our cities grows every year. Vehicle accidents are one of the most common causes generating traffic jams in urban scenarios, which yield a higher cost of fuel, increasing air pollution.

Emergency services can dynamically redistribute traffic by communicating or suggesting new routes to vehicles. These routes can be calculated using different methods such as Dijkstra-based algorithms, genetic algorithms, or evolution strategies.

There are several works where intelligent systems are used to avoid traffic jams (e.g., [ONI06], [SMGMRR10], and [DGDM12]). However, they do not focus on reducing the rescue time of the emergency services, or exploiting the advantages of using vehicular communication capabilities. Additionally, in all these works, authors only consider a specific scenario for simulations to assess their proposal, which might lead to unrepresentative results and wrong conclusions.

In this chapter, we propose four different approaches to minimize the emergency services arrival time when an accident occurs in urban scenarios, also trying to avoid traffic jams scenarios. In particular, two of them are based on the Dijkstra algorithm, and the other two are based on Evolution Strategies. Additionally, we evaluated the four proposed solutions in three different scenarios with different topologies to determine the best solution in terms of travel times of the emergency services, without penalizing the rest of vehicles.

This chapter is organized as follows: Section 6.2 reviews the related work regarding intelligent systems used to avoid traffic jams and minimize vehicle travel times. In Section 6.3 we present our four different re-routing systems (i.e., Dijkstra, Density-Based Dijkstra, Evolution Strategy, and Density-Based Evolution Strategy). Section 6.4 introduces the simulation environment used to assess our proposed schemes. Section 6.5 shows the obtained results, and finally, Section 6.6 concludes this chapter.

6.2 Related Work

Evolutionary algorithms have been widely used in the field of dynamic traffic distribution. However, unlike our proposal, existing works do not focus on reducing the rescue time of the emergency services. In this section, we present some of the most relevant works related to our work.

Ohara et al. [ONI06] examined two routing methods to reduce the average vehicle travel time: one of them used a centralized system, and the other provided drivers some selection agents, but each driver had to select his route. Since the number of combinations of vehicles routes exponentially increases as the number of vehicles grows, authors employed a genetic algorithm to search for a near-optimal route combination for all vehicles.

Yoshikawa and Terai [YT09] discussed a route selection algorithm, particularly focused on a hybrid technique which combines genetic algorithms with the Dijkstra algorithm [Dij59] to achieve high quality route guidance. They presented a solution similar to *The Traveling Salesman Problem* [JM97]. Specifically, their proposal is based on an individual vehicle which has an order of the passing points as genes. Authors estimated distances between nodes based on Manhattan street distances, although the topology of real urban areas are usually quite different from regular and simple Manhattan-style roads. In addition, they only took into account route distances for each individual vehicle without using vehicle density information to develop their genetic algorithm.

More recently, Dezani et al. [DGDM12] presented an application for real-time traffic lights control in congested urban traffic environments, taking as input the locations and routes of the vehicles in the involved areas. Authors used V2I communications to gather the location of vehicles in order to calculate traffic density. Additionally, they developed a genetic algorithm to solve traffic jams by controlling traffic lights. With respect to their proposed traffic density estimation system, we consider that it is not realistic since the vehicles circulating outside the infrastructure coverage area cannot communicate their position.

In all these previous works, authors validate their proposals just by considering a theoretical scenario. However, we consider that these simulations are not realistic, since real-world roads do not follow a general pattern, especially in urban scenarios.

Other authors proposed intelligent systems for traffic distribution using real scenarios to assess their proposal. Collins and Muntean [CM08] presented a novel adaptive vehicle routing algorithm enabled by wireless vehicular networks. Their system was based on the client-server architecture, where clients are vehicles. They used a genetic algorithm to select the best route for each vehicle, using a fitness function taking into account road congestion, vehicle travel time, and fuel consumption. Specifically, they used four different kinds of simulations: (i) the shortest route is selected, but it does not vary during the travel, (ii) each vehicle drives towards its own destination according to the route management solution, but without adaptation during the travel, (iii) each vehicle drives towards its own destination according to the route management solution with dynamic adaptation during the travel, and, (iv) the hypothetical 'ideal' solution based on traffic saturation and able to dynamically re-route vehicles is selected. However, the only scenario used in their simulations was a fragment of the city of Boston (USA).

Sanchez-Medina et al. [SMGMRR10] developed a model for traffic signal optimization based on the combination of three key techniques: (i) genetic algorithms for the optimization task, (ii) cellular-automata-based microsimulators for evaluating every possible solution for traffic-light programming times, and (iii) a Beowulf

Table 6.1: Features of our proposals

	Dijkstra	**Density-Based Dijkstra**	**Evolution Strategy**	**Density-Based Evolution Strategy**
Deterministic	✓	✓	✗	✗
Nondeterministic	✗	✗	✓	✓
Considering traffic density	✗	✓	✗	✓

Cluster, which used a multiple-instruction-multiple-data (MIMD) price/performance ratio. They tested the genetic algorithm with four different fitness functions: (i) number of vehicles that reach their destination point easily, (ii) mean travel time, (iii) time of occupancy and state of occupancy, and (iv) global mean speed. Authors used a traffic model based on both Krauss [KWG97], and Schadschneider and Chowdhury [SCB$^+$99] mobility models. However, they focused their simulations on a specific scenario, i.e., 'La Almozara' district in Zaragoza.

To the best of our knowledge, although there are several works where intelligent systems are used to avoid traffic jams, none of them neither is focused on reducing the arrival time of the emergency services to the accident location, nor uses a street priority scheme to calculate vehicles routes. Additionally, in all previous studies, authors only consider a specific scenario for simulations in order to assess their proposal. From our point of view, simulating only one specific scenario is inadequate when presenting a vehicle routing model (even in real scenarios since it can lead to nonrepresentative and inaccurate results). We consider that simulating different (and realistic) topologies is necessary, since the roadmap topology significantly affects the obtained results [FGM$^+$11a].

6.3 Our Proposed Vehicle Routing Systems

In this section, we propose four different vehicle routing approaches with the aim of ensuring that emergency services arrive at the place of the accident as soon as possible, whereas the rest of vehicles are not significantly affected, i.e., their travel times do not increase considerably, avoiding the possible traffic jams caused by the accident. Specifically, they are: (i) Dijkstra, (ii) Density-Based Dijkstra, (iii) Evolution Strategy, and (iv) Density-Based Evolution Strategy.

Table 6.1 presents the main features of these proposed approaches. As shown, the first two proposed approaches are simple and deterministic. The first one accounts for the number of lanes of each street to find the solution, and the second scheme additionally takes into account the traffic density. The other two proposed approaches are implemented using evolution strategies, and additionally, our last mechanism uses a real-time traffic density estimation to get better solutions.

6.3.1 Dijkstra

This system aims at obtaining the shortest route between two map positions by using the Dijkstra algorithm [Dij59], specifically adapted to roads and streets, and taking into account the length and priority of the streets. The priority of each

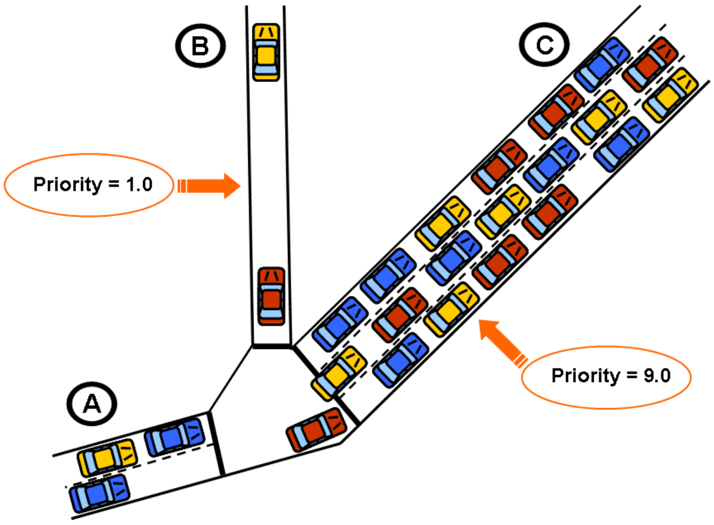


Figure 6.1: Example of a traffic jam when the street priority is given by the number of lanes.

street indicates the preference it has with respect to the others for a vehicle when it arrives to an intersection.

In this system, the street priority is calculated by using the number of lanes per street, assigning higher priority to the widest streets (i.e., with higher number of lanes). The main disadvantage of this system is noticeable when there is a high number of vehicles in a specific area, since it might produce traffic jams even in the widest streets. Figure 6.1 shows an example of this situation. As shown, vehicles arrive to the junction through street A. Using this system and considering the priorities shown in the figure (1.0 for street B and 9.0 for street C), the majority of vehicles continue their route through street C (90% of vehicles since this street has a greater number of lanes), collapsing it. However, street B has less traffic density, with a more fluid traffic.

This proposed scheme uses a static model for street priorities, where a priority is given to each street, and priorities do not change under any circumstance. This issue could generate two kind of problems when an accident occurs: (i) there could be traffic jams in specific areas of the scenario, whereas other areas present very low traffic, and (ii) the streets selected as routes for the emergency services do not present low priority for the rest of vehicles in order to reduce the number of potential vehicles blocking the streets.

The main advantage of this system is the low computational cost since it does not need to know the current traffic density or the emergency service routes; in addition, when an accident occurs, this approach can be applied immediately.

6.3.2 Density-Based Dijkstra

This proposed system is similar to the previous one, with the difference that, in this case, we take into account the traffic density in the area when the street priorities are assigned. To develop this method, those streets leading vehicles to high traffic density areas, are penalized. When an accident occurs, all the vehicles involved send a warning message using Vehicular Networks Communications. When control systems are notified, they apply the vehicular density estimation approach presented in Chapter 5. In addition, the streets through which emergency services circulate to arrive at the accident site are penalized for the rest of vehicles. Specifically, in this proposed system, we proceed as follows:

- *Step 1*: we prioritize streets by normalizing the values (see Equation 6.1). As shown, the normalized values start in 1 and end in 10 (N_{min} and N_{max}, respectively).

$$\begin{aligned} N_x = &\frac{(P_x - P_{min}) \cdot (N_{max} - N_{min})}{P_{max} - P_{min}} + N_{min} \\ where: & \\ & N_{min} = 1 \\ & N_{max} = 10 \end{aligned} \tag{6.1}$$

- *Step 2*: the normalized value for the rest of the areas (N_x) is calculated by using a proportion between the minimum and the maximum traffic density percentages, and the traffic density of the area which we want to calculate the normalized value (P_{min}, P_{max}, and P_x, respectively).

- *Step 3*: with the aim of penalizing streets with a high traffic density, we apply Equation 6.2. In this equation, we obtain the inverse value calculated above (S_x), since a higher priority value has more priority, and we multiply this value by the number of lanes of the street (L_x).

$$S_x = (N_{max} - N_x + 1) \cdot L_x \tag{6.2}$$

- *Step 4*: with the aim of calculating the fastest route for the emergency services vehicle, this approach applies a simple Dijkstra algorithm for each one, calculating the shortest route between two map positions (accident site and hospital, police station, firehouse, etc.), regardless of traffic density. Note that, in this case, we do not take into account the street priorities since emergency vehicles always have more priority than the rest of vehicles, regardless of the street they are circulating in.

- *Step 5*: as shown in Equation 6.3, we penalize these streets through which emergency services circulate (S_{x_e}) by giving them a priority corresponding to the number of lanes (e.g., a street with four lanes has a priority of 4).

$$S_{x_e} = L_x \tag{6.3}$$

- *Step 6*: we calculate the new vehicle routes using a Dijkstra-Based algorithm taking into account the streets priorities, since the shortest path could not be the fastest path.

Equation 6.4 shows an example of street priorities calculation. As shown, we have three different areas which contain the following percentage of traffic vehicles: $P_{min} = 20\%$, $P_{max} = 50\%$, and $P_x = 30\%$ of the total of vehicles. Also, we have three streets located in the aforementioned areas with these numbers of lanes ($L_{min} = 3, L_{max} = 2$, and $L_x = 1$). Since we have the maximum and minimum normalized values (N_{min} and N_{max}), we calculate the other street normalized value (N_x) by using Equation 6.1. Finally, we obtain the street priorities (S_{min}, S_{max}, and S_x) by using Equation 6.2, thereby obtaining street priorities of 30, 2, and 7, respectively.

$$
\begin{aligned}
&P_{min} = 20, P_{max} = 50, P_x = 30\\
&N_{min} = 1, N_{max} = 10\\
&L_{min} = 3, L_{max} = 2, L_x = 1\\
&N_x = \frac{(P_x - P_{min}) \cdot (N_{max} - N_{min})}{P_{max} - P_{min}} + N_{min}\\
&N_x = \frac{(30 - 20) \cdot (10 - 1)}{50 - 20} + 1 = 4\\
&S_x = (11 - N_x) \cdot L_x\\
&S_{min} = (11 - 1) \cdot 3 = 30\\
&S_{max} = (11 - 10) \cdot 2 = 2\\
&S_x = (11 - 4) \cdot 1 = 7
\end{aligned}
\tag{6.4}
$$

This system requires from the estimated traffic density proposed in Chapter 5, or any other available. In that chapter we presented a system which needs to receive beacons during 30 seconds to estimate traffic density. To reduce this 30 seconds period, control units could continuously execute the aforementioned estimation system in order to know immediately the traffic density estimation, assuming an error of non-real-time estimation with a maximum threshold of 30 seconds. Using this approximation, our system would only require calculating the emergency services routes.

6.3.3 Evolution Strategy

As shown in Chapter 2, evolution strategies are a variant of evolutionary algorithms with the following features:

- They are typically used for conditions parameter optimization.
- There is a strong emphasis on mutation for creating offspring.

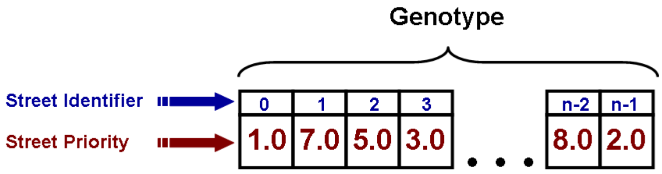


Figure 6.2: Example of a genotype for street priorities.

- Mutation is implemented by adding some random noise drawn from a Gaussian distribution.
- Mutation parameters are changed during a run of the algorithm, achieving faster results.

Due to the high computational cost of calculating all possible combinations of street priorities, to find the optimal solution, we consider interesting to apply an Evolution Strategy. Evolution Strategies are typically used to solve optimization problems of continuous variables. As in the previous proposed approaches, this scheme applies the Dijkstra algorithm for each emergency vehicle in order to calculate the emergency services routes. In this case we do not take traffic density into account, but we penalize the streets selected for the emergency services vehicles. Then, we calculate new routes for vehicles using a priority-based Dijkstra algorithm (with the same aims of the previously proposed system).

In the following Subsections we present the main characteristics of our Evolution Strategy (i.e., definition of variables, fitness function, mutation, recombination, parents selection, and survivors selection).

6.3.3.1 Definition of Variables

An individual, i.e., a potential solution of our system, encodes a possible solution into a chromosome based structure (genotype) [MB05]. In this case, a vector of float point numbers which contains the priority value of each street (as shown in Figure 6.2) is considered. Street priorities are randomly selected in the vectors of the initial population for each street for the first time.

6.3.3.2 Fitness Function

Selection is a process in which solutions are selected for recombination based on their fitness values. Here, fitness refers to a measure of profit, utility, or goodness to be maximized while exploring the solution space. Our system has three different fitness functions designed to minimize the arrival time for the emergency vehicles and the travel time of the rest of vehicles: (i) Fitness Function 1 gives double importance to the arrival time of emergency services (‘e’ represents emergency services vehicles, and ‘r’ represents the rest of Regular vehicles) (see Equation 6.5), (ii) Fitness Function 2 assigns the same importance to both arrival times (see Equation 6.6), and (iii) Fitness Function 3 gives double importance to the arrival time of the rest of vehicles (see Equation 6.7). Although the latter should not perform well, since our main goal is to reduce the time required by the emergency vehicles to reach the accident location, we consider interesting to evaluate it to assess whether the system is able to significantly reduce the travel time of the rest of vehicles, while slightly increasing the the emergency services' arrival time. Next, we compare these functions to determine which one provides better results when simulating the testbed.

$$FitnessFunction1 = 2 \cdot \frac{\sum_{i_e=0}^{n_e} t_{i_e}}{n_e} + \frac{\sum_{i_r=0}^{n_r} t_{i_r}}{n_r} \tag{6.5}$$

$$FitnessFunction2 = \frac{\sum_{i_e=0}^{n_e} t_{i_e}}{n_e} + \frac{\sum_{i_r=0}^{n_r} t_{i_r}}{n_r} \tag{6.6}$$

$$FitnessFunction3 = \frac{\sum_{i_e=0}^{n_e} t_{i_e}}{n_e} + 2 \cdot \frac{\sum_{i_r=0}^{n_r} t_{i_r}}{n_r} \tag{6.7}$$

6.3.3.3 Mutation

In an Evolution Strategy there is a strong emphasis on the mutation to create the offspring. Additionally, mutation is implemented by adding a random 'noise' obtained from a Gaussian distribution. Mutation parameters change during the execution of the algorithm. In our proposal, we use an Uncorrelated Mutation with n Step Sizes. The mutation mechanism applies the functions included in Equation 6.8, where σ is the mutation step size, τ is the scale parameter for the mutation step sizes, and n is the number of individuals.

$$\begin{aligned}
\sigma_i' &= \sigma \cdot e^{\tau' \cdot N(0,1) + \tau \cdot N_i(0,1)}, \\
x_i' &= x_i + \sigma_i' \cdot N_i(0,1) \\
&where: \\
&\quad \tau' \propto \frac{1}{\sqrt{2n}} \\
&\quad \tau \propto \frac{1}{\sqrt{2\sqrt{n}}}
\end{aligned} \tag{6.8}$$

Using this kind of mutation, our genotype contains values x (street priority) and values σ (mutation step sizes), as shown in Figure 6.3.

To avoid too small standard deviations providing a negligible effect, we limit the value of the step sizes using a threshold (ε_0), i.e., $\sigma' < \varepsilon_0 \Rightarrow \sigma' = \varepsilon_0$.

6.3.3.4 Recombination

The basic recombination scheme in Evolution Strategies requires two parents to create a child. For λ descendants, the recombination process is performed λ times. There are two variants of recombination depending on how parental alleles are recombined:

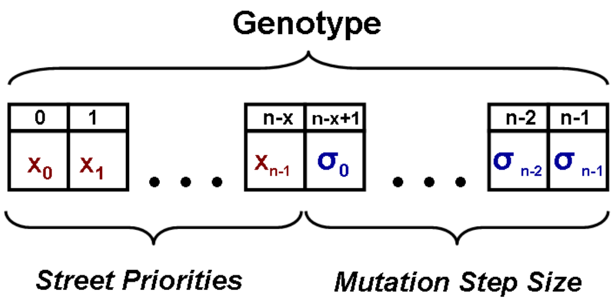


Figure 6.3: Example of genotype formed by street priorities and mutation step sizes.

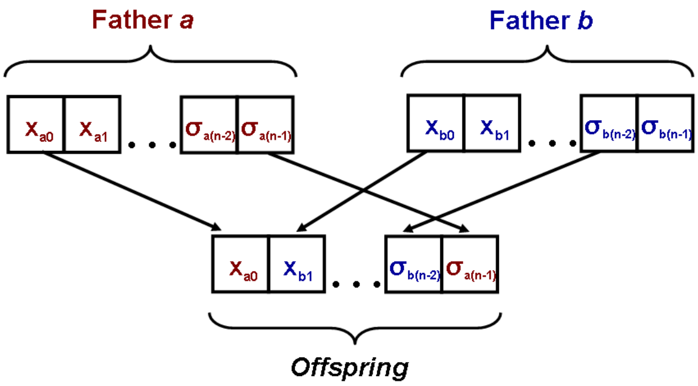


Figure 6.4: Example of local discrete recombination.

- Discrete Recombination: one of the alleles of the parents is chosen with equal probability for both parents.
- Intermediate Recombination: the parental allele values are averaged.

Furthermore, two parents can be used, randomly obtained from the population of μ individuals, for each component ($i \in \{1...n\}$) of the offspring. This is known as *Global* recombination, and the variant in which only two parents are selected for the total of components is called *Local* recombination.

In our proposed system, we apply Local Discrete Recombination, since this method is one of the most widely used in this kind of algorithms, and it provides a good performance in most cases. As shown in Figure 6.4, each child allele is chosen with equal probability for both parents.

6.3.3.5 Parents Selection

The parents selection in Evolution Strategies does not depend on their fitness values. Parents are chosen randomly by using a uniform distribution from the population of μ individuals.

6.3.3.6 Survivors Selection

The Survivors Selection consists on deterministically choosing the μ best individuals, after creating λ descendants and calculating their fitness. There are two kinds of Survivor Selection:

- Selection (μ, λ): only the individuals of the offspring are considered to generate the next generation.

- Selection $(\mu + \lambda)$: survivors are selected from the union of parents and descendants.

Our proposed scheme uses Selection $(\mu+\lambda)$, since using Selection (μ, λ) descendants could produce worse results, delaying the achievement of the best solution.

6.3.4 Density-Based Evolution Strategy

With the aim of reducing the system runtime, we propose an Evolution Strategy with the same characteristics as the Evolution Strategy System (presented in the previous subsection), but in this case we do not obtain the initial population randomly. We consider that by using the traffic density information, our system will be able to reduce the time required to find the optimal solution (by reducing the number of generations). Specifically, this approach combines both the Density-Based Dijkstra and the Evolution Strategy schemes.

Instead of getting the initial population randomly, we start the procedure by taking into account two different genotypes: (i) a genotype which contains street priorities based on the number of lanes, and (ii) a genotype which contains street priorities based on traffic density. The rest of individuals of the initial population are obtained by recombining these two genotypes. Street priorities based on the number of lanes are obtained by squaring the number of lanes of each street, and the street priorities based on traffic density and emergency vehicles routes are obtained by using the method proposed in the Density-Based Dijkstra approach. Then, we make a first recombination with them, selecting the n best descendants in order to generate a first offspring, so approaching to the best solution. This improvement will make the system reach the optimal solution in less time than using a random initial population.

Figure 6.5 shows an example of the objective of this solution. As shown, initializing the population accounting for the traffic density and the number of lanes could make it possible to obtain better solutions with a lower number of offsprings, thereby reducing the system runtime. As shown, while the non-density-based system would have created x_{ndb} generations to obtain the y_{db} fitness value, our density-based proposed system would obtain this value in its first generation. The initial executions would be avoided and, therefore, this approach would save crucial time.

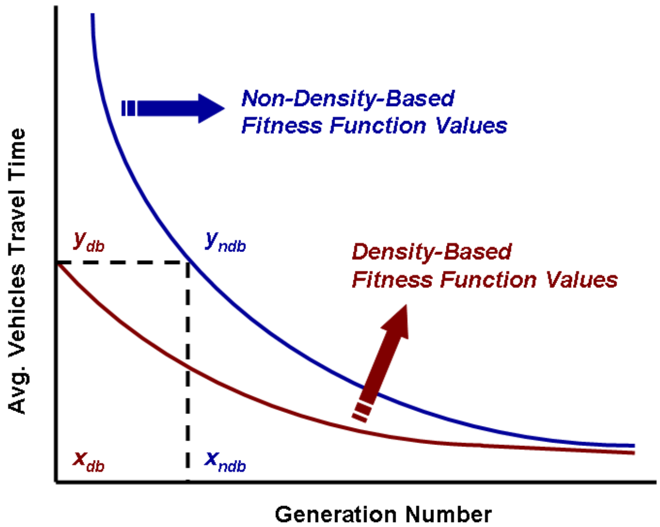


Figure 6.5: Example of fitness function values using both proposed intelligent systems (i.e., Evolution Strategy and Density-Based Evolution Strategy).

6.4 Simulation Environment

Traffic simulation is known to be a very complex issue. One of the main reasons is due to the fact that traffic simulators must model the discrete dynamics that arise from the interaction among individual vehicles [BDS97]. The Simulation of Urban MObility (SUMO) is an open source, microscopic, continuous-space traffic simulator designed to handle large road networks, and it is mainly developed by employees of the Institute of Transportation Systems at the German Aerospace Center[1] [KEB12].

The SUMO mobility generator supports several mobility models, such as the Krauss mobility model [KWG97]. In addition, SUMO allows customizing a wide variety of parameters including the initial and final position of the vehicles, the type of vehicles, the maximum speed of each street, or the street's priority. Table 6.2 shows the SUMO street attributes that we use in our system. Moreover, each SUMO lane has an attribute indicating the street to which it belongs. This allows us to obtain the number of lanes at every street. We use the attributes *from* and *to* in order to determine the heading of the street, the attribute *id* to link lanes with streets, and the attribute *priority* to implement our proposed schemes.

To increase the level of realism of our simulations, we use real scenarios consisting of downtown areas from the cities of Rome (Italy), San Francisco (USA), and New York (USA) imported directly from OpenStreetMap [Ope14]. As mentioned in Chapter 5, according the SJ Ratio, these cities are examples of the roadmaps with the highest SJ Ratio, an intermediate SJ Ratio, and the lowest SJ Ratio, respectively (see Figure 6.6). So, we assess our proposal under different and rep-

[1] http://www.dlr.de/fs/en/desktopdefault.aspx

Table 6.2: Attributes of SUMO Streets

Attribute	**Description**
id	The unique id of the street
from	The id of the starting junction
to	The id of the final junction
priority	Street weight regarding the rest of the streets

Table 6.3: Parameters used for the simulations

Parameter	**Value**
number of simulations	100
roadmaps	Rome, San Francisco, and New York
warm up time	60 seconds
number of vehicles	500 and 1000
number of collided vehicles	1
warning message size	18KB [BGF+12c]
beacon message size	$512B$
RSU deployment policy	Uniform Mesh [BGF+12b]
MAC/PHY	802.11p
mobility model	Krauss [KWG97]
channel bandwidth	$6Mbps$

resentative roadmap profiles.

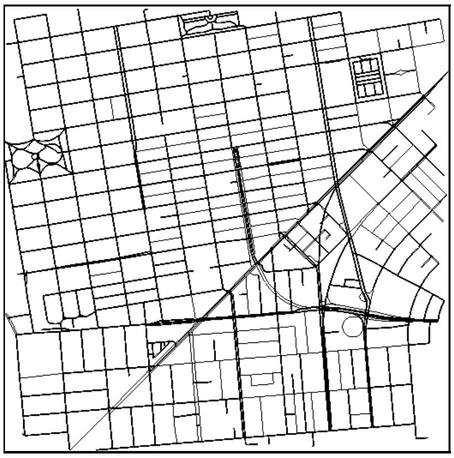
All simulation results consist of an average of over 100 runs with different scenarios, densities and fitness functions. Each simulation consist on vehicles circulating during 600 seconds. We simulate a car accident taking place at 60 seconds. We use the first 60 seconds as a warm up period to achieve a stable state. During this time, vehicles follow random routes. At the time of the accident we capture the current estimated location of all the vehicles and their target location. Then, we apply our proposed approaches to calculate the new vehicle routes, and to perform a comparison analysis. Additionally, we consider a non-static start and end position for the emergence vehicle, since an ambulance does not have to be always at the same place and the accident can occur in any location. Table 6.3 shows the parameters used for the simulations.

In order to obtain the real-time traffic density to provide this information to the system, we apply the Density Estimation Function presented in Chapter 5.

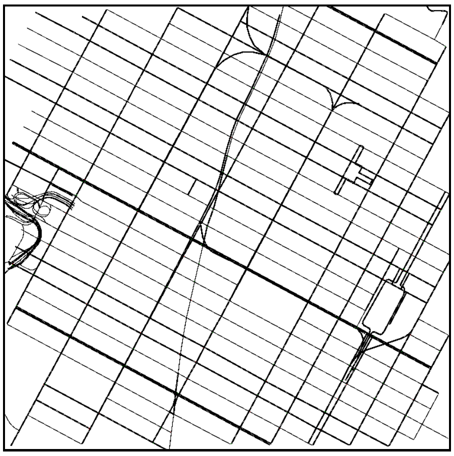
6.5 Simulation Results

In this section we present the simulation results of our four proposed approaches. First, we show the results obtained using the Evolution Strategy System. Our goal is to study the number of required generations to obtain the function convergence values. Then, we compare the Dijkstra, the Density-Based Dijkstra, and the Evolution Strategy Systems, demonstrating that by applying an evolution strategy we are able to obtain better results. Later, we present a comparison between the Evolution Strategy and Density-Based Evolution Strategy Systems, with the aim of proving that adding traffic density information allows the evolution strategy to obtain better results using a smaller number of generations. Finally, we study the impact of reducing the population size and the number of descendants on the ob-

(a)



(b)



(c)

Figure 6.6: Scenarios used in our simulations. Fragments of the cities of: (a) Rome (Italy), (b) San Francisco (USA), and (c) New York (USA).

Table 6.4: Parameters used for the Evolution Strategy

Parameter	Value
number of simulations	100
population number	5
number of descendants	10
number of generations	20
fitness functions	Equations 6.5, 6.6, and 6.7
mutation	Uncorrelated Mutation with n Step Sizes
recombination	Local Discrete
parents selection	Randomly
survivors selection	$(\mu + \lambda)$

tained results; our goal is to reduce the system runtime, while reducing the needed time for emergency services to arrive.

6.5.1 Evolution Strategy

In this subsection, we show the obtained results using our proposed Evolution Strategy and we analyze the number of generations required to obtain the function convergence value. Table 6.4 shows the parameters used for the Evolution Strategy used. Figures 6.7 and 6.8 present the obtained results. As expected, the system obtains the best emergency services arrival times when applying Equation 6.5 as a fitness function (i.e., the fitness function that gives doubled importance to the emergency services arrival time) in all simulated scenarios. Also, we can observe that, when using Equation 6.7 as a fitness function, our system is able to reduce the travel times of the rest of vehicles, although this solution slightly increases the emergency services arrival times. On the other hand, results indicate that when applying Equation 6.6 as a fitness function we are able to reduce both the emergency services arrival time and the rest of vehicles travel time, but they are not reduced in the same degree as when using the other two fitness functions. Since the main goal of our proposal is to reduce the emergency services arrival time as much as possible, we select Equation 6.5 as the best fitness function, which is able to minimize this time. In addition, as shown in Figure 6.7, by using this configuration the system obtains the function convergence values in 10 generations or less.

6.5.2 Dijkstra, Density-Based Dijkstra, and Evolution Strategy Comparison

For the purpose of knowing which one is the best system, we analyze the results obtained with the configuration proposed in the previous Subsection (i.e., 10 number of generations, and Equation 6.5 as the fitness function), since they were the best parameter values when using the Evolution Strategy.

Table 6.5 shows the average travel times of the emergency vehicles and the rest of vehicles (in seconds), when varying the roadmap scenario, the vehicle density, and the traffic re-routing approach. As shown, when using the Density-Based Dijkstra scheme we improve in all scenarios compared with the application of pure Dijkstra. In particular, we reduce emergency services travel times by 16.84% on

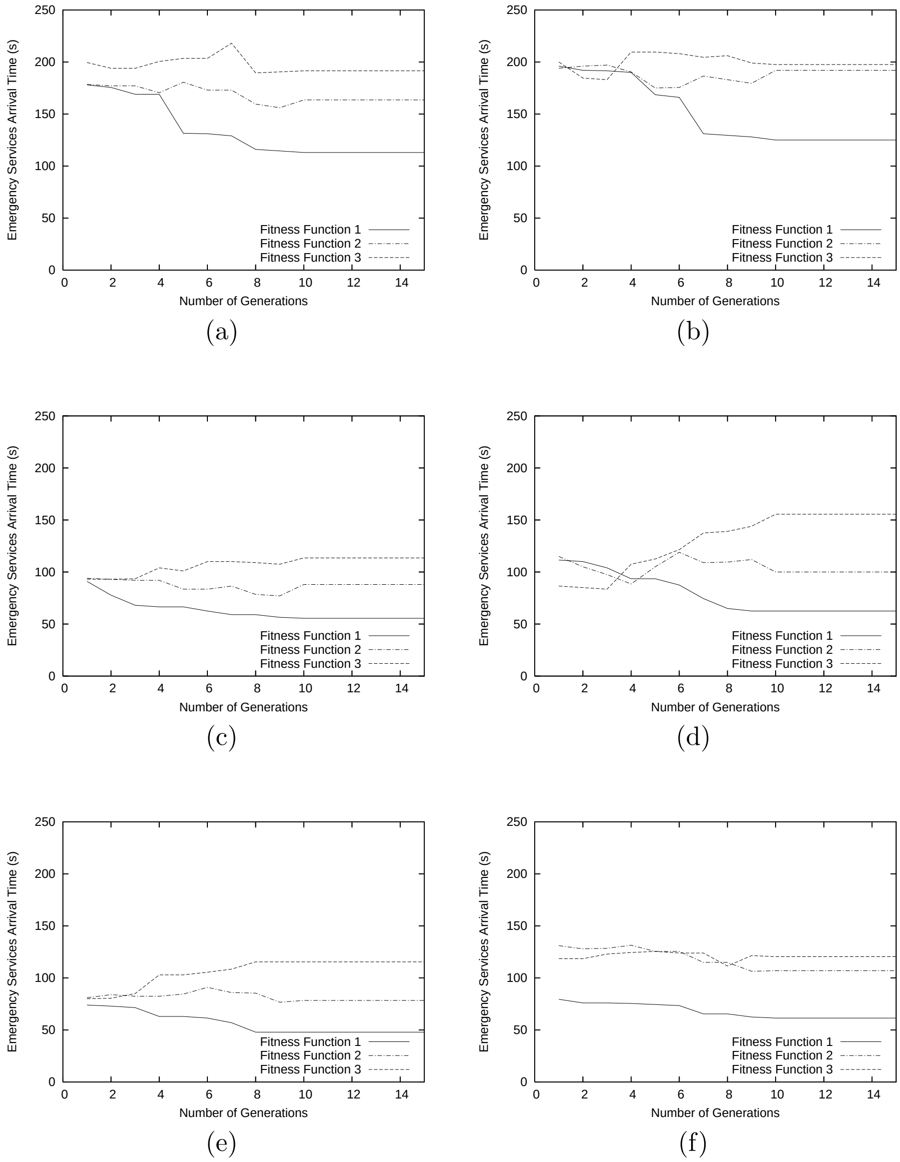


Figure 6.7: Emergency services arrival times, using the Evolution Strategy in the scenarios of: Rome (Italy) (a) 125 vehicles/km^2, and (b) 250 vehicles/km^2, San Francisco (USA) (c) 125 vehicles/km^2, and (d) 250 vehicles/km^2, and New York (USA) (e) 125 vehicles/km^2, and (f) 250 vehicles/km^2.

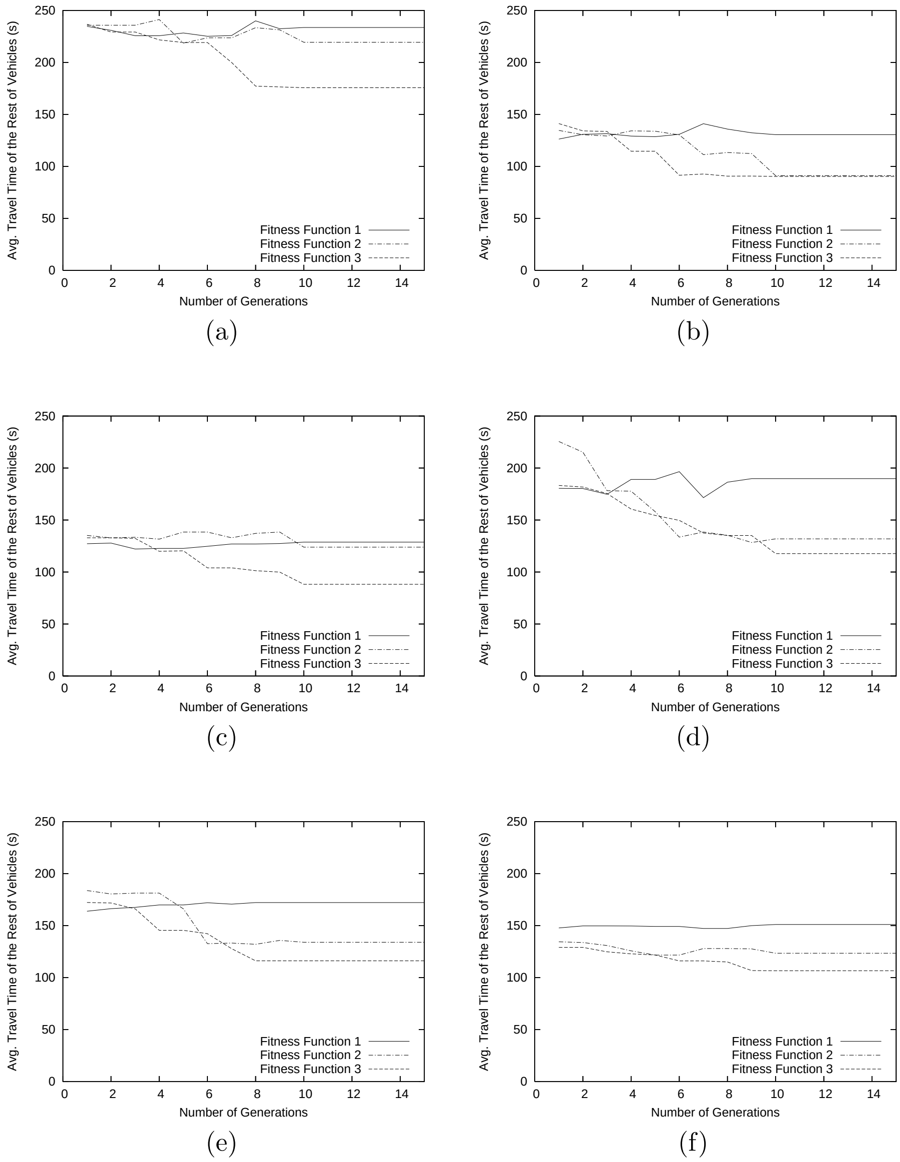


Figure 6.8: Mean travel times of the rest of the vehicles, using the Evolution Strategy in the scenarios of: Rome (Italy) (a) 125 vehicles/km^2, and (b) 250 vehicles/km^2, San Francisco (USA) (c) 125 vehicles/km^2, and (d) 250 vehicles/km^2, and New York (USA) (e) 125 vehicles/km^2, and (f) 250 vehicles/km^2.

Table 6.5: Simulation Results

Scenario	Vehicles/km^2	Dijkstra		Density-Based Dijkstra		Evolution Strategy	
		Vehicles Avg. t.	Emgcy. Serv.	Vehicles Avg. t.	Emgcy. Serv.	Vehicles Avg. t.	Emgcy. Serv.
Rome	125	222.91	190	205.09	162	233.59	**113**
	250	12.27	209	109.01	159	130.54	**125**
San Francisco	125	112.02	92.5	106.86	82.5	128.74	**55.5**
	250	148.08	126	145.14	82.5	189.81	**62.5**
New York	125	151.43	68	134.04	60.5	172.19	**48**
	250	143.46	83.5	126.61	78.5	151.14	**61.5**

average (i. e., 19.33% in Rome, 22.67% in San Francisco, and 8.51% in New York). Also, we reduce the rest of vehicles travel time by an average of 6.79% (i.e., 5.45% in Rome, 3.3% in San Francisco, and 11.61% in New York).

On the other hand, the Evolution Strategy significantly reduces the emergency services arrival time, although it increases the travel time for the rest of the vehicles. Specifically, this scheme reduces emergency services travel times by an average of 37.81% (40.36% in Rome, 45.2% in San Francisco, and 27.88% in New York). However, it increases the travel time for the rest of the vehicles by 13.87% on average (10.53% in Rome, 21.55% in San Francisco, and 9.53% in New York). Although this intelligent system increases the travel time for the rest of the vehicles (a maximum of 28.18%), it can significantly reduce the emergency services travel time (a minimum of 26.35%).

6.5.3 Comparison Between Evolution Strategy and Density-Based Evolution Strategy Systems

In this subsection we compare our two proposed intelligent algorithms (i.e., Evolution Strategy and Density-Based Evolution Strategy). Simulations were performed using the parameters showed in Table 6.4, but, in order to simplify the comparison, we only simulate our systems using Equation 6.5 as the fitness function. As shown in Figure 6.9, the results obtained when applying the Density-Based Evolution Strategy system are better than when using the Evolution Strategy. Also, we can observe that the Density-Based approach allows obtaining smaller emergency services arrival times with fewer generations, since we consider traffic density when initializing the population.

In addition, we compare the Density-Based Evolution Strategy system results with those obtained when using the Dijkstra system. As shown in Table 6.6, we reduce the emergency services travel times by 54.33% on average (53.58% in Rome, 55.26% in San Francisco, and 51.16% in New York). However, this system increases the rest of vehicles travel time by 11.49% on average (12.27% in Rome, 10.85% in San Francisco, and 11.36% in New York). Although this intelligent system increases the travel time for the rest of vehicles (a maximum of 14.39%), it can significantly reduce the emergency services arrival time (a minimum of 47.9%).

Since one of the most important goals of our approach is reducing the emergency services travel times, the Density-Based Evolution Strategy system is the best one among all the proposed solutions. Once again, we demonstrate that traffic

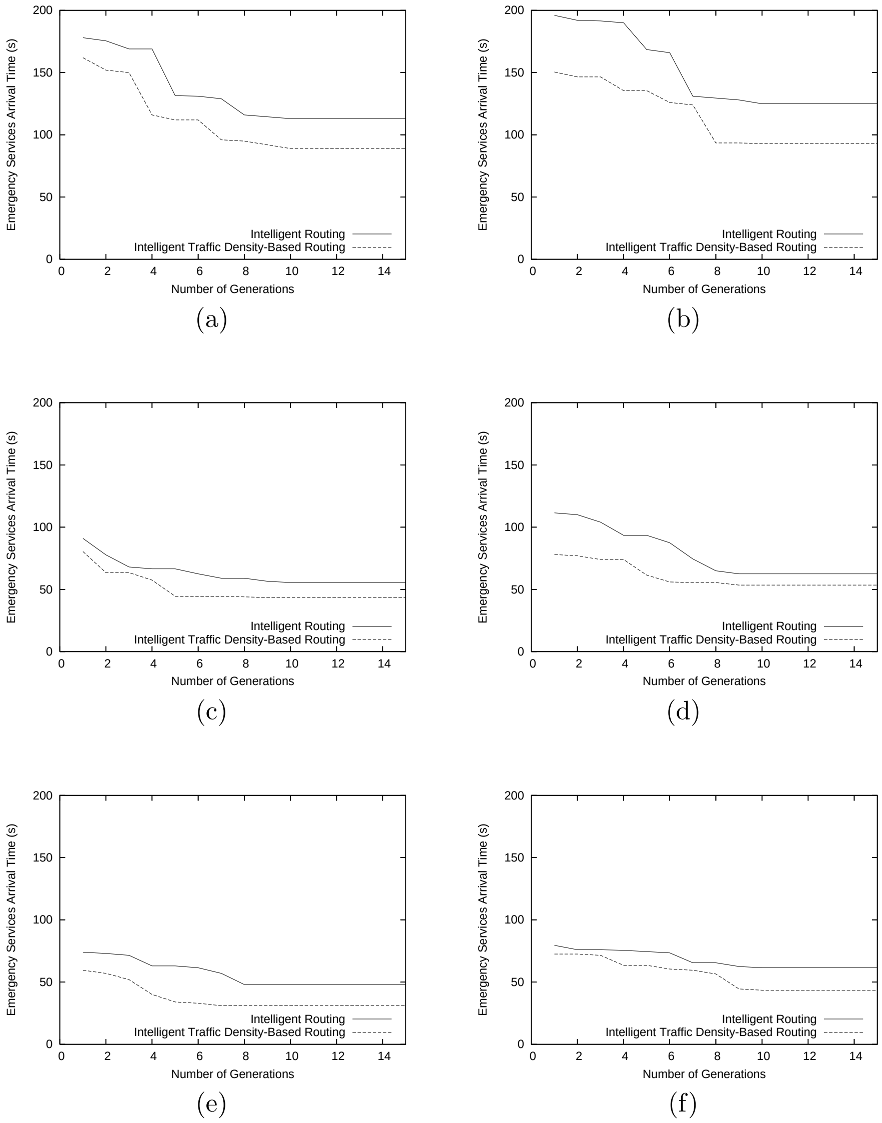


Figure 6.9: Evolution Strategy and Density-Based Evolution Strategy systems emergency services arrival times on average after 100 simulations in the scenarios of: Rome (Italy) (a) 125 vehicles/km^2, and (b) 250 vehicles/km^2, San Francisco (USA) (c) 125 vehicles/km^2, and (d) 250 vehicles/km^2, and New York (USA) (e) 125 vehicles/km^2, and (f) 250 vehicles/km^2.

Table 6.6: Simulation Results

Scenario	Vehicles/km^2	Dijkstra		Density-Based Evolution Strategy	
		Vehicles Avg. t.	Emgcy. Serv.	Vehicles Avg. t.	Emgcy. Serv.
Rome	125	222.91	190	249.36	**89**
	250	12.27	209	126.51	**93**
San Francisco	125	112.02	92.5	120.21	**43.5**
	250	148.08	126	169.38	**53.5**
New York	125	151.43	68	171.06	**31**
	250	143.46	83.5	157.44	**43.5**

Table 6.7: Parameters used for the Density-Based Evolution Strategy System

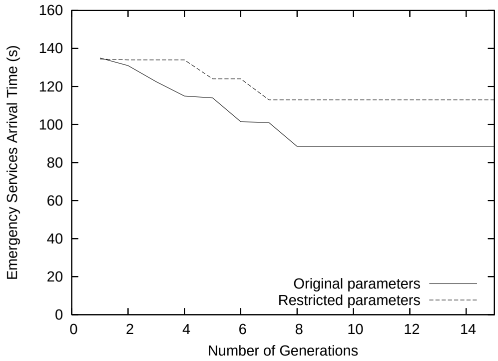
Parameter	Value
number of simulations	100
population number	5 and 3
number of descendants	10 and 5
number of generations	20
fitness function	Equation 6.5
mutation	Uncorrelated Mutation with n Step Sizes
recombination	Local Discrete
parents selection	Randomly
survivors selection	$(\mu + \lambda)$

density is a key factor in vehicular scenarios.

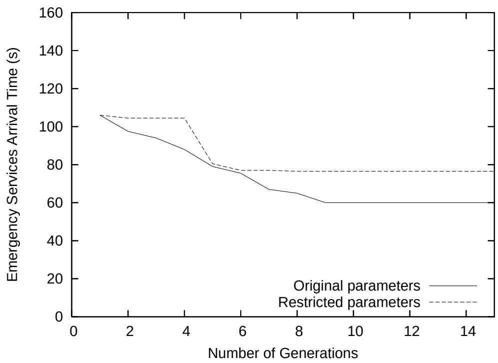
6.5.4 Density-Based Evolution Strategy System Reducing Population and Number of Descendants

As stated above, the emergency services arrival time is a critical factor when an accident occurs. Simulations performed by using Evolution Strategies require a high computational cost, increasing its application time. Hence, reducing the necessary simulations would decrease the system action time which directly affects the time required by emergency services to arrive at the accident location. For this reason, in this Subsection we assess our best proposed system's performance (i.e., the Density-Based Evolution Strategy) but reducing the population size and the number of descendants. Table 6.7 presents the parameters used in these simulations. As shown, we reduce the number of population individuals from 5 to 3, and the number of descendants from 10 to 5. Note that we only use the Density-Based Evolution Strategy system in conjunction with Equation 6.5, since we obtained the best results using this configuration.

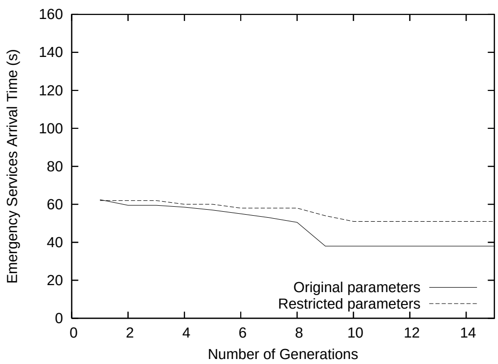
Figure 6.10 shows the obtained results. As can be seen, when reducing the number of population individuals and descendants, the emergency services arrival time increases: 27.68% in Rome, 27.5% in San Francisco, and 34.21% in New York. This occurs because we generate a smaller number of possible population individuals in each generation, thereby restricting the probability to achieve better individuals.



(a)



(b)



(c)

Figure 6.10: Emergency services arrival times simulating 250 vehicles/km^2 varying the number of population individuals and descendants numbers in the scenarios of: (a) Rome (Italy), (b) San Francisco (USA), and (c) New York (USA).

6.6 Conclusions

In this chapter we proposed four different approaches to reduce the emergency services arrival time when an accident occurs, trying to avoid traffic jams that could result from this particular situation. Specifically, we presented two systems based on Evolution Strategies which obtain a sub-optimal solution in a reduced time. Moreover, we demonstrated that traffic density is a key factor to distribute traffic in an efficient manner.

Our proposals have been tested in three different scenarios with different topologies and traffic densities. Results showed that the best solution is to combine an Evolution Strategy with the traffic density information collected at the time of the accident, which is used to initialize the population. The improvement obtained with this approach reduces the emergency services arrival time by a minimum of 47.9%, increasing the travel time of the rest of vehicles by just 14.39% in the worst case when compared to the rest of our proposed algorithms that obtain an improvement of 5.99% (Density-Based Dijkstra), and 26.35% (Evolution Strategy), respectively.

Chapter 7

Conclusions, Publications and Future Work

Throughout this Thesis several contributions have been made to the area of Intelligent Transportation Systems. Our purpose was to design a system for automatically providing of the necessary information to the Emergency Services when an accident occurs, and for reducing their arrival time to the crash location, in order to improve the chances of survival for passengers involved in car accidents. In addition, we took into account that other vehicles which were circulating near the site of the accident were not affected for this special event. Hence, we propose an intelligent system combining Ontologies, Evolution Strategies and Vehicular Networks that satisfies these issues.

Since the objective of this Thesis includes the efficient automatic notification of accidents, including the necessary information for the emergency services, and the efficient routes for the medical care vehicles, we proposed an architecture that fulfills all these objectives. Vehicles in our system incorporate an On-Board Unit responsible of the accident notification to an external Control Unit using Road-Side units. The Control Unit alerts to the emergency services when an accident occurs providing them with information of the accident and the injured persons, as well as the optimal route to reach the scene of the accident. In addition, it communicates to the nearby vehicles to change their routes in order to avoid traffic jams. For avoiding traffic jams and reducing emergency services arrival time, the Control Unit takes into account the real-time traffic density information.

The obtained results show that our system significantly reduces the emergency services arrival time. In addition, it provides relevant information related to the accident to the emergency services, allowing them to prepare the rescue process based on the severity of the accident.

We now proceed to summarize the most relevant contributions of this work:

- Development of a system for reducing the Emergency Services arrival time to the accident location. We consider the traffic density of the areas surrounding the accident for the purpose of redistributing traffic efficiently. In addition, we demonstrate that traffic density is a key factor to distribute the rest of traffic in an efficient manner.

- Proposal of a Vehicle Accident Ontology for Vehicular Networks (VEACON), which aims to structure and encode the information collected by vehicles and RSUs when an accident takes place, in order to enable the interoperatibility among all the agents involved in modern Intelligent Transportation Systems.

- Development of a density-based approach for Road Side Unit deployment in urban scenarios (D-RSU). Specifically, it consists on placing more RSUs in areas with lower vehicle densities. This particular distribution allows that vehicles driving in less dense areas have better Internet access by increasing the number of nearby available RSUs. Our contribution allows to efficiently equip vehicular networks with infrastructure, giving coverage to the majority of vehicles using the smaller number of RSUs.

- Proposal of a method that allows estimating the vehicular density in urban environments at any given time by using the communication capabilities between vehicles and RSUs. Our vehicular density estimation algorithm takes into account not only the number of beacons received by the RSUs, but also the topology of the map where the vehicles are located.

Having accomplished all of our predefined goals, we consider that the ultimate purpose of this Thesis has been achieved successfully, and so we conclude this dissertation.

7.1 Publications

The research work related to this Thesis has resulted in 9 publications; among them, we have 3 journal articles (all of them indexed by the Journal Citation Reports (JCR) database or the SCImago Journal & Country Rank (SJR)), and 6 conference papers (4 of them indexed by the Computer Science Conference Ranking or the Computing Research and Education (CORE) lists). In addition, we have another journal paper under revision. We now proceed by presenting a brief description of each of them.

7.1.1 Journals

[BGF$^+$14b] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "Reducing Emergence Services arrival time by using Vehicular Communications and Evolution Strategies", in *Expert Systems with Applications*, vol. 41, issue 4, Part 1, pp. 1206-1217. January 2014. ISSN: 0957-4174.
Available at: http://dx.doi.org/10.1016/j.eswa.2013.08.004

In this paper, we propose four different approaches addressing the traffic congestion problem, comparing them to obtain the best solution. Specifically, we propose two approaches based on the Dijkstra algorithm, and two approaches based on Evolution Strategies. The strategies here proposed contribute to find the optimal solution within a short time period.

Expert Systems With Applications is a refereed international journal whose focus is on exchanging information relating to expert and intelligent systems applied in industry, government, and universities worldwide. According to the latest Journal Citation Reports list (JCR, 2012), this magazine has an impact factor of 1.854, being in position 13 of 79 (Q1) in the category OPERATIONS RESEARCH & MANAGEMENT SCIENCE.

[BGF$^+$13b] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "Road Side Unit Deployment: A Density-Based Approach", in *IEEE Intelligent Transportation Systems Magazine*, vol. 5, num. 3, pp. 30-39. September 2013. ISSN: 1939-1390.
Available at http://dx.doi.org/10.1109/MITS.2013.2253159

In this paper, we propose a Density-based Road Side Unit deployment policy (D-RSU), specially designed to obtain an efficient system with the lowest possible cost to alert emergency services in case of an accident.

The IEEE Intelligent Transportation Systems Magazine is sponsored by the IEEE Intelligent Transportation Systems Society. According to the SCImago Journal & Country Rank[1] (SJR, 2012), this magazine has an impact factor of 0.955, being in position 3 of 36 (Q1) in the category AUTOMOTIVE ENGINEERING.

[BGF$^+$12c] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "VEACON: a Vehicular Accident Ontology Designed to Improve Safety on the Roads", in *Journal of Network and Computer Applications*. Vol. 35, pp. 1891-1900, Elsevier. 2012. ISSN: 1084-8045. Available at: http://dx.doi.org/10.1016/j.jnca.2012.07.013

In this paper, we present the VEhicular ACcident ONtology (VEACON) designed to improve traffic safety. Our ontology combines the information collected when an accident occurs, and the data available in the General Estimates System (GES) accidents database.

The Journal of Network and Computer Applications publishes research contributions, surveys and notes in all areas relating to computer networks and applications thereof. According to the latest Journal Citation Reports list (JCR, 2012), this magazine has an impact factor of 1.467, being in position 11 of 50 (Q1) in the category COMPUTER SCIENCE, HARDWARE & ARCHITECTURE.

7.1.2 Indexed Conferences

[BGF$^+$13a] J. Barrachina, M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "Using Evolution Strategies to Reduce Emergency Services Arrival Time in Case of Accident", in *IEEE 25th International*

[1] http://www.scimagojr.com/

Conference on Tools with Artificial Intelligence (ICTAI), Washington DC, USA, pp. 833-840, 4-6 November 2013. ISSN: 1082-3409.
Available at: http://dx.doi.org/10.1109/ICTAI.2013.127

In this paper, we propose an approach addressing the traffic congestion problem, comparing it with three other approaches. Specifically, we propose an Evolution Strategy-based approach and compare it with two approaches based on the Dijkstra algorithm, and other approach based on Evolution Strategies.

The annual IEEE International Conference on Tools with Artificial Intelligence (ICTAI) provides a major international forum where the creation and exchange of ideas related to artificial intelligence are fostered among academia, industry, and government agencies. According to the Computing Research and Education (CORE) list[2], it is classified as CORE B.

[BFG$^+$13b] J. Barrachina, M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "I-VDE: A Novel Approach to Estimate Vehicular Density by Using Vehicular Networks", in *The 12th International Conference on Ad Hoc Networks and Wireless (ADHOC-NOW 2013)*, Wroclaw, Poland, pp. 63-74, 8-10 July 2013. ISBN: 978-3-642-39246-7.
Available at: http://dx.doi.org/10.1007/978-3-642-39247-4_6

In this paper, we present I-VDE, a solution to estimate the density of vehicles that has been specially designed for Vehicular Networks. Our proposal allows Intelligent Transportation Systems to continuously estimate the vehicular density by accounting for the number of beacons received per Road Side Unit, as well as the roadmap topology.

The International Conference on Ad Hoc Networks and Wireless (ADHOC-NOW) is one of the most important conferences related to wireless and mobile computing. According to the Computing Research and Education (CORE) list, it is classified as CORE B.

[BFG$^+$13a] J. Barrachina, M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "Assessing Vehicular Density Estimation Using Vehicle-to-Infrastructure Communications", in *The Fourteenth International Symposium on a World of Wireless, Mobile and Multimedia Networks (IEEE WoWMoM)*, Madrid, Spain, pp. 1-3, 4-7 June 2013.
Available at: http://dx.doi.org/10.1109/WoWMoM.2013.6583416

In this paper, we present a solution to estimate the density of vehicles that has been specially designed for Vehicular Networks. Our proposal allows Intelligent Transportation Systems to continuously estimate the vehicular density by accounting for the number of beacons received per Road Side Unit, as well as the roadmap topology. Simulation results indicate that our approach accurately estimates the vehicular density, and therefore automatic traffic controlling systems may use it to predict traffic jams and introduce countermeasures.

[2] http://www.core.edu.au/

The International Symposium on a World of Wireless, Mobile and Multimedia Networks (IEEE WoWMoM) is one of the most important symposium related to wireless and mobile computing. According to the Computing Research and Education (CORE) list, it is classified as CORE A.

[BGF+12a] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "CAOVA: A Car Accident Ontology for VANETs", in *IEEE Wireless Communications and Networking Conference (WCNC)*, Paris, France, pp. 1864-1869, 1-4 April 2012.
Available at http://dx.doi.org/10.1109/WCNC.2012.6214089

In this paper, we focus on traffic safety; specifically, we present a Car Accident lightweight Ontology for VANETs (CAOVA). We assess the reliability of our proposal in two different ways: one via realistic crash tests, and the other one using a network simulation framework.

IEEE Wireless Communications and Networking Conference (WCNC) is the world premier wireless event that brings together industry professionals, academics, and individuals from government agencies and other institutions to exchange information and ideas on the advancement of wireless communications and networking technology. According to the Computing Research and Education (CORE) list, it is classified as CORE B.

7.1.3 International Conferences

[BSF+13] Javier Barrachina, Julio A. Sanguesa, M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "V2X-d: a Vehicular Density Estimation System that combines V2V and V2I Communications", in *6th IFIP Wireless Days Conference*, Valencia, Spain, pp. 1-6, November 2013. ISSN: 2156-9711. Available at: http://dx.doi.org/10.1109/WD.2013.6686518

In this work, we present a V2X architecture to estimate traffic density on the road that relies on the advantages of combining V2V and V2I communications. Our proposal uses both the number of beacons received per vehicle (V2V) and per RSU (V2I), as well as the roadmap topology features to estimate the vehicle density. By using our approach, modern Intelligent Transportation Systems will be able to reduce traffic congestion and also to adopt more efficient message dissemination protocols.

The Wireless Days Conference is a major international conference which aims to bring together researchers, technologists and visionaries from academia, research centers and industry, engineers and students to exchange, discuss, and share their experiences, ideas and research results about theoretical and practical aspects of wireless networking. The WD'13 Technical Program Committee received 184 technical paper submissions from 30 different countries. From these 184 submissions, 63 full papers were selected for presentation at the 2013 edition in Valencia. The overall acceptance ratio was 34.24%.

[BGF+12b] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "D-RSU: A Density-Based Approach for Road

Side Unit Deployment in Urban Scenarios", in *International Workshop on IPv6-based Vehicular Networks (Vehi6), collocated with the 2012 IEEE Intelligent Vehicles Symposium*, Alcalá de Henares, Spain, pp. 1-6, 3 June 2012. Available at http://docencia-eupt.unizar.es/paco/papers/DRSU_W1_P03.pdf

Road Side Units (RSUs) act similarly to a wireless LAN access point and can provide communications with the infrastructure. Since RSUs are usually very expensive to install, authorities limit their number, especially in suburbs and areas of sparse population, making RSUs a precious resource in vehicular environments. In this paper, we propose a Density-based Road Side Unit deployment policy (D-RSU), specially designed to obtain an efficient system with the lowest possible cost.

The International Workshop on IPv6-based Vehicular Networks (Vehi6) is collocated with the IEEE Intelligent Vehicles Symposium, which is the premier annual forum sponsored by the IEEE Intelligent Transportation System Society (ITSS).

7.1.4 Papers Under Revision

[BGF+14a] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "A V2I-based Real-Time Traffic Density Estimation System", in *Wireless Personal Communications*, 2014. ISSN: 0929-6212. (Acceptance pending)

In this paper, we present a novel solution to accurately estimate the density of vehicles in urban scenarios. Our proposal allows Intelligent Transportation Systems to continuously estimate vehicular density by accounting for the number of beacons received per Road Side Unit (RSU), and also considering the roadmap topology where the RSUs are located.

Wireless Personal Communications is an archival, peer reviewed, scientific and technical journal addressing mobile communications and computing. It investigates theoretical, engineering, and experimental aspects of radio communications, voice, data, images, and multimedia. For 2012, the journal WIRELESS PERSONAL COMMUNICATIONS has an impact factor of 0.428 and it is ranked in 65th place (of 78) of TELECOMMUNICATIONS category (Q4) of the JCR database.

7.2 Future Work

In the development of this Thesis several issues emerged which deserve further scrutiny in a future. The ones we consider most relevant are the following:

- To adapt our system to be able to use smartphones. Since nowadays most of vehicles do not integrate on-board units operating with 802.11p communication protocol, using smartphones for this task would allow the immediate implementation of the system. In this sense, we are working together with *Transport Sanitari de Catalunya (TSC)* [Tra14], an important company which has 400 workers and 100 ambulances.

- To study the percentage of necessary intelligent vehicles (network nodes), in order to achieve a proper function of our system. When vehicular networks start to be implemented in real environments, intelligent vehicles will coexist with non-intelligent vehicles. In this situation, our proposed system might not operate correctly.

- To adapt our system for other unpredictable situations, as floods, fires, or fallen obstacles on the road, which could obstruct some of the streets.

- To increase or proposed ontology for, apart from structuring and encoding information related to accidents, working with information related to commercial and entertainment applications.

- To adjust our system to different scenarios, as highways or non-urban roads. All proposals of this Thesis are focused on urban scenarios, but it might be interesting to test the impact in non-urban scenarios.

- To make our approach adaptive, since the density of vehicles is a time-varying factor, i.e., we will propose an adaptive RSU deployment algorithm capable of enabling or disabling the RSUs based on the density detected at that moment.

Bibliography

[ACN+13] C. Ameixieira, A. Cardote, F. Neves, R. Meireles, S. Sargento, L. Coelho, J. Afonso, B. Areias, E. Mota, R. Costa, R. Matos, and J. Barros. Harbornet: A real-world testbed for vehicular networks. In *arXiv.org*, 2013.

[App11] Applus+ IDIADA. Product development in the automotive sector, 2011. Available at http://www.idiada.es.

[ARBOGZMP11] D. Antolino Rivas, J.M. Barceló-Ordinas, M. Guerrero Zapata, and J.D. Morillo-Pozo. Security on VANETs: Privacy, misbehaving nodes, false information and secure data aggregation. *Journal of Network and Computer Applications*, 34(6):1942–1955, 2011.

[AVS11] R. A. Anand, L. Vanajakshi, and S. C. Subramanian. Traffic density estimation under heterogeneous traffic conditions using data fusion. In *IEEE Intelligent Vehicles Symposium (IV)*, pages 31–36, Jun. 2011.

[BCCM13] A. Balador, C. T. Calafate, J.-C. Cano, and P. Manzoni. Reducing channel contention in vehicular environments through an adaptive contention window solution. In *Wireless Days (WD), 2013 IFIP*, pages 1–4, Nov 2013.

[BCJD98] D. S. Breed, V. Castelli, W. C. Johnson, and W. E. DuVall. Vehicle Occupant Position and Velocity Sensor, Patent US 5848802, 12 1998.

[BDS97] S. Benjaafar, K. Dooley, and W. Setyawan. Cellular automata for traffic flow modeling. Technical report, Center for Transportation Studies University of Minnesota, 1997.

[BFG+13a] J. Barrachina, M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. Assessing Vehicular Density Estimation Using Vehicle-to-Infrastructure Communications. In *The Fourteenth International Symposium on a World of Wireless, Mobile and Multimedia Networks (IEEE WoWMoM)*, pages 1–3, June 2013.

[BFG+13b] J. Barrachina, M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. I-VDE: A Novel Approach to Estimate Vehicular Density by Using Vehicular Networks. In *The 12th International Conference on Ad Hoc Networks and Wireless (ADHOC-NOW 2013)*, pages 63–74, July 2013.

[BGF+12a] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. CAOVA: A Car Accident Ontology for VANETs. In *IEEE Wireless Communications and Networking Conference (WCNC)*, pages 1864–1869, April 2012.

[BGF+12b] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. D-RSU: A Density-Based Approach for Road Side Unit Deployment in Urban Scenarios. In *International Workshop on IPv6-based Vehicular Networks (Vehi6), collocated with the 2012 IEEE Intelligent Vehicles Symposium*, pages 1–6, Jun. 2012.

[BGF+12c] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. VEACON: A Vehicular Accident Ontology designed to improve safety on the roads. *Journal of Network and Computer Applications*, 35(6):1891–1900, Nov. 2012.

[BGF+13a] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. Redistribute traffic in case of an accident combining VNs and AI. In *IEEE International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 833–840, Nov. 2013.

[BGF+13b] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. Road Side Unit Deployment: A Density-Based Approach. *IEEE Intelligent Transportation Systems Magazine*, 5(3):30–39, 2013.

[BGF+14a] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. A V2I-based Real-Time Traffic Density Estimation System. *Wireless Personal Communications*, 2014.

[BGF+14b] J. Barrachina, P. Garrido, M. Fogue, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. Reducing Emergence Services arrival time by using Vehicular Communications and Evolution Strategies. *Expert Systems with Applications*, 41(4, Part 1):1206–1217, 2014.

[BGL11] M. Bakhouya, J. Gaber, and P. Lorenz. An adaptive approach for information dissemination in Vehicular Ad hoc Networks. *Journal of Network and Computer Applications*, 34(6):1971–1978, 2011.

[Bre91] D. S. Breed. Vehicle Crush Zone Crash Sensor, Patent US 4995639, 02 1991.

[BS08] M. Balcilar and A. C. Sonmez. Extracting vehicle density from background estimation using Kalman filter. In *23rd International Symposium on Computer and Information Sciences (ISCIS '08)*, pages 1–5, Oct. 2008.

[BS13] K.R.K. Bhargav and R. Singhal. Zigbee based VANETs for accident rescue missions in 3G WCDMA networks. In *Global Humanitarian Technology Conference: South Asia Satellite (GHTC-SAS), 2013 IEEE*, pages 310–313, Aug 2013.

[BSF+13] J. Barrachina, J. A. Sanguesa, M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. V2X-d: A vehicular density estimation system that combines V2V and V2I communications. In *IFIP Wireless Days (WD)*, pages 1–6, Nov 2013.

[CM08] K. Collins and G.-M. Muntean. An adaptive vehicle route management solution enabled by wireless vehicular networks. In *IEEE 68th Vehicular Technology Conference (VTC)*, pages 1–5, Sept. 2008.

[CSEJ+07] Q. Chen, F. Schmidt-Eisenlohr, D. Jiang, M. Torrent-Moreno, L. Delgrossi, and H. Hartenstein. Overhaul of IEEE 802.11 modeling and simulation in ns-2. *Proceedings of the 10th ACM Symposium on Modeling, Analysis, and Simulation of Wireless and Mobile Systems (MSWiM)*, pages 159–168, 2007.

[CT13] C.-L. Chen and W.-C. Tsai. Using a Stored-Value Card to Provide an Added-Value Service of Payment Protocol in VANET. In *Seventh International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS)*, pages 660–665, July 2013.

[CTS13] S. Cespedes, S. Taha, and X Shen. A Multihop-Authenticated Proxy Mobile IP Scheme for Asymmetric VANETs. *Vehicular Technology, IEEE Transactions on*, 62(7):3271–3286, Sept 2013.

[CWD+13] L. Chunxiao, C. Weijia, H. Dawei, H. Xuelong, and Shigeru S. A Travel-Efficient Driving Assistance Scheme in VANETs by Providing Recommended Speed. In *IEICE TRANSACTIONS on Fundamentals of Electronics, Communications and Computer Sciences*, pages 2007–2015, Oct 2013.

[CXCQ09] X. B. Cao, Y. W. Xu, D. Chen, and H. Qiao. Associated evolution of a support vector machine-based classifier for pedestrian detection. *Information Sciences*, 179(8):107–1077, 2009.

[Dar59] C. Darwin. The origin of species. In *Murray*, London, UK, 1859.

[DGDM12] H. Dezani, L. Gomes, F. Damiani, and N. Marranghello. Controlling traffic jams on urban roads modeled in Coloured Petri net using Genetic Algorithm. In *IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society*, pages 3043–3048, Oct. 2012.

[Dij59] E. W. Dijkstra. A note on two problems in connexion with graphs. *Numerische Mathematik*, 1:269–271, 1959.

[DM13] R. Doolan and G.-M. Muntean. VANET-Enabled Eco-Friendly Road Characteristics-Aware Routing for Vehicular Traffic. In *IEEE 77th Vehicular Technology Conference (VTC Spring)*, pages 1–5, June 2013.

[DPRK11] A. Daeinabi, A. G. Pour Rahbar, and A. Khademzadeh. VWCA: An efficient clustering algorithm in vehicular ad hoc networks. *Journal of Network and Computer Applications*, 34(1):207–222, 2011.

[DR02] J. Daemen and V. Rijmen. *The Design of Rijndael: AES – The Advanced Encryption Standard*. Springer-Verlag, 2002.

[EEC+13] A. Elbery, M. ElNainay, F. Chen, C.-T. Lu, and J. Kendall. A Carpooling Recommendation System Based on Social VANET and Geo-social Data. In *Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 546–549, 2013.

[EL08] R. Eigner and G. Lutz. Collision avoidance in VANETs - an application for ontological context models. In *Sixth Annual IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pages 412–416, March 2008.

[ES03] E. Eiben and J. E. Smith. *Introduction to Evolutionary Computing*. Springer-Verlag, 2003.

[Eur11] EuroNCAP: European New Car Assessment Programme. Evaluation procedures and test results, 2011. Available at http://www.euroncap.com/testprocedures.aspx.

[FDRL13] P. Fazio, F. De Rango, and A. Lupia. A new application for enhancing VANET services in emergency situations using the WAVE/802.11p standard. In *IFIP Wireless Days (WD)*, pages 1–3, Nov 2013.

[FGM+11a] M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. Analysis of the most representative factors affecting Warning Message Dissemination in VANETs under real roadmaps. In *19th annual meeting of the IEEE International Symposium on Modeling, Analysis and Simulation of Computer and Telecommunication Systems (MASCOTS)*, pages 197–204, Singapore, July 2011.

[FGM+11b] M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, P. Manzoni, and M. Sanchez. Prototyping an automatic notification scheme for traffic accidents in vehicular networks. In *2011 IFIP Wireless Days (WD)*, pages 1–5, 2011.

[FGM+12a] M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. Calafate, and P. Manzoni. Using data mining and vehicular networks to estimate the severity of traffic accidents. In *International Symposium on Management Intelligent Systems (IS-MiS)*, July 2012.

[FGM+12b] M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. A Realistic Simulation Framework for Vehicular Networks. In *5th International ICST Conference on Simulation Tools and Techniques (SIMUTools 2012), Desenzano, Italy*, March 2012.

[FGM+12c] M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. An adaptive system based on roadmap profiling to enhance warning message dissemination in vanets. *IEEE/ACM Transactions on Networking*, 21:883–895, 2012.

[FGM+12d] M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. Evaluating the impact of a novel message dissemination scheme for vehicular networks using real maps. *Transportation Research Part C: Emerging Technologies*, 25:61–80, Dec. 2012.

[FGM+13] Manuel Fogue, Piedad Garrido, Francisco J. Martinez, Juan-Carlos Cano, Carlos T. Calafate, and Pietro Manzoni. A novel approach for traffic accidents sanitary resource allocation based on multi-objective genetic algorithms. *Expert Systems with Applications*, 40(1):323 – 336, 2013.

[FMG+13] M. Fogue, F. J. Martinez, P. Garrido, M. Fiore, C.F. Chiasserini, C. Casetti, J.-C. Cano, C. T. Calafate, and P. Manzoni. On the Use of a Cooperative Neighbor Position Verification Scheme to Secure Warning Message Dissemination in VANETs. In *The 38th IEEE Conference on Local Computer Networks (LCN)*, Sydney, Australia, Oct 2013.

[Fog98] D. B. Fogel. Evolutionary computation: the fossil record. In *IEEE Press*, Piscataway, NJ, 1998.

[For11] Ford Motor Company. Ford researchers develop car seat that monitors drivers's heart activity, 2011. Available at http://media.ford.com/news/fordresearchersdevelopcarseatthatmonitorsdriversheartactivity.htm.

[FV00] K. Fall and K. Varadhan. ns notes and documents. The VINT Project. UC Berkeley, LBL, USC/ISI, and Xerox PARC, February 2000. Available at http://www.isi.edu/nsnam/ns/ns-documentation.html.

[Gar04] L. M. Garshol. Metadata? Thesauri? Taxonomies? Topic maps! Making sense of it all. *Journal of Information Science*, 30(4):378–391, 2004.

[GAS13] H. Guo, D. T. Ahmed, and A. E. Saddik. Web services for vanet: A service oriented architecturefor infotainment system based on mashup using open apis. In *Proceedings of the Third ACM International Symposium on Design and Analysis of Intelligent Vehicular Networks and Applications*, pages 61–68, 2013.

[GJA+13] F. Garcia, F. Jimenez, J. J. Anaya, J. M. Armingol, J. E. Naranjo, and A. de la Escalera. Distributed pedestrian detection alerts based on data fusion with accurate localization. In *Sensors*, volume 13, pages 11687–11708, 2013.

[GTN08] GTNetS. The Georgia Tech Network Simulator, 2008. Available at http://www.ece.gatech.edu/research/labs/MANIACS/GTNetS.

[HFBF06] J. Haerri, F. Filali, C. Bonnet, and M. Fiore. Vanetmobisim: Generating realistic mobility patterns for vanets. In *Proceedings of the 3rd International Workshop on Vehicular Ad Hoc Networks*, pages 96–97, 2006.

[HS00] H. S. Husby and L. Simpson. Seat Belt Tension Sensor, Patent US 6081759, 06 2000.

[HWC+13] C.-J. Huang, Y.-W. Wang, H.-M. Chen, A.-L. Cheng, J.-J. Jian, H.-W. Tsai, and J.-J. Liao. An adaptive multimedia streaming dissemination system for vehicular networks. *Applied Soft Computing*, 13(12):4508–4518, 2013.

[IEE10] IEEE 802.11 Working Group. IEEE Standard for Information Technology – Telecommunications and information exchange between systems – Local and metropolitan area networks – Specific requirements – Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) specifications Amendment 6: Wireless Access in Vehicular Environments, July 2010.

[Inc08] SimReal Inc. NCTUns network simulator and emulator, 2008. Available at http://nsl10.csie.nctu.edu.tw.

[JiS04] JiST/SWANS. Java in Simulation Time/Scalable Wireless Ad hoc Network Simulator, 2004. Available at http://jist.ece.cornell.edu.

[JK08] J. Jakubiak and Y. Koucheryavy. State of the art and research challenges for VANETs. In *Consumer Communications and Networking Conference (CCNC)*, pages 912–916, Jan. 2008.

[JM97] D. S. Johnson and L. A. McGeoch. The travelling salesman problem: A case study in local optimization. In *Local Search in Combinatorial Optimization. Wiley*, pages 215–310, 1997.

[JY13] Q. Jiang and L. Y. Yu. TEAP: A Traffic Jam Early Alert Protocol in VANET. In *Applied Mechanics and Materials*, volume 416-417, pages 1978–1982, 2013.

[KAL13] S. Kwatirayo, J. Almhana, and Z. Liu. Adaptive Traffic Light Control using VANET: A case study. In *9th International Wireless Communications and Mobile Computing Conference (IWCMC)*, pages 752–757, July 2013.

[KEB12] D. Krajzewicz, M. Erdmann, J. Behrisch, and L. Bieker. Recent Development and Applications of SUMO - Simulation of Urban MObility. In *International Journal On Advances in Systems and Measurements*, volume 5, pages 128–138, Dec. 2012.

[Ker98] B. S. Kerner. Experimental features of self-organization in traffic flow. *Phys. Rev. Lett.*, 81(17):3797–3800, October 1998. Available at `http://dx.doi.org/10.1103/PhysRevLett.81.3797`.

[KH08] H. Kanoh and K. Hara. Hybrid genetic algorithm for dynamic multi-objective route planning with predicted traffic in a real-world road network. In *Proceedings of the 10th Annual Conference on Genetic and Evolutionary Computation*, GECCO '08, pages 657–664. ACM, 2008.

[KHS13] A. S. Koyamparambil, U. Hernandez, and N. Sainz. Cluster-based mac in vanets for safety applications. In *Advances in Computing, Communications and Informatics (ICACCI), 2013 International Conference on*, pages 1424–1429, Aug 2013.

[KK10] A. Kchiche and F. Kamoun. Centrality-based access-points deployment for vehicular networks. In *IEEE 17th International Conference on Telecommunications (ICT)*, pages 700–706, Apr. 2010.

[KRS+07] S. Kaul, K. Ramachandran, P. Shankar, S. Oh, M. Gruteser, I. Seskar, and T. Nadeem. Effect of antenna placement and diversity on vehicular network communications. In *4th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON'07)*, pages 112–121, 2007.

[KS13] G. S. Khekare and A. V. Sakhare. A smart city framework for intelligent traffic system using vanet. In *International Multi-Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s)*, pages 302–305, March 2013.

[KT10] H. Kanoh and S. Tsukahara. Solving real-world vehicle routing problems with time windows using virus evolution strategy. *Int. J. Know.-Based Intell. Eng. Syst.*, 14(3):115–126, 2010.

[KTK10] S. Kannan, A. Thangavelu, and R. Kalivaradhan. An intelligent Driver Assistance System (I-DAS) for vehicle safety modelling using ontology approach. *International Journal Of UbiComp (IJU)*, 1(3):1–13, July 2010.

[KWG97] S. Krauss, P. Wagner, and C. Gawron. Metastable states in a microscopic model of traffic flow. *Physical Review E*, 55(5):5597–5602, 1997.

[LK10] J. Lee and C. Kim. A roadside unit placement scheme for vehicular telematics networks. In Tai-Hoon Kim and Hojjat Adeli, editors, *Advances in Computer Science and Information Technology*, volume 6059 of *Lecture Notes in Computer Science*, pages 196–202. Springer Berlin / Heidelberg, 2010.

[LSW+08] C. Lochert, B. Scheuermann, C. Wewetzer, A. Luebke, and M. Mauve. Data aggregation and roadside unit placement for a VANET traffic information system. In *Proceedings of the fifth ACM international workshop on VehiculAr inter-NETworking*, VANET '08, pages 58–65, New York, NY, USA, 2008. ACM.

[MAG12] K. Mershad, H. Artail, and M. Gerla. ROAMER: Roadside Units as message routers in VANETs. *Ad Hoc Networks*, 10(3):479–496, 2012.

[Mar01] J. Martin. GloMoSim. Global mobile information systems simulation library. UCLA Parallel Computing Laboratory, 2001. Available at http://pcl.cs.ucla.edu/projects/glomosim.

[MB05] D. Mester and O. Bräysy. Active guided evolution strategies for large-scale vehicle routing problems with time windows. *Computers & Operations Research*, 32(6):1593–1614, 2005.

[MBML11] N. Maslekar, M. Boussedjra, J. Mouzna, and H. Labiod. A stable clustering algorithm for efficiency applications in VANETs. In *7th International Wireless Communications and Mobile Computing Conference (IWCMC)*, pages 1188–1193, July 2011.

[MCCM08a] F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. A VANET Solution to Prevent Car Accidents. In *XIX Jornadas de Paralelismo, Castellon*, pages 611–616, 2008.

[MCCM08b] F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. CityMob: a mobility model pattern generator for VANETs. In *IEEE Vehicular Networks and Applications Workshop (Vehi-Mobi, held with ICC), Beijing, China*, pages 370–374, May 2008. Available at `http://dx.doi.org/10.1109/ICCW.2008.76`.

[MFC+10] F. J. Martinez, M. Fogue, M. Coll, J.-C. Cano, C. T. Calafate, and P. Manzoni. Assessing the Impact of a Realistic Radio Propagation Model on VANET Scenarios Using Real Maps. In *9th IEEE International Symposium on Network Computing and Applications (NCA)*, pages 132–139, Boston, USA, July 2010.

[MFHF04] M. Moske, H. Fussler, H. Hartenstein, and W. Franz. Performance measurements of a vehicular ad hoc network. In *IEEE 59th Vehicular Technology Conference (VTC)*, volume 4, pages 2116–2120, May 2004.

[MFT+13] F. J. Martinez, M. Fogue, C. K. Toh, J.-C. Cano, C. T. Calafate, and P. Manzoni. Computer simulations of VANETs using realistic city topologies. *Wireless Personal Communications*, 69(2):639–663, 2013.

[MH07] J. Miller and E. Horowitz. Freesim - a free real-time freeway traffic simulator. In *IEEE Intelligent Transportation Systems Conference (ITSC)*, pages 18–23, Sept 2007.

[MKT08] H. Mori, H. Kitaoka, and E. Teramoto. Traffic simulation for predicting traffic situations at expo 2005. *R&D Review of Toyota CRDL*, 41(4):45–51, 2008.

[Mob08] MobiREAL. A Realistic Network Simulator, 2008. Available at http://www.mobireal.net/.

[MOV12] MOVE. MObility model generator for VEhicular networks: Rapid Generation of Realistic Simulation for VANET, 2012. Available at http://lens1.csie.ncku.edu.tw/MOVE/index.htm.

[MTC+10] F. J. Martinez, C. K. Toh, J.-C. Cano, C. T. Calafate, and P. Manzoni. Emergency services in future intelligent transportation systems based on vehicular communication networks. *IEEE Intelligent Transportation Systems Magazine*, 2(2):6–20, summer 2010.

[MTC+11a] F. J. Martinez, C. K. Toh, J.-C. Cano, C. T. Calafate, and P. Manzoni. A Survey and Comparative Study of Simulators for Vehicular Ad Hoc Networks (VANETs). *Wireless Communications & Mobile Computing*, 11(7):813–828, Jul 2011.

[MTC+11b] F. J. Martinez, C.-K. Toh, J.-C. Cano, C. T. Calafate, and P. Manzoni. Determining the representative factors affecting warning message dissemination in VANETs. *Wireless Personal Communications*, 2011. DOI: 10.1007/s11277-011-0379-3.

[MWR+06] R. Mangharam, D. Weller, R. Rajkumar, P. Mudalige, and Bai F. GrooveNet: A Hybrid Simulator for Vehicle-to-Vehicle Networks. Carnegie Mellon University, 2006. Available at http://www.seas.upenn.edu/rahulm/Research/GrooveNet.

[Nat11] National Highway Traffic Safety Administration (NHTSA). National Automotive Sampling System, 2011. Available at http://www.nhtsa.gov/NASS.

[NCMS11] F. Neves, A. Cardote, R. Moreira, and S. Sargento. Real-world Evaluation of IEEE 802.11P for Vehicular Networks. In *Proceedings of the Eighth ACM International Workshop on Vehicular Inter-networking*, pages 89–90, 2011.

[ONI06] K. Ohara, Y. Nojima, and H. Ishibuchi. Comparison between Centralized Global Optimization and Distributed Local Optimization for Traffic Jam Avoidance. In *Proc. of 2006 Genetic and Evolutionary Computation Conference Late Breaking Papers*, page 6p CD ROM, Jul. 2006.

[Ope14] OpenStreetMap. Collaborative project to create a free editable map of the world, 2014. Available at http://www.openstreetmap.org.

[Pet99] S. Petzold. Rain Sensor System for a Motor Vehicle, Patent US 5900821, 05 1999.

[PRL+07] M. Piorkowski, M. Raya, A.L. Lugo, P. Papadimitratos, M. Grossglauser, and J.-P. Hubaux. TraNS (Traffic and Network Simulation Environment). Ecole Polytechnique Fdrale de Lausanne, EPFL, Switzerland, 2007. Available at http://trans.epfl.ch.

[RCA11] RCAR, the Research Council for Automobile Repairs. Design guides and information for manufacturers, 2011. Available at http://www.rcar.org.

[SCB+99] A. Schadschneider, D. Chowdhury, E. Brockfeld, K. Klauck, L. Santen, and J. Zittartz. *Traffic and Granular Flow: Social, Traffic, and Granular Dynamics*. Springer-Verlag, 1999.

[SCB11] R. Stanica, E. Chaput, and A. Beylot. Local density estimation for contention window adaptation in vehicular networks. In *IEEE 22nd International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC)*, pages 730–734, Sept. 2011.

[SCC06] D. Srinivasan, M. C. Choy, and R. L. Cheu. Neural networks for real-time traffic signal control. *Intelligent Transportation Systems, IEEE Transactions on*, 7(3):261–272, 2006.

[SFG+13] J. A. Sanguesa, M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni. An infrastructureless approach to estimate vehicular density in urban environments. *Sensors*, 13:2399–2406, 2013.

[SHG09] R. Shirani, F. Hendessi, and T. A. Gulliver. Store-carry-forward message dissemination in vehicular ad-hoc networks with local density estimation. In *IEEE 70th Vehicular Technology Conference Fall (VTC 2009-Fall)*, pages 1–6, Sept. 2009.

[SMA12] M. Slavik, I. Mahgoub, and M. M. Alwakeel. Adapting statistical multi-hop wireless broadcast protocol decision thresholds using rate control. In *High Capacity Optical Networks and Enabling Technologies (HONET), 2012 9th International Conference on*, pages 32–36, Dec 2012.

[SMGMRR10] J. J. Sanchez-Medina, M. J. Galan-Moreno, and E. Rubio-Royo. Traffic Signal Optimization 'La Almozara' District in Saragossa Under Congestion Conditions, Using Genetic Algorithms, Traffic Microsimulation, and Cluster Computing. *IEEE Transactions on Intelligent Transportation Systems*, 11(1):132–141, Mar. 2010.

[SRS+08] R. Sengupta, S. Rezaei, S. E. Shladover, D. Cody, S. Dickey, and H. Krishnan. Cross-layer-based adaptive vertical handoff with predictive RSS in heterogeneous wireless networks. *IEEE Transactions on Vehicular Technology*, 57(6):3679–3692, 2008.

[STR08] STRAW (STreet RAndom Waypoint). Vehicular mobility model for network simulations (e.g., car networks), 2008. Available at http://www.aqualab.cs.northwestern.edu/projects/STRAW/index.php.

[TC07] E. Tan and J. Chen. Vehicular traffic density estimation via statistical methods with automated state learning. In *IEEE Conference on Advanced Video and Signal Based Surveillance (AVSS)*, pages 164–169, Sept. 2007.

[TCG07] K. C. Tan, C. Y. Cheong, and C. K. Goh. Solving multiobjective vehicle routing problem with stochastic demand via evolutionary computation. *European Journal of Operational Research*, 177(2):813–839, 2007.

[The01] The CMU Monarch Project. The CMU Monarch Projects wireless and mobility enhancements to ns. Carnegie-Mellon University, 2001. Available at http://www.monarch.cs.cmu.edu.

[The04] The World Wide Web Consortium (W3C). OWL Web Ontology Language Reference, 2004. Available at http://www.w3.org/TR/owl-ref/.

[THH00] M. Treiber, A. Hennecke, and D. Helbing. Congested traffic states in empirical observations and microscopic simulations. *Physical Review E*, 62:1805, 2000.

[THKH11] G. S. Thakur, P. Hui, H. Ketabdar, and A. Helmy. Spatial and temporal analysis of planet scale vehicular imagery data. In *IEEE 11th International Conference on Data Mining Workshops (ICDMW)*, pages 905–910, Dec. 2011.

[TKK12] V. Tyagi, S. Kalyanaraman, and R. Krishnapuram. Vehicular traffic density state estimation based on cumulative road acoustics. *IEEE Transactions on Intelligent Transportation Systems*, 13(3):1156–1166, Sept. 2012.

[TNCS02] Y.-C. Tseng, S.-Y. Ni, Y.-S. Chen, and J.-P. Sheu. The broadcast storm problem in a mobile ad hoc network. *Wireless Networks*, 8:153–167, 2002.

[Tra14] Transport Sanitari de Catalunya (TSC). Leading medical transport company operating in Catalonia, 2014. Available at `http://www.tscambulancies.com/`.

[UDSAM09] R. A. Uzcategui, A. J. De Sucre, and G. Acosta-Marum. WAVE: a tutorial - [topics in automotive networking]. *IEEE Communications Magazine*, 47(5):126–133, May 2009. Available at `http://dx.doi.org/10.1109/MCOM.2009.4939288`.

[Wag06] P. Wagner. How human drivers control their vehicle. *The European Physical Journal B - Condensed Matter and Complex Systems*, 52(3):427–431, 2006.

[WGLL12] T.-Y. Wu, S. Guizani, W.-T. Lee, and K.-H. Liao. Improving RSU service time by Distributed Sorting Mechanism. *Ad Hoc Networks*, 10(2):212–221, 2012.

[WKPG13] J.-T. Weng, I. Ku, G. Pau, and M. Gerla. Running consistent parallel experiments in vehicular environment. In *International Journal Sensors and Sensor Network*, volume 1, pages 10–20, 2013.

[WS03] K. Walsh and E.G. Sirer. A staged network simulator (SNS). Computer Science Department, Cornell University, 2003. Available at http://www.cs.cornell.edu/people/egs/sns.

[WTL07] J.-Q. Wang, X.-N. Tong, and Z.-M. Li. An improved evolutionary algorithm for dynamic vehicle routing problem with time windows. In Yong Shi, GeertDick Albada, Jack Dongarra, and PeterM.A. Sloot, editors, *Computational Science ICCS 2007*, volume 4490 of *Lecture Notes in Computer Science*, pages 1147–1154. Springer Berlin Heidelberg, 2007.

[WTP+07] N. Wisitpongphan, O.K. Tonguz, J.S. Parikh, P. Mudalige, F. Bai, and V. Sadekar. Broadcast storm mitigation techniques in vehicular ad hoc networks. *IEEE Wireless Communications*, 14:84–94, 2007.

[XMM13] Z. Y. Xie, T.-S. Moh, and M. Moh. ASAP: Ad-hoc Streaming Adaptive Protocol for Supporting P2P Streaming over Vehicular Ad-hoc Networks. In *Proceedings of the 51st ACM Southeast Conference*, pages 1–6, 2013.

[YOCH07] K. Yang, S. Ou, H.-H. Chen, and J. He. A Multihop Peer-Communication Protocol With Fairness Guarantee for IEEE 802.16-Based Vehicular Networks. *IEEE Transactions on Vehicular Technology*, 56(6):3358–3370, 2007.

[YT09] M. Yoshikawa and H. Terai. Car navigation system based on hybrid genetic algorithm. In *2009 WRI World Congress on Computer Science and Information Engineering*, volume 5, pages 62–65, Apr. 2009.

[Zun12] ZunZun. Online Curve Fitting and Surface Fitting Web Site, 2012. Available at http://www.zunzun.com.

[ZWL08] J. Zhai, Q. Wang, and M. Lv. Application of XML Topic Maps to knowledge navigation and information retrieval for urban traffic information portal. In *27th Chinese Control Conference (CCC)*, pages 458–462, July 2008.

[ZZSS08] J. Zhai, Z. Zhou, Z. Shi, and L. Shen. An integrated information platform for intelligent transportation systems based on ontology. In Li Xu, A. Tjoa, and Sohail Chaudhry, editors, *Research and Practical Issues of Enterprise Information Systems II Volume 1*, IFIP International Federation for Information Processing, pages 787–796. Springer Boston, 2008.