VANET: Evaluating Smart Parking Performance in a Dublin Scenario

by

Wesley Fung

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Declaration of Authorship

I, Wesley Fung, declare that the following dissertation, except where otherwise stated, is entirely my own work; that it has not previously been submitted as an exercise for a degree, either in Trinity College Dublin, or in any other University; and that the library may lend or copy it or any part thereof on request.

Wesley Fung

May 17, 2017

Summary

This dissertation focuses on evaluating Vehicular Ad-Hoc Networking (VANET) in Dublin. More specifically, the goal is to investigate whether VANET can assist with the dissemination of parking data within a small scale city like Dublin. Parking data allows drivers know where vacant parking spaces are at any given time. However, there are potential problems regarding making parking space information public. One of the central concepts for the introduction of smart parking systems is to minimise traffic congestion within an urban area. By making the parking information public, it does not guarantee that traffic congestion and traffic emissions would decrease. Drivers may run into scenarios where they are en-route to a vacant parking spot, only to find that space has been taken seconds before they arrive. There is a need for a system that oversees the parking spaces, coordinates with cars, roadside units, or other traffic systems to take advantage of the real-time parking data fully. Smart parking may be broken down into two distinct areas. One being the utilisation of sensors to locate parking space occupancies. And the other is the dissemination of the sensed parking data to the relevant users. While the dissertation focuses on the dissemination of data within Dublin, various sensory techniques will also be explored.

While VANET has been around since the early 2000s, vehicular networking has not been put into practice until now. With the roll-out of autonomous vehicles worldwide, one of the next steps for full vehicular automation is to allow cars be aware of parking spaces in their nearby area. Various research proposals have been explored to capture parking space vacancies. Using parking sensors located on every parking spot is the most straightforward solution. However, the cost of deployment is by far the highest of all the considerable options. Other solutions include utilising city-wide Closed Circuit Television (CCTV) for detection of parking vacancies, while others have explored utilising laser range-finders on taxis circling the city to detect spaces. This dissertation includes a current state of

the art of the various parking sensing technology to date. Additionally, the dissemination of parking data has also been discussed by several researchers. These include considerations for VANET based models, while others have explored more centralised versions of parking data administration; where one single system coordinates parking information to all drivers. In larger cities, parking information dissemination may be distributed into districts, each district managing its set of parking spaces and notifying the relevant users when spaces become available within their respective vicinity.

The goal of this dissertation is to evaluate VANET integration with smart parking facilities. The solution involves simulation of the Dublin road network with Vehicles in Network Simulation (VEINS). This software package couples Simulation of Urban MObility (SUMO), a microscopic traffic simulator, and Objective Modular Network Testbed in C++ (OMNeT++), a discrete event simulator. Dublin traffic volumes and parking data will be factored into the evaluation process to provide a realistic simulator model.

The metrics used are the number of drivers that had to defer to alternate parking areas due to the parking area being fully occupied. Additional evaluation metrics are the emissions of vehicles in each evaluation, comparing if there are any significant differences in the environmental pollution from vehicles between all the scenarios.

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Wesley Fung, Master in Computer Science

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Traffic congestions and pollution is a major issue in many cities worldwide. Drivers cruising for parking spaces contribute heavily to these issues. For this reason, many researchers have performed studies on the topic of smart parking, as well as VANET. With the introduction of smart parking, drivers can know where vacant parking spaces are. However, as an argument proposed by this dissertation, the surfacing of parking space information is not enough. Simply by knowing a parking spot is vacant does not guarantee any driver a parking spot. A solution must be found to minimise the chances of a driver arriving at a parking spot that became occupied minutes beforehand.

VANET is a technology that supports inter-vehicular communications. VANET technologies allow vehicles to communicate with other vehicles to ensure driver safety. As well as this, vehicles may relay information to Road Side Unit (RSU) for traffic light coordinate as well as traffic queue management. This work is concerned with the integration of a smart parking system supported by VANET.

Dublin City is the domain of interest in this dissertation. For this reason, Dublin City-specific data is acquired from various sources. The data is used in the simulation to build a realistic view on the current parking behaviours of Dublin City. This work is concerned with using a simulation software to build a VANET smart parking system evaluated on Dublin City. Vehicles communicate with each other regarding parking space occupancies and vacancies. This involves the integration of Dublin specific traffic and parking data into the simulation.

The evaluation process involves comparing a baseline model to the VANET model as described above. The evaluation results show that VANET smart parking model minimises the amount of emissions produced. As well as this, a VANET smart parking model minimises the chances of drivers arriving at parking spots that are occupied minutes beforehand.

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WESLEY FUNG

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List of Acronyms

ANPR Automatic Number Plate Recognition

CNN Convolutional Neural Network

DCC Dublin City Council

CCTV Closed Circuit Television

CLI Command Line Interface

EPA Environmental Protection Agency

GUI Graphical User Interface

HC Hybird Cloud

ITS Intelligent Traffic System

IVC Inter-Vehicle Communication

JOSM Java OpenStreetMaps

MANET Mobile Ad-Hoc Networking

OBU On-Board Unit

OMNeT++ Objective Modular Network Testbed in C++

OSM OpenStreetMaps

RFID Radio Frequency IDentification

RSU Road Side Unit

SUMO Simulation of Urban MObility

SVM Supported Vector Machines

TSA Travelling Salesman Algorithm

VANET Vehicular Ad-Hoc Networking

VEINS Vehicles in Network Simulation

VCC Vehicle Cloud Computing

VC Vehicle Cloud

VuC Vehicle using Cloud

V2G Vehicle-to-Grid

V2I Vehicle-to-Infrastructure

V2V Vehicle-to-Vehicle

Chapter 1

Introduction

In this chapter, the motivations behind this dissertation are outlined. The research question that this dissertation poses to answer is introduced, along with the research objectives and challenges that go with it. A final section explaining the organisation of the dissertation concludes this introductory chapter.

1.1 Motivation

One of the core motivation behind smart parking is to minimise the number of drivers driving around looking for a vacant parking spot within a city. By minimising the process of looking for parking spaces, it will have a positive effect on the environment, as there will be fewer vehicles on the road and fewer vehicle emissions. The minimisation of cruising vehicles is also advantageous regarding traffic congestion in an urban setting, with fewer vehicles on the road, traffic levels may be alleviated. In a study by Donald Shoup (Shoup, 2006), “Between 8 and 74 percent of the traffic was cruising for parking, and the average time to find a kerb space ranged between 3.5 and 14 min”.

Minimising the number of drivers driving around looking for a vacant parking spot can be achieved in different ways. One of the methods for achieving this is to introduce parking sensors in parking locations. The parking sensors will be able to sense if a parking spot is vacant or not. This parking data may be disseminated to all drivers. However, by surfacing the parking information to drivers, it does not guarantee that a driver will get a parking spot. In other words, drivers will still need to cruise for parking spots. For this reason, smart parking methodologies could potentially be improved.

Parking data dissemination methods is a significant aspect of developing an intelligent parking system. Parking data dissemination explores how parking data should be made available to drivers. In this paper (Verroios et al., 2011), various data dissemination techniques are explored. The paper proposes three ways in which parking data could be disseminated. The “live” approach is one of the three data dissemination techniques. It proposes inter-vehicles communications regarding parking space availabilities. This introduces the concept of VANET.

VANET is the utilisation of vehicular communications to achieve various goals. There are multiple VANET models; vehicle-to-infrastructure (V2I), vehicle-to-device (V2D), vehicle-to-vehicle (V2V) and vehicle-to-grid (V2G). The VANET model of interest in this dissertation is vehicle-to-vehicle (V2V). There are various motivations for VANET, some of those included are vehicle platooning, and forward collision mitigation. Vehicle platooning involves vehicles sharing their current speed, acceleration and positioning information with other vehicles within their vicinity. By doing so, vehicles may move in a more streamline motion along a street. In this Japanese study conducted in 2008 (Sugiyamal et al., 2008), one of the reasons of traffic build-up is due to a small fluctuation in the speed of an individual vehicle. The study was able to recreate a traffic jam that produced a "shockwave" effect down the street, similar to a traffic jam in the real world. With the introduction of inter-vehicular communication, cars may be able to keep the flow of traffic in a consistent manner, thus avoiding unnecessary traffic congestions. Forward collision mitigation may assist drivers in times of traffic accidents. Information regarding an accident that occurred on the street may be propagated back along the road through vehicles on that street. Vehicles further along the street may be able to make alternative routes to their destinations to alleviate traffic in that area.

Additionally, as self-driving vehicles are becoming increasingly popular, VANET and vehicular cloud networking has become more and more likely. As outlined in (Gerla et al., 2014), the next step in evolution is just around the corner: The Internet of Autonomous Vehicles.

This dissertation involves designing a VANET smart parking system. More specifically, a simulation of a VANET based smart parking system will be evaluated on the city of Dublin. Dublin traffic and parking data will be incorporated into the simulation to provide a realistic simulation model.

1.2 Research Question

The research question that this dissertation poses to answer is whether a VANET incorporated smart parking system is beneficial to a small scale city like Dublin City. This involves questions regarding whether a VANET smart parking system would minimise the number of drivers cruising looking for parking spots. Evaluation metrics includes the amount of CO2 emission reductions if any, and the number of drivers that arrive at a destined parking location to find that it has just been occupied.

1.3 Research Objectives

The research objectives that have been set and completed throughout the course of the year are listed as follows.

- To explore the current state of the art for smart parking sensors.
- To explore the current smart parking enabled cities and their solutions.
- To explore parking data dissemination methodologies.
- To gather Dublin city-specific traffic and parking information for use in this dissertations' simulation.
- To simulate Dublin with a VANET model that supports smart parking.

1.4 Research Challenges

Various challenges had to be overcome to achieve the goal of this dissertation. In this section, the research challenges, as well as limitations, are explained.

The primary objective of this dissertation is to investigate and evaluate the feasibility of a VANET supported smart parking system for Dublin City. To achieve this, various Dublin specific data must be obtained. This includes Dublin City traffic data and Dublin City parking data, both on-street parking data and parking lot data. The lists below were compiled during the designing phase of this dissertation. The first list highlights the available data that is readily available on public Irish databases and websites. The second list includes data that is unavailable online and that had to be acquired by other means.

Obtainable Data

- Parking Lot Occupancies - The Dublin City traffic website includes real-time information regarding available spaces in 14 parking lots within inner city Dublin. This data is useful and is incorporated into the simulation.
- Parking Lots Locations - Knowledge of the location of parking lots within inner city Dublin is necessary to route drivers to the desired parking lot in the simulation. The 14 parking lots that the Dublin city traffic website provide is easily identifiable on Google Maps; their coordinates are recorded.
- On-Street Parking Locations - Each on-street parking location is not available. However, data.gov.ie features a dataset that contains all available parking meters in the county of Dublin. Included in the dataset is the number of on-street parking spaces that they serve. This approximation of on-street parking locations is used in the simulation.

- Average Traffic Volumes - Traffic volumes datasets are available on data.gov.ie. However, the online traffic data is composed only of traffic data outside of inner city Dublin. More specifically, the datasets only include inbound and outbound traffic of national roads along the M50. The region of interest in this dissertation is central Dublin. Thus inner city Dublin traffic volumes must be acquired by other means.

- Emissions - Used as an evaluation metric. VEINS features an emissions model that allows for emissions results.

Unavailable Data

- Occupancy data on on-street parking spots - The parking duration of Dublin drivers in on-street parking locations within the central Dublin city district is required to model a realistic environment for this dissertations' simulation.

- Inner Dublin city traffic data - More fine grain data of inner city traffic could be used to model a more realistic traffic flow environment. The average traffic volumes as listed above are unable to give a reasonable estimation of the traffic within inner city Dublin.

Despite the occupancy and traffic data not being accessible online, the process of acquiring the data alternatively is explained in detail in section 3.2.

Research limitations also included the computational power required to run the simulations. There were attempts to run simulations on university computers and from a personal laptop. However, in both cases, the estimated completion time exceeded three weeks. Initially, the simulations were run with the simulations' GUI which would have impacted the run-time. University virtual machines were requested to perform the simulations via the command line. Even from the college virtual machines, the simulations took more than two weeks. Eventually, the simulations were scaled down substantially so that the simulation could be complete in a reasonable time.

1.5 Organisation

The structure of the dissertation is split into six chapters. This organisation section concludes the introductory chapter. Chapter two gives an in-depth analysis of the current state-of-the-art of smart parking. This involves a literature review on the current VANET technologies, parking space sensing technologies, parking data dissemination techniques, security and privacy considerations, smart parking models and an assessment of smart parking solutions in other cities. Chapter three outlines the design considerations before the implementation of the simulation model. The process of obtaining the required traffic and parking data, as well as simulation software reviews. Chapter four discusses the implementation process of the chosen simulation overview. Chapter five details the evaluation process and an analysis of the results. This is followed by the final chapter; Chapter six explores possible future works and a conclusion to this dissertation.

This concludes the introductory chapter.

Chapter 2

State of the Art

In this chapter, an overview of smart parking is provided. The overview includes parking data sensing and parking data dissemination methodologies. As well as this, VANET and Vehicular Cloud Computing (VCC) is discussed. Additionally, security considerations of vehicle networking protocols are explored. This is followed by an analysis of solutions implemented in other cities worldwide.

2.1 Background

Kuhn defines a paradigm shift as a fundamental change in the basic concepts and experimental practices of scientific disciplines (Kuhn, 1970). In this paper (Eltoweissy et al., 2010), it mentions that within the computing industry, various infrastructure providers with large computing resources are often underutilised. The paper highlights the shift in which business models and computing resource allocations have shifted towards an on-demand model. This shift is known today as cloud computing. The same paper also envisions a shift in the ever increasing fleet of vehicles on the roads. In that, they could potentially shift towards a system that can support a networking environment.

> *The huge fleet of energy-sufficient vehicles that crisscross our roadways, airways, and waterways, most of them with a permanent Internet presence, featuring substantial on-board computational, storage, and sensing capabilities can be thought of as a huge farm of computers on the move.*

The paper stresses that the computational power and sensing capabilities of vehicles, could potentially be pooled together, to *autonomously self-organise into the cloud* and form what the paper has called "Autonomous Vehicular Cloud (AVC)". The comparison is made between the previously underutilised computing resources of infrastructure providers to that of current autonomous vehicles with no vehicular networking capabilities. In a similar way where cloud computing has introduced the concept of on-demand computing resource models for consumers to utilise its resources entirely, vehicles may act in a similar way to fully utilise their real-time on-the-road sensing capabilities as well as coordination of communications and physical resources in an ad-hoc manner in traffic.

2.2 Smart Parking

In this section, the current state of the art of smart parking is explored. The initial section is an analysis of various parking space sensors. The following section is an analysis of various parking data dissemination approaches.

2.2.1 Parking Data Sensing

There are various tradeoffs to be considered as well as the applicability of the sensors for different scenarios. An analysis of each sensor is provided along with a brief conclusion regarding the sensors applicability to sense parking spaces. Figure 2.1 provides a brief overview of the sensors to be discussed.

Sensor Technology	**Use in Parking Space Detection**
Accelerometer	Accelerometers in phones can be used to detect whether a driver has taken a parking space
Acoustic	Analysis of sound waves of the vehicles to track where vehicles park within a parking lot
Computer Vision	Utilisation of public CCTV or private parking lot cameras to track vehicles
Crowdsensing	Pooling of information from participating drivers to detect parking space occupancies
Laser Range Finders	Scanning on-street locations for parking space occupancies
Magnetometer	Magnetometers in mobile phones to detect parked vehicles
Optical Fibre	Detection of vehicles that cross an optical cable. Placement can be at the entrances and exits of parking lots
RFID	RFID readers to scan vehicles' RFID tags upon entry to parking lots
Ultrasonic	Emits sound waves at a known location to detect if parking space is occupied

Table 2.1: An overview of parking sensors

Accelerometer

Accelerometers can be found in many smartphones. Accelerometers can be used to detect a phone's orientation, motion and rotation. Information regarding a phones' orientation can allow the phone's screen to adjust to landscape mode or portrait mode. Accelerometers in mobile phones can also be used to recognise activity of a user (Brezmes et al., 2009).

PhonePark is a solution that includes a real-time analysis of device mode transitions to detect parking space occupancies (Xu et al., 2013). It works by utilising information of a users' mobile phone. PhonePark proposes three detection methods of parking space occupancies. These are listed below with an overview of how they work.

1. *Bluetooth*: This method of detection involves a mobile phone tethered to a vehicles' Bluetooth system. If the device is tethered to the vehicle, then it assumes that the vehicle is being driven. When the Bluetooth disconnects, as the driver walks (10 meters) away from the vehicle, it infers that the vehicle is parked.

2. *Transition Models*: Different states are used to classify whether a user is driving, walking or stationary. If a transition sequence of driving to stationary, and stationary to walking is observed. PhonePark infers that the vehicle is recently parked. The phone's accelerometer is used to make estimations as to whether the user is driving, walking or stationary.

3. *Pay-by-Phone Piggyback*: Pay-by-phone piggyback is to allow the user to pay through their mobile phone. Upon payment, the user will be asked for their parking space number. This information is forwarded from the pay-by-phone company to a central system that keeps track of the parking spaces. Thus the parking space occupancy can be detected in this way.

While the methods of detection are possible, the paper acknowledges that not all drivers have mobile phones. Thus the solution provided by PhonePark is not always possible. Additionally, the paper acknowledges GPS errors, Bluetooth pairing difficulties and incorrect transition classifications. All these errors contribute to inaccurately detecting parking space occupancies.

Acoustic

Acoustic sensors can detect the noise emitted from vehicle engine sounds. Within a parking lot environment, a solution is proposed to utilise acoustic sensors to detect vehicles (Na et al., 2009). Acoustic sensors are placed in areas within the parking lot. An acoustic localisation algorithm is introduced to narrow the scope of where it estimates the vehicle has parked. In the parking lot scenario, it assumes that cameras are available. Thus, by re-positioning the cameras' viewing angle towards the acoustically localised area, the parking lot system can confirm whether the parking spot has been occupied.

Acoustic sensors are very sensitive to the environment they operate within. Although this paper (Lee et al., 2008) does not directly focus on the analysis of an acoustic sensor parking space detector, it mentions a possible solution that is worth considering. The paper states that each vehicle has its characteristics, vehicle size, magnetic wave pattern and engine sound. With the combination of magnetometers, ultrasonic sensors and acoustic sensors placed at the entrance of a parking lot. It could build a database of the vehicles entering the parking lot, recording the vehicles' body shape, magnetic wave pattern and engine sounds with the above-mentioned sensors. With the placement of sensors throughout the parking lot, it may be possible to track and localise where a particular vehicle has parked, thus supplying information as to where a vehicle has taken up a parking spot.

While acoustic sensors might not be the most accurate method of detecting parking space occupancies due to its sensitivity to its environment, they provide a fascinating insight to the utilisation of non-obvious sensors to seek parking space occupancy rates. In both of the mentioned papers, acoustic sensors do not act alone to obtain parking data. The combination of cameras, magnetometers and ultrasonic sensors are necessary to verify the data obtained from acoustic sensors.

Computer Vision

Computer vision involves parsing information from images of a video feed. Applications of computer vision range from the detection of defective products on manufacturing assembly lines to facial recognition software. Additionally, computer vision can be applied to the detection of vacant parking spaces. This section includes an analysis of two papers that utilise computer vision to sense parking information.

In this paper (Cho et al., 2016), it discusses taking advantage of CCTV cameras inside parking lots to guide autonomous vehicles to a parking spot. The system proposes a central computing unit that communicates with the autonomous vehicles. This assumes that a type of vehicular networking is supported by the vehicles. The work was tested within a lab environment with a USB 3.0 camera. The identification of parking spaces is identified by placing a coloured piece of paper in the centre of each parking location. The coloured paper is hidden when the body of a vehicle is in its position. Thus, the camera can identify whether a parking spot is vacant or occupied. However, the paper concludes that dynamic characteristics, such as camera image noise and geometric orientations may impede its use in general parking lot scenarios.

In this paper (Amato et al., 2017), it proposes a deep learning decentralised parking lot occupancy detector. The solution is based on a deep Convolutional Neural Network (CNN) designed for use on smart cameras. CNN involves the classification of images and recognising persistent attributes of items and objects (Krizhevsky et al., 2012). Smart cameras are defined in the paper as "cameras capable of processing the acquired images and transmitting just the result to a remote server". The proposed solution can learn where parking spaces are and detect whether a vehicle is parked on it or not. The advantages of designing a decentralised detection system are that it may be deployed to other smart cameras and learn by itself to detect parking space occupancies. This research took place on publicly available parking lot datasets. "PKLot" and "Cnrpark-ext" are the two datasets used in this study (*PKLot*, 2017; *CNR-EXT*, 2017). In both datasets, parking areas in different weather conditions are available. With the datasets, the deep learning agent can classify parking spaces and detect their occupancy statuses. This paper concludes that its solution outperforms other existing solutions within the field of parking space occupancy detection with computer vision.

While the initial paper (Cho et al., 2016) discusses the utilisation of CCTV cameras inside parking lots to guide autonomous vehicles, it could be extended to utilising city CCTV cameras to detect parking spaces. However, since the detection method involves a coloured identifier on the parking location, it may prove difficult to do the same with on-street parking locations.

On the analysis of the second paper (Amato et al., 2017), utilisation of a deep learning CNN to detect parking space occupancies can be extended to many other smart cameras. This is a very promising solution in assisting parking lots and urban areas equipped with CCTV cameras to detect parking space occupancies.

Crowdsensing

Crowdsensing can be defined as the collection of data from citizens to provide a dataset where useful information can be extracted from (Villanueva et al., 2016).

ParkJam (Kopeck & Domingue, 2012) is a proposal for a crowdsensing parking space app. It uses publicly available geographic data to get parking areas. The app relies on participating users to submit information regarding parking space availabilities. Incentives for users to take part in updating the parking spaces include receiving information regarding vacant parking space in return.

While crowdsensing can provide up-to-date parking data, it requires constant user attention and participation. ParkJam could be utilised more efficiently if users are not obliged to input the data manually. PhonePark (Xu et al., 2013), as mentioned in the previous accelerometer section, uses mobile phone accelerometers to detect whether a driver has parked. This information could be relayed to a central system and broadcasted to other participating drivers. As a result, PhonePark is essentially a crowdsensing application that uses an accelerometer to detect parking space occupancies.

Laser Scanners

Laser range finders are used to detect the distances from a source point into the distance. In a research paper (Ono et al., 2002), a test vehicle with laser range finders attached to the side of the test vehicle makes an attempt to detect on-street parking space occupancies. The laser scanners can retrieve depth information from the side of the test vehicle to the side of the street. With a known location of parking spaces, it would be able to analyse the distance between the test vehicle to the side of the street at a known parking spot location. Thus, it would be able to infer whether or not the parking space is occupied by analysing the distance between the test vehicle and the side of the street. If the distance exceeds the distance between the test vehicle and the kerb, then it's likely that that space is vacant. Whereas if the distance is less than the normal distance between the test vehicle and the kerb, then it is probably taken.

At times, the study found that the detection of black vehicles goes unnoticed. Thus, this paper has devised two algorithms to further enhance the analysis of a normalised depth image obtained from the laser range finder. They are known as the height-curve method and the depth-curve method. The methods include computer vision techniques, such as edge detection to obtain additional information from the depth images. With the depth-curve method, it can find the edge of the road, and if a vehicle is present, it can detect the outline of the vehicle. Using the height-curve method, it can infer whether the height of outline obtained through the depth-curve method is a vehicle or a wall. Through the utilisation of both methods, the study concludes that it provides an accurate solution for the detection of parking space occupancies with a laser range finder.

While the use of laser range finders is possible in the discovery of parking spaces, it requires a vehicle to drive around, scanning all known parking spaces to provide updates. One idea would be to attach these laser range-finders to the side of taxis. Similarly, they could be attached to other forms of public transport systems. However, taxis are expected to cover more ground and circulate more granular areas within an urban environment than general public transport.

Magnetometer

Magnetometers are used to detect large bodies of metal. This can be a useful application for the detection of parked vehicles in parking spaces. As illustrated in this paper (Villanueva et al., 2016), tests are carried out with the magnetometer on a Samsung Galaxy S4. The study was conducted in three different scenarios. In the first scenario, the goal was to try and classify different magnetometer readings in various situations. Additionally, an investigation into whether an active engine interferes with the magnetometer readings is performed. The combinations investigated in the study are as follows:

- (ssb) Test vehicle engine stopped, test vehicle stopped, adjacent vehicles on both side of test vehicle

- (rsb) Test vehicle engine running, test vehicle stopped, adjacent vehicles on both sides of test vehicle

- (rsl) Test vehicle engine running, test vehicle stopped, vehicle on left side of test vehicle
- (rsn) Test vehicle engine running, test vehicle stopped, no vehicles close to test vehicle
- (ssn) Test vehicle engine stopped, test vehicle stopped, no vehicles close to test vehicle
- (ssl) Test vehicle engine stopped, test vehicle stopped, vehicle on the left side of test vehicle

The study successfully classifies readings through the use of Supported Vector Machines (SVM). SVM is a supervised machine learning algorithm. SVM is generally used for classifications and regression (Suykens & Vandewalle, 1999).

Through the use of SVM, the readings from the magnetometer can be classified. For the purpose of illustration, figure 2.1 shows the magnetometer readings obtained by the study. From figure 2.1, it is clear that the magnetometer readings can be used for detecting whether a vehicle is stationed nearby.

With these classifications, the mobile phone that performed the information sensing could relay this information to a central server. In this way, the central server will have additional knowledge regarding parking space occupancies within that specific magnetometers' area.

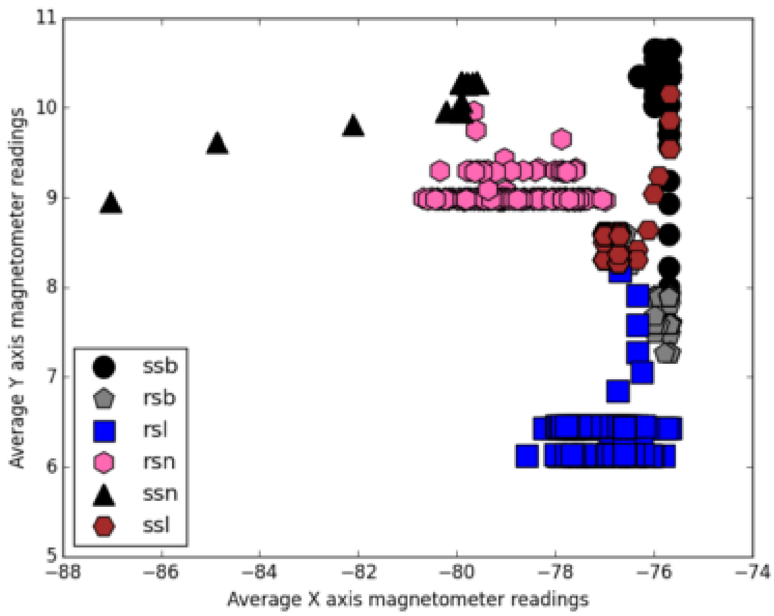


Figure 2.1: Magnetometer Readings

In the second scenario, the aim was to investigate whether a moving test vehicle equipped with a portable magnetometer can detect vacant parking spaces. The setup to this test case includes a line of parked vehicles with one empty spot. The test vehicle drives alongside the line of parked vehicles, emulating a vehicle driving down a street of parked vehicles. The magnetometer showed a significant reading as it passed the vacant spot. Thus the investigation concludes that it is successful in detecting empty parking spots while the test vehicle is moving.

In the third scenario, the distance of a parked vehicle to the test vehicle is investigated. The test begins with the test vehicle parked beside another vehicle. The test vehicle is then moved further and further away from a parked vehicle. The results show that the magnetometer readings are useless unless vehicles are very near.

The results obtained through this paper indicates that it is possible to use magnetometers to detect parking space occupancies. However, a suitable application has yet to be discussed. A magnetometer may only sense parking spaces when the device is relatively near. Unless this is incorporated into a crowdsensing scheme, there is no incentive for drivers to cruise a parking lot or urban streets sensing spaces for other drivers. Integration of magnetometers onto taxis, as previously discussed in the laser range finder section, could also be considered. By attaching magnetometers to public transport or taxis, they may be able to scan parking areas for parking space availabilities.

Optical Fibre

Optical fibres can be used as load sensors to measure the weight of vehicles. A proposal for vehicle detection with optical fibres is explored in this paper (Gupta & Upadhyaya, 2016). The study uses phase-shift and amplitude analysis on the propagation of the optical fibre path to detect when a vehicles' is on it. The results show that optical fibres produce a high accuracy rating for the detection of vehicles. The detection of individual vehicles could be useful by placing optical fibres at the entrances and exits of parking lots; they may be able to accurately record how many vehicles are in the parking lot at any given time. Additionally, optical fibres may be placed at both ends of a one-way street that contains on-street parking locations. This could provide information regarding some parking spaces on that street by finding the difference between the vehicles that have entered the street but have not exited on the other end.

RFID

RFID is a technology that uses radio waves to read and capture information stored on a tag attached to an object. RFID tags do not require a direct line of sight to function. RFID can be described with two main components, a RFID tag and a RFID reader. The tag consists of a microchip that can store data, as well as an antenna to transfer information bidirectionally. A reader emits a signal to RFID tags, and tags can respond with the information that they have in their storage (Want, 2006).

RFID tags may be placed on vehicles, with RFID readers installed at parking lot entrances and exits. As described in this paper (Pala & Inanc, 2007), tags can be generated for vehicles and stored in a central database system. When vehicles enter the parking lot, the RFID reader scans the RFID tags and checks whether they are authorised to enter the parking lot. If authorised, the barrier will be raised to allow the vehicle to enter. The same process is performed to allow the vehicle to exit.

From the paper, it is observed that if two or more vehicles enter the parking lot at the same time, the RFID readers will not be able to process both vehicles' information correctly. For this reason, it is advised to only process one vehicle at a time.

According to this paper (Dokur et al., 2016), RFID readers are very expensive. However, the use of RFID sensors is highly accurate when performed in a controlled environment.

Ultrasonic

Ultrasonic sensors are widely used to sense parking space occupancies. The largest shopping centre in Ireland, located in Dundrum, serves more than 3,500 spaces. Above every parking space in the underground parking lot is an ultrasonic sensor (Gavin, 2008). The ultrasonic sensors are used to sense the occupancy of an individual parking space, and the information is relayed to electronic display boards both inside and outside the parking lot. Parking information signs inside the parking lot guide drivers up and down levels and in between aisles. External electronic display boards guide drivers to different parking lots.

Similarly, in this paper (Kianpisheh et al., 2012), ultrasonic sensors are placed above parking spaces within a parking lot. The proposed smart parking system can use the ultrasonic sensors to detect improper parking as well as parking space occupancy detection. In the same way, the smart parking system relays information to the information display boards to inform drivers of the current parking space occupancies in the area.

The use of ultrasonic sensors are highly accurate, and the cost of each sensor is relatively cheap (Dokur et al., 2016). It is also worth noting that since ultrasonic sensors do not support multiple detections of vehicles, the cost of deployment could become much more.

Comparison of Sensing Technologies

Table 2.2 and 2.3 illustrates general considerations put forward when comparing parking sensor technologies as defined in this paper (Lin et al., 2008). Additional information is obtained from (Dokur et al., 2016) regarding the cost and accuracy of sensors mentioned.

An explanation of the columns of tables 2.2 and 2.3 are as follows:

Intrusive Installation (IV) Intrusive installation is defined as whether the sensor needs to be embedded into the road. This could yield significant costs. For example, on-street ultrasonic sensors may require installers to dig up the road to install the sensors securely into the ground.

Multiple Detection (MD) The ability to detect multiple parking space vacancies at once.

Cost (C) The cost of each sensor is an important consideration. This also depends on whether the sensor can detect multiple spaces. Detection of multiple spaces would bypass the need for a single sensor per parking spot. Additionally, if the sensor requires intrusive installation, then the cost is likely to increase.

Accuracy (A) The accuracy of a sensor device depends on environmental factors, as well as the method for detecting parking spaces.

In tables 2.2 and 2.3, the discussed parking sensors are compared.

Stationary Sensors

Sensor	C	IV	MD	A
Accelerometer	*	✗	✓	*
Acoustic	***	✗	✓	*
Fibre Optics	*	✗	✗	**
Magnetometer	**	✓	✗	***
RFID	**	✓	✗	**
Ultrasonic	*	✗	✓	***
Vision	***	✗	✓	**

Table 2.2: Stationary Sensors Comparison Table

Mobile Sensors

Sensor	C	IV	MD	A
Crowdsource (Smartphone)	✗	✗	✓	✗
Laser Range Sensor	***	✗	✓	***
Ultrasonic	*	✗	✓	***

Table 2.3: Mobile Sensors Comparison Table

Conclusion

A wide range of parking space sensing technologies has been discussed. There are many ways in which parking space occupancies can be detected. From the unconventional ways of detection with fibre optics and laser range sensors to the utilisation of ultrasonic sensors and RFID readers. Each and every sensing solution provide adequate results for the detection of occupied parking spaces.

2.2.2 Parking Data Dissemination

Parking data dissemination refers to the method of sending parking data to drivers. In this dissertation, the parking data dissemination model is assigned to the vehicles themselves; the parking data is disseminated from vehicle to vehicle. Parking data dissemination could also take the form of vehicle to infrastructure communications. This may take the form of utilising a RSU to relay information to vehicles on the road. Different algorithms have been explored by various papers (Schlote et al., 2014), (Verroios et al., 2011) and (Lin et al., 2008). In the following three sections, different approaches outlined by (Verroios et al., 2011) are explained. Each approach is important as they lead up to this dissertations' simulation data dissemination process.

To note: The live model and cluster models are most applicable to this dissertations' simulation. However, information regarding the exact model is also outlined as part of an analysis of the paper.

Exact Model

As outlined in section 1.1, to avoid the scenario of drivers arriving at parking spaces that are just taken is an issue for smart parking. Three well-defined algorithms are discussed (Verroios et al., 2011), the paper takes into account various parking factors, including probabilities that the parking space will be taken and time required to walk from the parking space to the drivers' final destination. These factors are incorporated in calculating the best cost path for a driver to traverse through. The analysis that follows will be based on the formula below.

$$C(a, b, t_{\text{tot}}) = t_{\text{ab}} + p(t_{\text{tot}}) * \omega_{\text{b}} + [1 - p(t_{\text{tot}})] * D$$

The formula is based loosely on the travelling salesman method. The aim is to devise the least cost path for a driver to get to a parking spot that is not already taken.

t_{ab}: Time required to drive from space a to space b

ω_b : Time to walk from space to destination

D: Time penalty if space is taken

t_{tot}: Time until parking spot is reached

$p(t_{tot})$: Probability that the space is still available

ω_{b} : Time to walk to the destination is weighted by $p(t_{tot})$
$p(t_{tot})$ is calculated by a space average life-time (salt) variable.
Whereby:

$$p(t_{\mathrm{tot}}) = \frac{salt}{t_{\mathrm{tot}} + salt}$$

The time penalty denoted as *D* is calculated with the following factors:

- The amount of spaces missed (asm) by the driver as a result of arriving at already occupied parking spots.
- The time it takes to drive from an occupied parking spot to another. This is referred to as spot to spot (sts).
- The average walk time from all spaces to the destination (wat).

Thus the time penalty is formulated as:

$$D = asm * sts + wat$$

This formula forms the basis of calculating the best-cost path for a driver.

Cluster Model

Other forms of data dissemination discussed in the paper (Verroios et al., 2011) was to cluster parking spaces. The motivations behind clustering spaces is that there is a concern for the limited processing power that vehicles may possess. By clustering parking spaces, the computational power required to determine a drivers' trajectory will be minimised. The clusters are formed by the minimal distances between parking spaces. The algorithm to compute the best cost path for drivers is similar to the "exact" algorithm. However, instead of routing through exact spaces, it is altered to route through the defined clusters.

With computational power of on-board devices in vehicles, the cluster sizes must also be adjusted to avoid substantial computational load. Quality Threshold Clustering defines a threshold for the radius of clusters. K-medoid clustering is used to create clusters that have minimal distances between parking spots.

Live Model

The live approach focuses on inter-vehicle communications. As outlined in the paper (Verroios et al., 2011), vehicles communicate with other vehicles within their vicinity to update and report parking spaces occupancies and vacancies. Furthermore, re-adjustments may be made by vehicles to alter their route trajectories dynamically. As previously mentioned in the cluster model section, one of the focuses is to minimise the computations required on an on-board device of a vehicle. Thus the cluster model is incorporated into this live approach. In other words, instead of dealing with each parking spaces' status, it updates each parking area cluster.

The "live" approach to dissemination parking data between vehicles forms the foundation of this dissertations' simulation. The "clustering model" forms the basis of the structure of the parking spaces in this dissertations' simulation.

Comparison of Approaches

Table 2.4 features a comparison of the three different approaches.

- Time Complexity: Amount of time the algorithm would take
- Dissemination Protocol: The process of data dissemination
- Parking Spaces Scope: The parking spaces associated with the algorithm
- Algorithms Involved: Additional algorithms involved in the approach

Algorithm	Exact Approach	Cluster Approach	Live Approach
Time Complexity	$\mathcal{O}(n^3T2^{\mathrm{n}})$, where n = no. of parking spaces, T = time of longest trip	$\mathcal{O}(n^3T2^{\mathrm{n}})$, where n = no. of clusters, T = time of longest trip	$\mathcal{O}(n*m)$, where n = number of clusters, m = number of pre-existing spaces
Dissemination Protocol	On-board calculations obtained from external source (RSU)	On-board calculations obtained from external source (RSU)	Vehicles within vicinity
Parking Spaces Scope	All available spaces that match drivers' destination criteria	Only takes into account clustered areas that match driver's destination criteria	Nearby spaces only
Algorithms Involved	Travelling Salesman Algorithm (TSA)	K-medoids, Quality Threshold Clustering	Update system, re-calibration of trajectory algorithm

Table 2.4: Comparison of Parking Data Dissemination Approaches

As Verroios et al. discuss in (Verroios et al., 2011), the custom simulation that is built to evaluate the algorithms show that the "live" approach reaches close-to-optimal trajectories. Additionally, it produced positive results for trade-offs between optimality and the computational requirements.

2.3 Vehicle Networking

2.3.1 Vehicle Ad-Hoc Networking (VANET)

VANET is a subclass of Mobile Ad-Hoc Networking (MANET). The technology allows Inter-Vehicle Communication (IVC) and is used for various reasons. With IVC, vehicles can communicate with other vehicles within their vicinity. This is known as Vehicle-to-Vehicle (V2V). Applications for V2V communications include vehicle platooning and forward collision avoidance. In this survey (Kiess et al., 2007), it outlines a V2V safety application. The application involves an emergency braking signal that is propagated through vehicles along the road when a vehicle suddenly stops. As vehicles behind receive this information, the vehicles themselves may be able to react on time. Other applications include speed management to avoid traffic jams and a new form of a distress signal from approaching emergency vehicles.

There are other forms of VANET models. These include Vehicle-to-Infrastructure (V2I) and Vehicle-to-Grid (V2G). V2I allow vehicle communication with V2I supported junctions, traffic lights, as well as road signs. In this paper (Milanés et al., 2012), it proposes an Intelligent Traffic System (ITS) through the use of V2I communications. By proposing an intelligent traffic system, regulation of traffic flow is possible. As well as this, the system can monitor each vehicles' position and speed. By monitoring these characteristics, the system may alert the driver of the vehicle when it estimates a collision. Additionally, ITS has the potential to guide autonomous vehicles through bends on the road. Road signs on road bends may act as a RSU and notify an approaching autonomous vehicle of the speed and angle that the vehicle should approach the bend at. Alternatively, the road signs could notify the driver of the vehicle through their dashboard.

With V2G, battery vehicles would be able to communicate with the electricity grid. Communication with the electric grid could allow vehicles to contribute to levelling the off-peak load (Guille & Gross, 2009).

VANET models can also allow the dissemination of parking information. This can be achieved in the form of V2I, where vehicles communicate with a RSU. Alternatively, V2V communications could be used to disseminate the parking data. For example, when a vehicle gives up a parking spot, it may announce as so, so that the information may be propagated to a vehicle nearby looking for a parking space.

An increasing amount of vehicles is being equipped with on-board wireless communication units to facilitate wireless network among vehicles and their environments (Lin et al., 2008). Thus more vehicles on the road could have the potential to support a smart parking system network environment.

In another paper (Panayappan & Trivedi, 2007), the proposal brought forward involves an urban area dissected in the form of a Voronoi diagram. This is illustrated in figure 2.2.

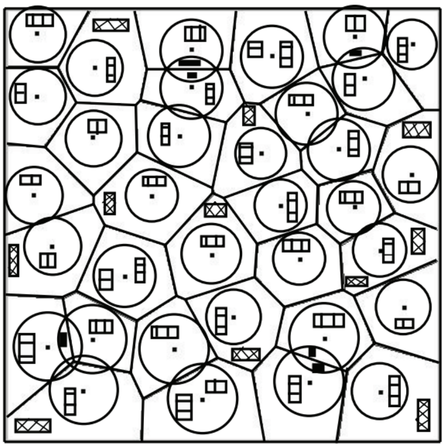


Figure 2.2: Voronoi Model

The paper proposes that a roadside unit RSU should be placed at the centre of each sector in the Voronoi diagram. The RSU is responsible for handling all the information regarding parking information within its corresponding sector. In other words, each unit can respond with the occupancy levels of the parking spaces in their designated sectors. Vehicles approaching a designated sector will be able to communicate with the appropriate RSU to query the parking space available within that sector.

2.3.2 Vehicular Cloud Computing (VCC)

Vehicle Cloud Computing (VCC) can be defined as a new paradigm in which vehicles interact and collaborate to sense the environment, process the data, propagate the results and share resources (Mehmood et al., 2017). VANET models require On-Board Unit (OBU) to process more and more information. As highlighted in this survey (Whaiduzzaman et al., 2014), vehicles are expected to carry more storage, processing power and sensing capabilities in the near future. VCC provides a solution to the influx of processing power required for OBU of vehicles. Additionally, vehicular sensing capabilities can be further enhanced through the use of the cloud. Often underutilised vehicle sensors could provide real-time environment information.

In this paper (Hussain et al., 2012), it proposes three different cloud architectures. These architectures are Vehicle Cloud (VC), Vehicle using Cloud (VuC), and Hybird Cloud (HC). In VC, the vehicles themselves form the cloud. The pooling of resources is performed between the vehicles themselves. The most appropriate example for VC is traffic light coordination. If there is vehicle build-up within a particular area, then vehicles in that area can communicate with each other and with the traffic light infrastructure to dynamically adjust junctions in real-time. In VuC, RSU are introduced and act as gateways to the cloud services. The cloud services provided could give vehicles access to real-time traffic information. The final cloud architecture is HC; it is the combination of the VC and VuC architectures.

To conclude, with the introduction of VANET, there is a concern for the required processing power of vehicles' OBU and underutilised capabilities of vehicle sensors and storage. The different VCC architecture types outlined above could provide a viable solution for handling future VANET models.

2.4 Security

In this section, security and privacy concerns are explored. This section discusses the security concerns of a smart parking system deployed on the dedicated 802.11p network.

2.4.1 802.11p

Inter-vehicular communication protocols have been explored in different forms. IEEE have devised a new protocol, known as 802.11p, a dedicated protocol for short range communication between vehicles. The goal is to provide an international standard for Wireless Access for Vehicular Environment (WAVE). As vehicles cannot tolerate excessive connectivity delays, the protocol focuses on resolving these issues. The technology originates from Dedicated Short Range Communication (DSRC), which is a short to medium range wireless communication channel for automotive use Miller & Shaw (2001).

The implementation of the 802.11p protocol focuses on communication between OBU and RSU. In this paper (Panayappan & Trivedi, 2007), it highlights key considerations regarding certificate authentication for vehicular networking. The vehicle manufacturer would be required to assign a certificate to each vehicles' OBU. The traffic authority would be required to assign certificates to each RSU. The messages transferred between OBU and RSU will be encrypted by their corresponding private keys. Additionally, they are required to attach their corresponding certificates during message transfers to authenticate one another.

A replay attack involves a malicious user eavesdropping on the connection between an OBU and a RSU and recording a set of messages between them. A replay attack is initiated when the malicious user replays the set of recorded messages into the channel. As explained in the paper (Panayappan & Trivedi, 2007), this can be avoided by appending a geo-synchronised time obtained from GPS.

In this paper Ucar et al. (2016), it discusses the potential of attacks on the platooning of vehicles that utilise the 802.11p protocol. Platooning of autonomous vehicles involves communication between cars to traverse through road segments. It works by adjusting the speed, acceleration and deceleration variables of each car within a platoon. The paper discusses how packet falsification may be used to alter the acceleration variables. Alternatively, attackers may demonstrate a replay attack. This will disrupt the stability of the platoon and is highly undesirable. In future works, it proposes implementing a secure DSRC protocol that prevents jamming, membership falsifications and hijacking. One of the proposed methods is to implement a secure key establishment to achieve confidentiality. Additionally, it proposes in using the authentication of verified members in the platoon to adopt key management and key refresh mechanisms.

The vulnerabilities of 802.11p have been explored by various papers. Not only could attackers affect platooning vehicles, but also in the case of disseminating parking information. The falsification of parking data is of concern as attackers may track and divert drivers from vacant spaces with malicious intentions.

2.5 Alternative Smart Parking Models

In this section, an overview of two alternative smart parking models is outlined.

Reservation-Based Models

Reservation-based systems have also been researched by various papers, whereby drivers can buy spaces before parking their cars. A central reservation-based system is discussed (Wang & He, 2011). The paper is mainly focused on parking lot infrastructure. Thus the parking management system may be easier to achieve. It devises a solution whereby drivers communicate directly with parking lots to obtain information and to reserve spots within the parking lot.

Founded in 2015, ParkPnp (*ParkPnp*, 2015) is an Irish parking reservation system. ParkPnp is an application, both on the web and on mobile. It promotes parking lot owners as well as homeowners who have reserved parking locations to sell their parking spots to other road drivers.

Demand Based Models

SFPark (SFMTA, 2011) is a pilot project for smart parking, utilisation of parking sensors installed into a selected amount of on-street parking spaces. A unique aspect of this system is that it tries to keep around 10-15% of parking spaces free on a street or block. Using a demand based pricing model, it increases the price for on-street parking spots if the street is near 85-90% occupancy. As well as this, if the street is 85-90% free, then the parking charges will be lower. In this way, it hopes to distribute the amount of parking space vacancies evenly throughout the city. The price rate also factors in the time of day, and if any events are currently taking place in the vicinity of the parking locations.

2.6 Real World Examples

By the end of this section, this literature review will be complete. Throughout this chapter, an analysis of how parking space sensing, data dissemination and vehicle networking can be achieved. To conclude this chapter, real world examples are analysed in this section. This involves an analysis of existing solution in cities around the world. Some of these smart parking systems are pilot schemes while others are outsourced to private firms.

SmartParking Limited

SmartParking (Robert C. Hampshire, 2011) is a private company that provides smart parking solutions for cities. In this section, the solutions provided by SmartParking are analysed. This is followed by a list of the cities that they currently serve.

Sensors

The sensors by SmartParking consists of a magnetic and infrared sensor. The sensors are wireless and are powered by long-life batteries. The occupancy information is broadcasted to electronic display boards, to the SmartParking app to assist drivers in finding a vacant spot. However, regarding network topology, it does not explicitly say whether a nearby RSU oversees these sensors or in what way they communicate with the smart parking system (*Sensors SmartParking*, 2017).

ANPR

Cameras are used to oversee off-street parking locations. Automatic Number Plate Recognition (ANPR) is used to detect the number plates of vehicles. This solution allows for barrier-free parking lots (*ANPR SmartParking*, 2017).

RFID

SmartParking also offers RFID solutions for both on-street and off-street locations. For on-street locations, permit holders can simply attach a RFID tag onto their vehicles to allow parking enforcers verify that they are authorised to park in that spot.

RFID tags can also be extended to vehicles in an off-street scenario. Vehicles may require an authorised tag to park in a specific space within a parking lot complex (*RFID SmartParking*, 2017).

Westminster - London (October 2014)

The deployment of 10,000 RFID intrusive sensors is installed around the city. Zone unit monitors are installed in street lamps monitor each sector. The service is accessible to drivers from an app, where they can receive real-time parking information as well as pay for spaces via their mobile phones (*Westminster SmartParking*, 2013).

Cardiff - Wales (January 2017)

The deployment of 3,000 Infrared/Magnetometer sensors. The parking information is accessible through an app and from electronic display boards. ANPR recognition technology are also deployed in off-street parking locations (*Cardiff SmartParking*, 2017).

Other solutions

San Francisco (2011)

San Francisco has been the leading example of the implementation of a smart parking facility.

Since its implementation, a study in March 2014 shows that drivers cruising looking for parking spots have been down by 50% (Millard-Ball et al., 2014). In another economic study on the SF-Park implementation (Shriver, 2016), it provides positive feedback from the dissemination of parking spaces around the city. Supported by the demand-based pricing model, the distribution of spaces have provided a wider variance in the spaces available in each sector of the city and also has managed to suppress drivers from cruising around looking for a spot. This is possible because the system poses to retain at least 20% of each regions parking spaces free. This is so that the probability of spaces being available as drivers drive into the area will be high.

Chapter 3

Design

3.1 Software

In this section, the software considerations are discussed. An outline on each software is introduced, along with the reasoning behind why the implementation was settled on VEINS, SUMO and OMNeT++.

3.1.1 SUMO

SUMO is a microscopic traffic simulator (Krajzewicz et al., 2012). A microscopic traffic simulator allows vehicles to be modelled and simulated individually. There are other types of traffic simulators; macroscopic and mesoscopic modelling. In this section, a brief description of the different types of traffic simulators is outlined. This is followed by figure 3.1, illustrating the differences between current traffic simulators.

Traffic Simulators

Microscopic Traffic Simulators Microscopic traffic simulators allow granular ground-based level modelling. This includes the simulation of individual pedestrians. Furthermore, microscopic simulators simulate each entity individually. In contrast to this, macroscopic traffic simulators focus on general traffic flows.

Macroscopic Traffic Simulators Macroscopic traffic simulators focus on traffic planning analysis workflows. Applications for macroscopic simulators include public transport modelling and construction works traffic planning. It may be useful to simulate public transport for various reasons. Some of the features included in macroscopic public transport simulations are optimisations to bus routes to minimise transfer times and fleet sizes. Public transport modelling may also be useful to estimate the costs and revenue generated from each transport route. With construction planning traffic analysis, traffic bottlenecks may be simulated, and it may be possible to quantify detour traffic.

Mesoscopic Traffic Simulators Mesoscopic traffic simulators are useful for simulating traffic in small groups. It may be seen as a grouping of microscopic simulation. Applications, where mesoscopic traffic simulations are necessary, is for the simulation of vehicle platooning.

Traffic Simulator Comparison

In figure 3.1 various traffic simulation packages are outlined. The columns of the table are aspects that were considered when choosing an appropriate traffic simulator for this dissertation. The list below is compiled for definitions for non-obvious columns for figure 3.1.

- Simulation Model identifies the type of traffic simulator (microscopic/mesoscopic/macroscopic).
- Multi-Modal is the ability to simulate more than one type of traffic.
- The possibility of OSM map conversion to simulation readable road network.

Software	Focus	Simulation Model	Multi-Modal	Open Source	OSM	Cost
SUMO	Traffic analysis and modelling	Microscopic	✓	✓	✓	Free
PVT VISSIM	Traffic Engineering, Urban Planning, Public Transport	Microscopic	✓	✗	✗	€250 (Student 3-day pass)
MATSIM	Large-scale agent-based transport simulation	Microscopic	✓	✓	✓	Free
AORTA	Optimisation of autonomous traffic at a city-wide scale	Microscopic	✓	✓	✓	Free
TransModeler	Traffic impact analysis, and signal optimisation	Microscopic	✓	✗	✓	$12,000
PVT VISUM	Public transport master plans, construction, traffic engineering	Macroscopic	✓	✗	✗	€250 (Student 3-day pass)
AIMSUN	Traffic engineering, traffic simulation, transportation planning, emergency evacuation planning	Microscopic	✓	✗	✗	N/A
Quadstone Paramics	Traffic modelling, traffic analysing	Microscopic	✓	✗	✓	N/A

Table 3.1: Traffic Simulation Software Considerations

SUMO is the chosen traffic simulation for this dissertation. It provides tools for OSM road network conversion, tools for trip generations, route generations and is widely supported by an active community on their forum (*Mailing List for SUMO*, 2017).

3.1.2 OMNeT++

OMNeT++ is a modular, C++ network simulation and framework (Varga & Hornig, 2008). OMNeT++ includes an INET framework that allows for simulation of different network protocols. The network protocol of concern is Mobile Ad-Hoc Networks (MANETs). VANET is a type of MANET and is used for vehicular communications. The ability for inter-vehicular communications is vital for this dissertation.

3.1.3 VEINS

Vehicles in Network Simulation (VEINS) is a simulation framework that tries to make the simulation of vehicular communications as realistic as possible. VEINS is set up to interact with both OMNeT++ and SUMO. As mentioned in section 3.1.1, SUMO simulates the traffic aspect of this dissertation. OMNeT++ as mentioned in section 3.1.2 is a network simulator that handles vehicular packet transmissions. A physical layer modelling toolkit MiXiM is used to enhance the simulation further. MiXiM provides models that can accurately describe radio interference and the shadowing of static and moving obstacles within the simulation. VEINS also sets up a running server for inter-communications between OMNeT++ and SUMO to provide additional realism of vehicular networking.

3.1.4 Conclusion

Another reason that SUMO is chosen as the traffic simulator, is that it allows the use of VEINS. VEINS can be seen as a framework that is capable of simulating VANET. For this reason, VEINS, SUMO and OMNeT++ are chosen for this dissertation.

3.2 Data

In this section, the obtained Dublin City traffic and parking data is discussed. The process of acquiring the data is outlined, as well as its application in relation to this dissertation.

3.2.1 Dublin City Parking Information

The list below is a general overview and reason to why they are required. The following sections explain the process of obtaining each set of parking data, on-street and off-street.

- Parking Area Geographic Coordinates: To simulate vehicles parking in areas that allow parking, all Dublin on-street parking locations, as well as parking lot locations, must be known. The coordinate locations are recorded so that vehicles may be able to calculate which parking areas are closest to their final destination during the simulation.

- Parking Area Capacities: The parking space capacity of each parking lot and the on-street location is recorded. The capacities are used to determine how full a parking area is throughout the simulation process.

- Parking Area SUMO Road ID: The SUMO road identifiers must be recorded for each parking area so that the vehicles may be routed to them. SUMO road identifiers are the only accepted parameter for the function for routeing vehicles dynamically within the simulation.

On-Street Parking Information

data.gov.ie offers various datasets for transport data in Ireland (*data.gov.ie — Ireland's open data portal*, 2017). The most granular transport dataset regarding on-street parking locations is the parking meters dataset (*Parking Meter Dataset*, 2017). It does not contain the precise locations of each parking spot, but it has the locations of every parking meter within Dublin city. More specifically, the dataset includes Irish grid reference coordinates of all parking meters as well as the number of on-street parking spaces that they serve. Thus this dataset is sufficient for the purpose of this simulation. The dataset is also substantial as it references all known parking meters in Dublin. The area of interest for this dissertation is inner city Dublin parking areas. This can be visualised as the "yellow" and "red" areas in terms of Dublin City Council (DCC) defined parking zones as shown in figure 3.1 (*Dublin Parking Zone Tariffs*, 2017).

The resultant dataset within the concerned zones includes 175 on-street parking meters that serve 12,289 parking spaces. Each parking meter coordinate is formatted to an Irish coordinate reference plane. For the data to be usable in this dissertation, they must be converted to the more commonly used geographic coordinate system. Online tools are available to complete this conversion process.

The SUMO road identifiers are obtained through a manual mapping process of each parking meter through the SUMO GUI.

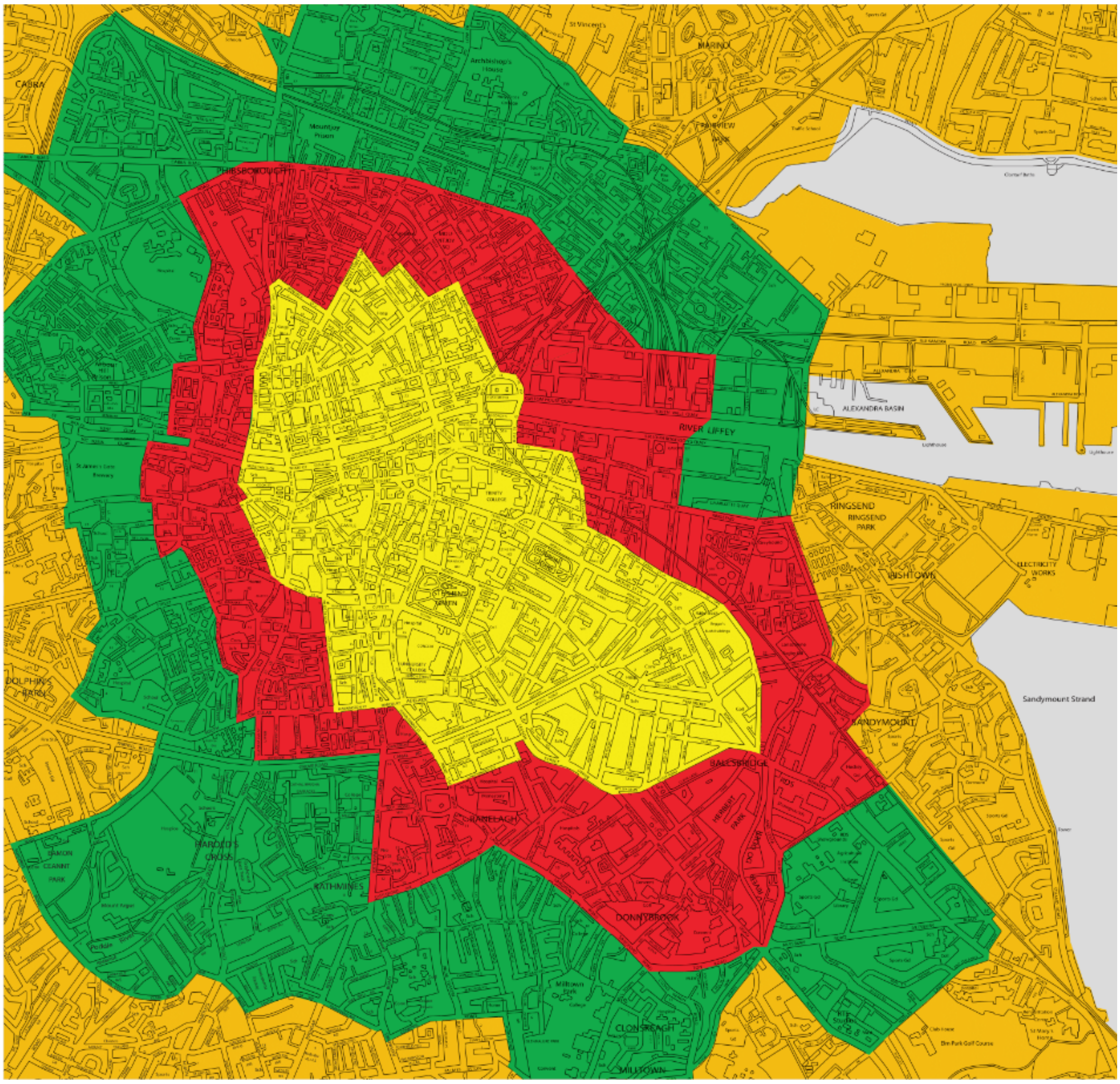


Figure 3.1: Dublin City Council Parking Zones Breakdown

Off-Street Parking Information

There are 14 parking lots that this dissertation takes into account. Table 3.2 includes the 14 parking lots and their capacities.

Car Park	Capacity
Arnotts Department Store	500
Christ Church	212
ILAC Shopping Centre	1000
Parnell Street	500
Marlboro Street	567
Abbey Street	340
Thomas Street	230
Setanta	145
Trinity Street	252
Stephen's Green	1127
Brown Thomas	380
Dawson Street	370
Jervis Shopping Centre	264

Table 3.2: Dublin Parking Lots and Capacities

Most of the car parks in Dublin are operated by QPark. Information regarding their capacities are available on each of the corresponding QPark parking lot websites. Other car parks are operated by the shopping centres that they serve and the capacities of them are listed on the corresponding shopping centre websites.

The coordinates of each of the car park locations are recorded through Google Maps.

The SUMO road identifiers are obtained through a manual mapping process of each car park through the SUMO GUI.

3.2.2 Dublin Traffic Flows

Dublin City traffic flow is incorporated into the simulation to build a realistic model.

A visit was made to the Dublin City Councils' traffic department to obtain this data. In most major junctions in Dublin, inductive loops are embedded beneath the ground just before the junctions' traffic lights. The sensor can detect whether a vehicle is above it. The sensor also acts as a counter, thus recording the amount of traffic that passes a particular lane on the road.

On some roads, there is a secondary sensor embedded into the ground further along the road. If there is a stationary vehicle detected above the secondary sensor, the traffic control station knows that that particular road segment has a traffic queue. At the time of writing, DCC traffic control centre does not have a sophisticated self-optimising traffic queue management system.

The obtained traffic flow data contains hourly intervals of the number of vehicles that have passed the junctions. The time interval of the data is from January 2016 through to December 2016. A subset of the data can be found in Appendix A.

Table 3.3 lists the roads that Dublin traffic flow data is recorded from, along with their national road identifier. The areas that they originate from are also included.

Road Name	Road ID	Areas Served
Amiens Street	R105	Fairview / Clontarf / Marino
Constitution Hill	R108	Phisboro / Glasnevin
East Wall Road	R131	Dublin Port Tunnel / East Wall
High Street	R810	Rialto / Inchicore
Mount Street Lower	R118	Ballsbridge
Parnell Square East	N/A	Drumcondra / Whitehall
Patrick Street	R137	Harold's Cross
Pearse Street	R802	Ringsend / Irishtown
Stephen's Green East	R138	Donnybrook
Victoria Quay	R148	Chapelizod / Ballyfermot
Wexford Street	R114	Rathmines / Ranelagh

Table 3.3: Dublin Traffic Flow Locations

3.2.3 Dublin Parking Lot Data

Live Dublin parking lot data is publicly available through the DCC website. Parking lot data is required to provide a realistic model on the occupancies of Dublin parking lots. The data is used to pad the spaces of parking lots in the simulation.

Scrapy is a Python crawler for extracting data from websites (*Scrapy - Python Crawler*, 2017). A cronjob is a scheduler that allows computing tasks to be run at a specified time interval (*CronTab Documentation*, 2017). A cronjob is set up for the crawler to scrape the live Dublin parking lot site every five minutes. The data is periodically saved to an SQLite database so that it can be extracted later on and used in the simulation. A subset of the parking lot data can be found in Appendix B.

3.2.4 Dublin On-Street Parking Data

Dublin on-street parking data involves obtaining the average park times of Dublin drivers within the city. ParkingTag is the on-street parking space operator for Dublin. A data dump of 30 anonymous drivers throughout the year of 2016 was provided from ParkingTag. The data dump includes the price that each driver paid as well as the zones that the drivers parked in. These zones are the same zones listed on figure 3.1.

The price to park in the yellow zone is €2.90, and red zones are €2.40. Given the price paid by a driver, their time duration spent parked can be calculated. This data is used to determine how long a driver is parked for during the simulation. A subset of the parking tag data provided by ParkingTag can be found in Appendix C.

3.2.5 Unused Data

Before obtaining the on-street parking data from ParkingTag, an attempt was made to manually source on-street parking behaviours of Dublin drivers. This involved observing a set amount of parking spaces for a limited amount of time. The observations were performed on two separate occasions.

The initial observations were carried out on Drury Street. Table 3.4 the rates of drivers leaving (L) and arriving (A) at parking spaces are shown. Another observation was conducted on South William Street. Table 3.5 illustrates the parking spots occupancy rates.

Space	1	2	3	4	5	6	7
11:28	L	-	-	-	-	-	-
11:29	A	-	-	-	-	-	-
12:11	-	-	-	-	-	L	-
12:14	-	-	-	-	-	A	-
12:18	-	-	-	-	-	-	L
12:21	L	-	-	-	-	-	-
12:22	A	-	-	-	-	-	-
12:26	-	-	-	-	-	L	-
12:26	-	-	-	-	-	-	A
12:28	-	-	-	-	-	A	-
12:30	-	L	-	-	-	-	-
12:34	-	A	-	-	-	-	-
12:43	-	-	-	-	-	L	-
12:44	-	L	-	-	-	-	-
12:45	-	-	-	-	-	-	L
12:49	-	-	-	-	-	A	-
13:06	-	-	-	-	-	L	-
13:08	-	A	-	-	-	-	-

Table 3.4: Drury Street (18th of February)

Space	1	2	3	4	5	6
12:20	A	-	-	-	-	-
12:23	-	L	-	-	-	-
12:24	-	A	-	-	-	-
12:25	-	-	-	-	L	-
12:26	-	-	-	-	A	-
12:29	-	-	L	-	-	-
12:31	-	-	A	-	-	-
12:59	-	-	L	-	-	-
12:59	-	-	A	-	-	-
13:08	-	-	-	-	L	-
13:15	-	-	-	-	A	-
13:17	-	-	-	-	L	-
13:19	-	-	-	-	A	-
13:51	-	-	-	-	-	L
13:52	-	-	-	-	-	A

Table 3.5: South William Street (28th of February)

Chapter 4

Implementation

In this chapter, the implementation process is explained in detail. The initial section explains the process of acquiring a suitable road network representation of Dublin City. This is followed by a section on the generation of traffic flow through tools supplied by SUMO. The third section details the various datasets that have been extracted and their role in the simulation. The final section features a thorough explanation of the implementation of a VANET smart parking model for the simulation.

4.1 Road network of Dublin

4.1.1 OpenStreetMaps + JOSM

OSM is a free world map editor. It is community driven and features a vast amount of geospatial information. Maps can be extracted straight from the website. A bounding box is used to extract the region of interest, and multiple APIs are available to download the necessary information within the bounding box. Since the data within a bounding box of a large urban area can be substantial, custom queries can also be made to omit unnecessary data. An example of this is to omit pedestrian walkways, storefront data and recreational areas from the map download query.

Java OpenStreetMaps (JOSM) is an OSM map editor(*JOSM*, 2017). It is a tool for editing OSM maps locally and is used to contribute to the update of an OSM. JOSM is useful for this dissertation as there are some minor roads leading to parking lots that are not defined within an OSM map. An example of this is the entrance to the Arnotts parking lot. JOSM is used to add the alley leading to the entrance to the parking lot.

Another reason for choosing OSM maps is that SUMO directly supports OSM map conversion for use within SUMO. NETCONVERT is a SUMO tool that translates an OSM .xml map file to the supported SUMO format (SUMO, 2008). OSM maps consist of “ways” and “nodes”. “Ways” represent each road within a map, and “nodes” represent the junctions where “ways” are connected.

Through NETCONVERT, a SUMO formatted map can be generated. The result can be seen in figure 4.1.

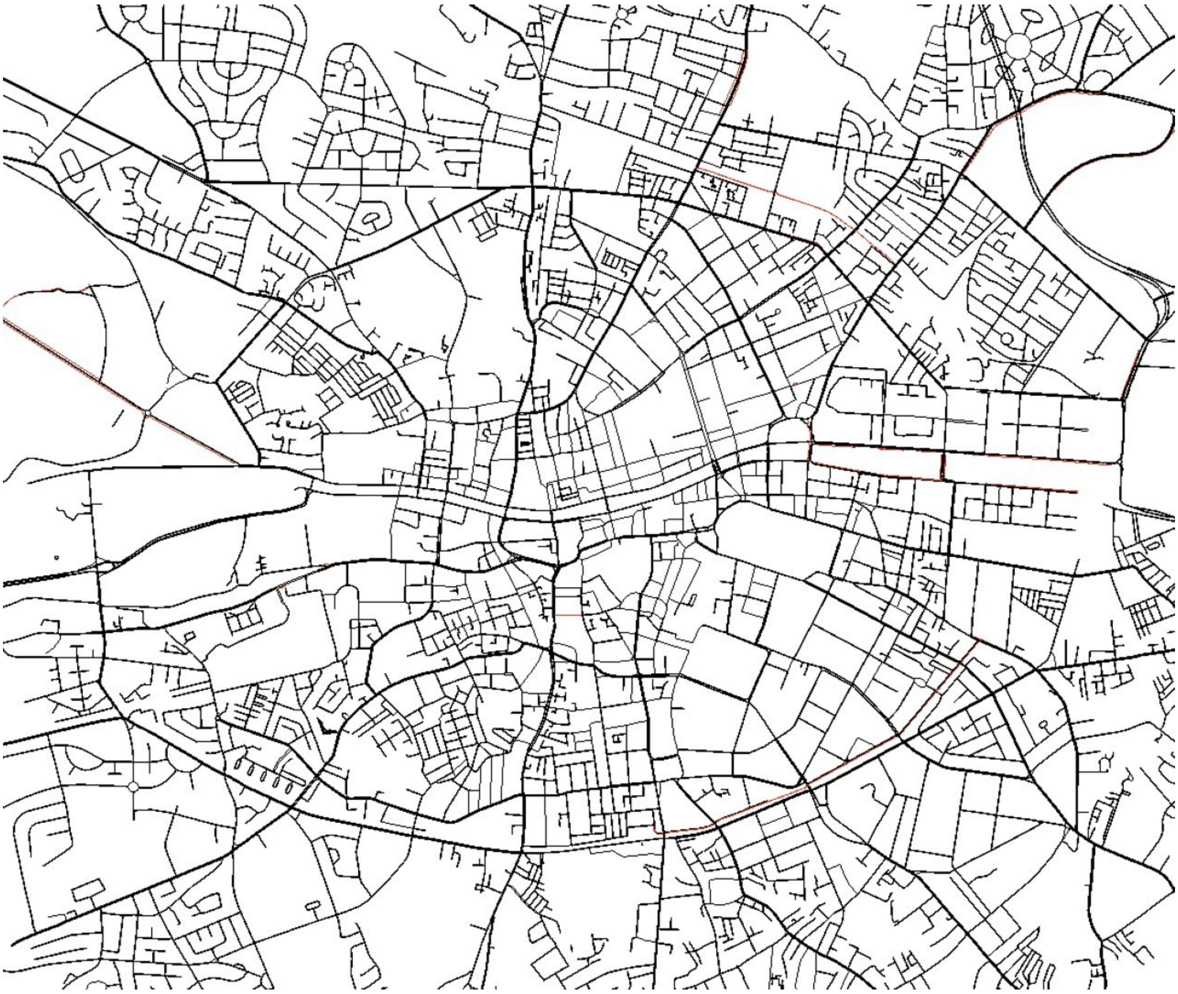


Figure 4.1: SUMO Converted OSM Map

4.2 Route Generation

SUMO is a microscopic simulator as discussed in 3.1.1. Microscopic simulators allow for individual vehicle simulation. SUMO supplies tools for trip and route generation for each vehicle. A python script for generating random trips is available. The script can also take parameters for specific start locations, the time to insert the vehicle into the simulation at, and the final destination of the routes.

4.2.1 Trips

Trips are defined as the start and end location of a vehicle. The random trips script is used to generate vehicles' random destinations. The script is a tool supplied by SUMO. Shown below is an example command of the creation of trips starting from Amiens Street.

> python /sumo/tools/randomTrips.py –trip-attributes="departLane="-4925959" -n net.net.xml -b 0 -e 3600 -p 3.07955518 -o ./amiensSt.xml

The depart lane attribute is the SUMO road identifier for Amiens Street. The .net.xml file is the road network file of Dublin. -b and -e indicate the start and end time of the simulation; this is used if using SUMO as the standalone simulator. However, in this case, VEINS itself redefines the simulation time when the VEINS simulation starts.

-p is the period in which vehicles are inserted into the simulation. The value for -p is calculated as follows. From the traffic flow data acquired from DCC, given that 1,169 vehicles head inbound via Amiens Street in one particular hour. By dividing an hour of simulation time, 3600, by a number of vehicles inbound, the period interval of when a car should be inserted into the simulation can be calculated. In this case, 3600/1169 would equate to inserting a vehicle every 3.07955518 simulation time.

For each route mentioned in section 3.2.2, random trips are created. Each route is outputted into a .xml file for further use in route generation.

4.2.2 Routes

Routes are generated with DUAROUTER, a SUMO tool that uses Dijkstra's Shortest Path Algorithm by default to compute the shortest route from the start and end location of a vehicle (*DUAROUTER*, 2017). Listed below is the command for route generation, with the trip files generated in section 4.2.1.

> duarouter -n net.net.xml –ignore-errors true –trip-files "./amiensSt.xml, ./constitution-Hill.xml, ..." -o routes.rou.xml

The road network file is included via the “-n” parameter. Errors occur when DUAROUTER is unable to find a path for a single trip within a trip file. This is suppressed by the “ignore-errors” parameter. The trip files are included after the “trip-files” attribute, and an output file is referenced.

The result is a SUMO readable route file that details each vehicles’ routes.

4.3 Simulation Data

Various data is needed for the simulation to work. Most of the data is manually acquired through SUMO Graphical User Interface (GUI) or translated and formatted from datasets acquired online. Section 3.2 details the data that have been acquired from external sources. In this section, a list is compiled of the formatted datasets that the simulation interacts with directly. An explanation of the data, as well as their purpose within the simulation, is also included.

To note: There are minor differences between SUMO coordinates and OMNeT++ coordinates. More specifically, the origin for the SUMO coordinate plane is in the top left corner, while the origin of OMNeT++ coordinates is on the bottom left corner. In the succeeding sections, there are references to both OMNeT++ and SUMO coordinates. VEINS supplies a function that allows for SUMO to OMNeT++ coordinate conversions and it is often used during and before the simulation.

4.3.1 Parking Lot

OMNeT++ Coordinates

Explanation OMNeT++ coordinates of each parking lot. The coordinates are initially obtained through the SUMO GUI and converted to OMNeT++ coordinates with a coordinate conversion function supplied by VEINS. This is done separately from the simulation process. The conversion took place pre-implementation and saved to a file for further use.

Purpose OMNeT++ coordinates of each parking lot are used to calculate the closest parking lot to a vehicles’ final destination.

SUMO Lane IDs

Explanation SUMO lane IDs for each parking lot. The lane IDs are obtained through SUMO GUI.

Purpose The parking lot lane ID is where each parking lot is situated in the SUMO road network. The lane ID is required to route a vehicle to the road that the parking lot is located. Additionally, it is the only accepted parameter for the vehicle routing function.

Capacity Data

Explanation The data includes the capacities of each parking lot. The process of acquiring this data is explained in section 3.2.1.

Purpose The parking lot capacities are used to calculate the percentage of available spaces of a particular parking lot during the simulation.

Vacancy Data

Explanation Dublin parking lot data is obtained as explained in section 3.2.3. The data includes Dublin parking lot vacancies at a particular time.

Purpose Dublin parking lot vacancy data is used to populate the parking lot spaces upon simulation initialization.

4.3.2 On-Street Parking

OMNeT++ Coordinates

Explanation OMNeT++ converted coordinates of each on-street parking location. The dataset is obtained through the VEINS supplied SUMO to OMNeT++ coordinate conversion function.

Purpose Used to calculate the distances between a vehicles' final destination to the on-street parking locations.

SUMO Lane ID

Explanation The SUMO lane ID for each on-street parking location. The lane IDs are obtained through the SUMO GUI.

Purpose The SUMO lane ID is used to route the vehicles to the location of the on-street parking location.

Capacity Data

Explanation The on-street parking capacities. The process of acquiring the data is explained in section 3.2.1

Purpose On-street capacities are used to calculate the percentage of available spaces for a specific on-street parking location during the simulation.

Parking Times

Explanation The parking duration of drivers. The dataset is obtained through ParkingTag as explained in section 3.2.4.

Purpose The parking duration of a driver is used to assign the wait time for a vehicle after it has parked during the simulation.

4.3.3 Other

Final Destination Sectors

Explanation A finite list of the final destinations that the vehicles randomly choose during the simulation.

Purpose The reason behind this is to localise the destination to a set region within inner city Dublin.

All SUMO Lanes and Coordinates

Explanation This is a dataset of the SUMO lane ID and the SUMO coordinate of each road within the Dublin road network. In other words, it is a subset of the road network file generated through NETCONVERT mentioned in section 4.1.1.

Purpose The purpose of this dataset stems from the dataset of destination sectors. Despite the localised randomness of the destination sectors, there was a need for more granular destinations for each vehicle within the destination sectors defined. The SUMO coordinates of a particular road are required to calculate the relative distance to the final destination sector, and the SUMO lane ID is used to assign the vehicle to the location if the destination criteria hold true. This is explained in detail in section 4.4.2.

Exit Lane ID

Explanation A finite list of the exit lane IDs. The lane IDs are chosen near the points where the vehicles enter.

Purpose The vehicles' route is destined for a randomly selected exit location. The lane ID is used after a vehicles' parking duration is up.

4.4 VANET Modelling

In this section, the main implementation part of the VANET smart parking simulation is explained. This section is split into three parts, the initialisation phase of the simulation is discussed in section 4.4.1. Section 4.4.2 explains each vehicles' initialisation upon entering the simulation. Finally, section 4.4.3 details the actions of the simulation at every time step.

4.4.1 Simulation Initialisation

The simulation initialization stage involves setting static variables for the duration of the simulation. This includes the allocation for all parking area capacities as well as the allocation of lane identifiers for parking lots. The simulation initialization stage is run once per simulation.

Assign Parking Area Capacities

Parking space capacities are used to calculate the remaining percentage of spaces left in a parking area during the simulation process. This involves both on-street and parking lot occupancy rates. A dedicated global vector is used to store each parking area capacity. In this way, each vehicle entering the simulation will be able to access the variable instead of accessing the parking space capacities file every time.

4.4.2 Vehicle Initialisation

Upon initialization, a vehicle is assigned a function for the duration of the simulation. The initial step is to determine whether or not the vehicle is destined to park. A random variable is introduced to determine whether the vehicle is driving into the city to park, or passing through the city. The latter is to simulate traffic flow within the city. When a vehicle is destined to park, it must determine whether they seek an on-street parking space or to park in a parking lot. This is determined through the use of another random variable.

Population of Parking Area Spaces

A local copy of the parking space availability of both on-street and parking lots are kept in each vehicle. In the initial setup, vehicles' parking lot data is updated with the data obtained through the

DCC website as described in section 3.2.3. On-street parking spaces are padded with spaces. The default setting for padding on-street parking spaces is set at 95%.

Setting Vehicles' Final Destination

The initial design of the system used the random trip destinations generated in section 4.2.1. However, an issue occurred when vehicles' final destinations ended up at the edge of the map. This became a problem as vehicles would traverse across the map, then proceed to search for the closest parking areas. At times, the closest parking areas from the edge of the map would require the vehicles to drive back towards the city. This is not a realistic scenario. Thus a solution of localising the randomness is introduced. Destination sectors are introduced to narrow down the acceptable final destination regions within inner city Dublin.

Destination Sectors Destination sectors are manually defined areas of inner Dublin City. Destination sectors are introduced to localise the randomness of the destinations. The idea of destination sectors came about during implementation. Initially, the design included both RSU and sensors. The sensors acted as nodes that supplied information regarding the occupancy status of a particular parking spot. The sensors would relay the information to a RSU, and the RSU would relay information to vehicles within their administrative region. These administrative regions eventually turned into the destination sectors on figure 4.2. There are two main reasons as to why these sectors are chosen.

1. It covers all the on-street and parking lot areas that the simulation is concerned with. The areas covered represent the "yellow" and "red" zones as defined by DCC as shown in figure 3.1.
2. To distribute the number of parking areas that each sector oversees evenly. More importantly, that there is not one single sector that covers the majority of parking areas.

Figure 4.2 illustrates the defined destination sectors.

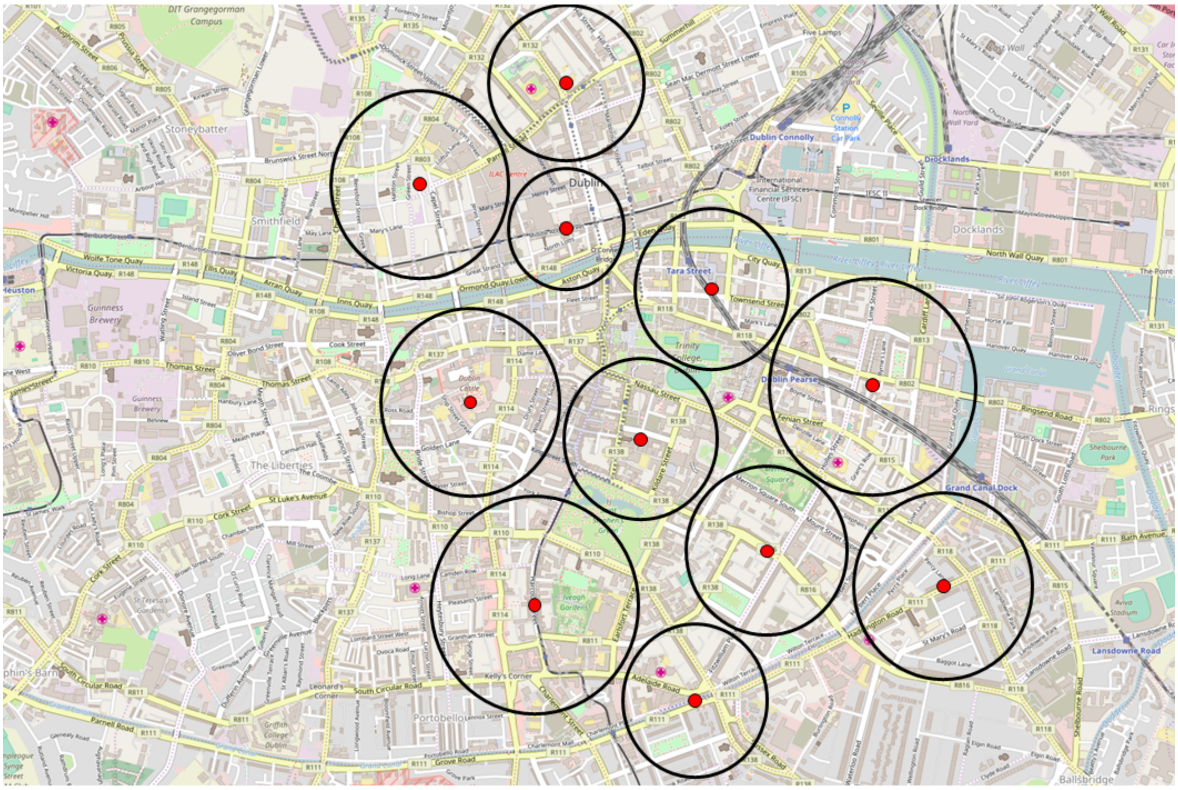


Figure 4.2: Destination Sectors

11 destination sectors are defined. Each represented by a red dot within the black circles in figure 4.2. The black circles represent the coverage of each sector. After the vehicle has randomly chosen one of the 11 destinations, the list of all known parking areas is iterated through to find the closest parking areas to the vehicles' destination. Whether a vehicle seeks an on-street parking location or in a parking lot is defined beforehand as mentioned at the beginning of section 4.4.2

However, this method of choosing the closest parking areas proved too deterministic. A vehicle choosing one of the red dots as seen in figure 4.2 would result in choosing identical closest parking areas for each vehicle travelling to that sector. Thus, a second pass is introduced to provide a more granular final destination allocator.

Granular Final Destination A vehicle assignment of a final destination from a finite list proved to be too deterministic. By picking a sector, the returned results for the closest parking areas within that sector will be identical to another vehicles' who chose that sector. Thus, a second pass is introduced to allow vehicle set a final destination that within the bounds of the destination sector that was initially chosen.

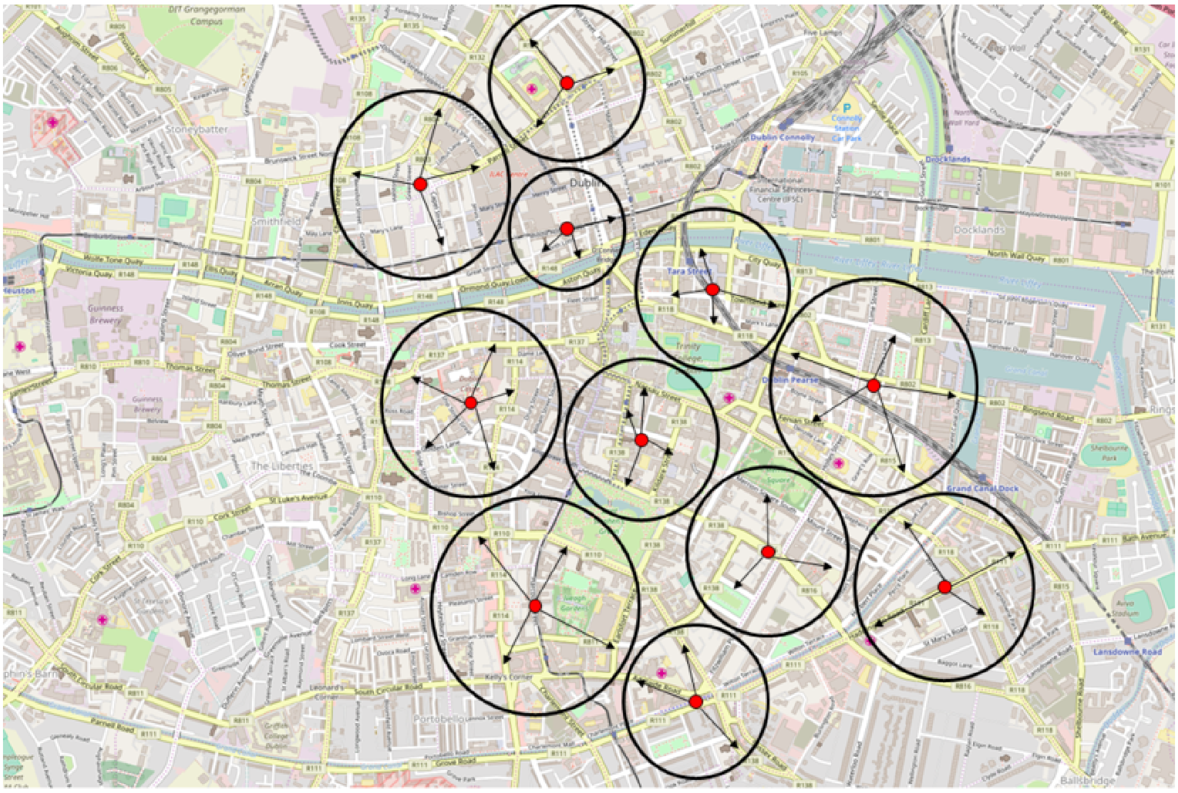


Figure 4.3: Granular Destinations

Figure 4.3 illustrates an example of the granular destinations that vehicles could discover. All granular destinations are checked whether they lie within the bounds of the sectors.

Finding Closest Parking Areas

After a final destination for the vehicle is determined, a list of the closest parking areas relative to the vehicles' destination must be found. The process is as follows:

1. Acknowledge if the vehicle is destined for an on-street parking space or a parking lot.

2. Using the distance formula, calculate the distances to all parking areas from the vehicles' final destination.

3. When calculating the distances between the parking areas and the destination, query the vehicles' local copy of parking space availability for parking areas greater than 95% full.

4. If the parking areas are greater than 95% full, it is not likely that they will arrive at that location and find a vacant parking space. Thus, these parking areas are discarded and not included in the resultant list.

5. Store the parking locations that are less than 95% full in a list.

6. Sort the list by ascending order so that the closest parking area is at the start of the list.

7. Trim the list and return the first ten parking areas.

8. The vehicle is now able to traverse through a list of the closest parking areas relative to their final destination. This resultant list also factors in the knowledge of parking space vacancy rates of the parking areas.

At this point, the vehicle can plan its route towards the closest parking area to their destination. Upon arrival, the vehicle increments its local table of parking spaces and broadcasts this update to all vehicles in its vicinity. If the parking area is full upon arrival, the vehicle re-routes to the next closest parking area on their list.

4.4.3 At Every Time Step

This section explains what occurs at every time step of the simulation. Each vehicle does the following at every time step:

1. A vehicle checks if they have arrived at their destined parking location. This is done simply by checking that the road that they are currently on equals to their final destinations' road identifier. If the vehicle has arrived at their final destination, then the parking space of their local parking tracker is incremented. An update message is broadcasted to other vehicles in their vicinity. The simulation time of this update is also included in this message so that on receipt, other vehicles may update their local copies if their local copies are outdated.

2. If they are not parked, then a message containing information regarding parking space availability is sent out. More specifically, this message contains their local parking area availability data as well as the simulation time on which it was updated. When a vehicle receives a message, it inspects the messages last updated time and updates its local copy of parking space availabilities accordingly.

3. A table for parked vehicles is checked. A detailed explanation of this is in section 4.4.4.

This concludes the explanation of the occurrences at every time step.

4.4.4 Parking Duration

A small issue was discovered during the implementation phase of the simulation. SUMO removes the vehicle from the simulation when the vehicle has reached the end of its route. In other terms, the vehicles are taken out of the simulation upon reaching its final destination. This became an issue as vehicles would take up the parking space indefinitely.

The solution involves keeping a list of the parking areas that the vehicles are parked, as well as the parking duration of the vehicle. At every time step, the list is checked for vehicles that have stayed for the parking duration time. When a parking duration is up, a vehicle is inserted into the simulation in the location that the previous vehicle was removed. The vehicle waits for an update on parking space availability from other vehicles. Once it receives an updated version of the parking space availabilities, the vehicle decrements its parking spot from its local copy and broadcasts the message to vehicles within the vicinity.

4.4.5 Exit Route Planning

Vehicles are destined to exit after their parking duration is up. An exit road is chosen randomly from a finite list. This is to simulate traffic heading outbounds as well as notifying vehicles in their vicinity that the parking space is now vacant.

4.4.6 Baseline

For the baseline simulation scenario, the inter-vehicle communication functions are removed. Vehicles define a final destination the same way as in the VANET model. A baseline vehicle travels to the closest parking area to their final destination and checks if there are any spaces available only when they arrive at the parking area. If the parking area is full, they iterate to the next closest parking are to their final destination. This emulates the current real world parking situation where inter-vehicular communications are not available.

Chapter 5

Evaluation

In this section, the results obtained from the simulation efforts are analysed. VEINS includes an emission model for calculating the emissions per vehicle during the simulation progress. The emissions are based on this study (Cappiello et al., 2002). The study was performed on two specific vehicles, a 1994 Dodge Spirit and a 1992 Suzuki Swift. The emissions from this study are extracted and integrated into the emissions model by VEINS. This emissions model is used for the output of the simulations in this dissertation.

The evaluation process takes two runs. One for the baseline and the second with a VANET smart parking system.

5.1 Limitations

The main limitation to the evaluation of the simulation is the computing power required to complete a simulation run. Numerous computers were used over the course of this dissertation. In this section, a timeline of the process of running the simulations and their limitations is explained.

Initially, a personal MacBook Pro was used. VMWare allowed the installation of Ubuntu 16.04. SUMO, VEINS and OMNeT++ was installed on the virtual machine. However, the MacBook Pro began exhibiting random shut downs. The random shut downs persisted, attempts were made to try and come to a resolution to the problem, but to no avail.

University computers in the computer science labs were then used for the simulations. However, estimations made for the duration of one complete run of simulations was assumed to be much lower. An attempt was made to scale down all the data; this included the parking spaces available, the number of vehicles inserted into the simulation as well as the parking duration of vehicles. Attempts were also made to run the simulation without the simulators' GUI and through the Command Line Interface (CLI). However, an estimation of the simulation duration to complete exceeded three weeks.

2 University VMs were then acquired to run the simulations. The VMs had to be set up and Ubuntu, along with SUMO, VEINS and OMNeT++ were installed on them. All simulations were run from the CLI. A list of the specifications of each machine used is outlined in section 5.3.

5.2 Simulation Data

In this section, the data loaded into the simulation runs are defined in tables 5.1 and 5.2.

In table 5.1, the parking lot spaces recorded on the *27th of February 2017 at 9:00am* are shown. The occupied spaces column is used to populate the parking lot tables in the simulation.

Parking Lot	Available Spaces	Total	Occupied
Parnell	168	500	332
ILAC	940	1000	60
Jervis	741	750	9
Arnotts	298	500	202
Marlboro	357	567	210
Abbey	274	340	66
Thomas Street	217	220	3
Christchurch	11	212	223
Setanta	35	145	110
Dawson	183	370	187
Trinity Street	249	252	3
Stephens Green	779	1127	348
Drury	367	465	98
Brown Thomas	357	380	23

Table 5.1: Parking Lot Data in Simulation

In table 5.2, traffic flow data on the *29th of April 2016 at 9:00am* are shown. The *period* columns indicate the rate at which vehicles are inserted into the simulation for that specific street. The percentages indicate the scaled down rate. 0% period indicates that there is no scaling, whereas 90% indicates that it is scaled down by 90%. Taking Amiens Street as an example, a count of 1,169 vehicles per hour is recorded. When there is no scaling, this equates to inserting a single vehicle every 3.08 simulation time. When the simulation is scaled at 90%, then a single vehicle is inserted every 30.80 simulation time.

Street	Traffic Flows	Period (0%)	Period (50%)	Period (90%)
Amiens Street	1169	3.08	6.16	30.80
Constitution Hill	647	5.56	18.70	55.47
East Wall Road	1593	2.26	4.52	22.60
High Street	613	5.87	11.75	58.73
Mount Street Lower	775	4.65	9.29	46.45
Parnell Square East	1031	3.49	6.98	34.92
Patrick Street	737	4.88	9.77	48.85
Pearse Street	520	6.92	13.85	69.23
Stephen's Green East	1344	2.68	5.36	26.79
Victoria Quay	968	3.72	7.44	37.19
Wexford Street	385	9.35	18.70	93.51

Table 5.2: Traffic Flow Data in Simulation

5.3 Simulation - Computer Specifications

Listed below are the computer system specifications of each of the mentioned machines used:

MacBook Pro

Processor 2.6GHz i7-4960HQ (8 cores)

RAM 16GB

Dell Optiplex 9020

Processor 3.6GHz i7-4790 (8 cores)

RAM 8GB

University VMs (x2)

Please note: 2 VMs were requested, the specifications listed below is for a single VM.

Processor Dual CPU "Intel(R) Xeon(R) CPU X5650 @2.67GHz"

RAM Dell R410 1U Servers with 32GB Ram

5.4 Simulation Results

In this section, the simulation results are shown. Three simulations are run in total. The first simulation run is scaled by 50% on the *Dell Optiplex 9020* college computers. The second simulation run is scaled by 50% on the *university VMs*. The third simulation run is scaled by 90% on *university VMs*. Only the baseline of simulation 3 managed to reach 100%. The list below is included in all scenarios of each simulation. The list provides an explanation of each statistic.

- Progress: The progress that the simulation made until it was terminated
- Time taken: The time the simulation ran for
- Events processed: The number of events processed
- Machine: The simulation machine
- Traffic Data: The date and time of the traffic data
- Parking Lot Data: The date and time of the parking lot data
- On-Street Initial Population: Initial population of on-street parking spaces
- Parking Duration Scale: Percentage indicating by how much parking space duration times are scaled down by

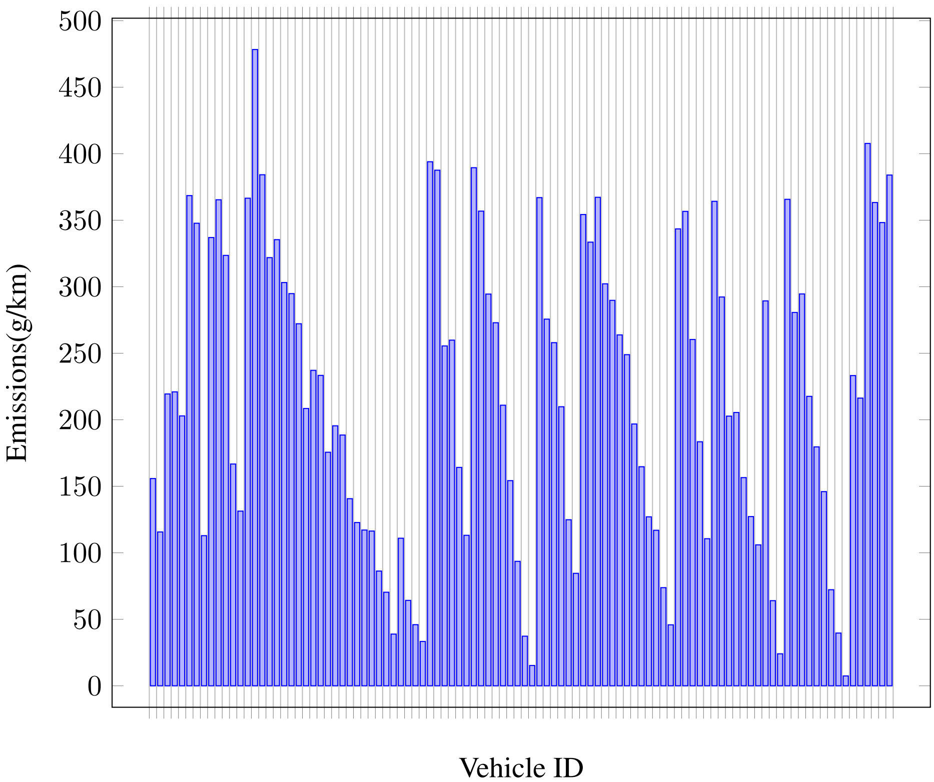
One of the evaluation metrics for this simulation is to compare the number of vehicles that had to re-route due to a parking space being taken. This evaluation metric is only outputted when simulations can reach 100%. Each simulation is set to run for 1800 simulation time, which equates to 30 minutes in real time.

5.4.1 Simulation run #1

In simulation #1, all the relevant data is scaled by 50%.

Baseline

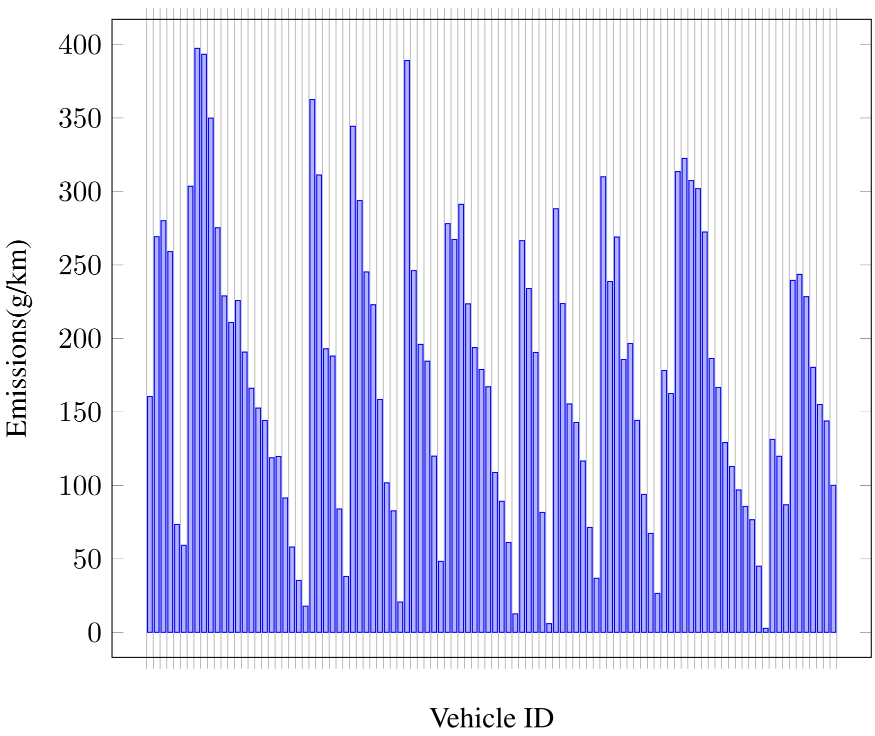
- Progress: N/A%
- Time taken: 2 days 18 hours
- Events processed: N/A
- Machine: Dell Optiplex 9020
- Traffic Data: 29th April 2016 - 9:00am
- Parking Lot Data: 27th February 2017 - 9:00am
- On-Street Initial Population: 95% Occupied
- Parking Duration Scale: 50%



Average Emissions: 218.711648476g/km

VANET

- Progress: N/A%
- Time taken: 3 days 15 hours
- Events processed: N/A
- Machine: Dell Optiplex 9020
- Traffic Data: 29th April 2016 - 9:00am
- Parking Lot Data: 27th February 2017 - 9:00am
- On-Street Initial Population: 95% Occupied
- Parking Duration Scale: 50%



Average Emissions: 175.389672828g/km

Conclusion

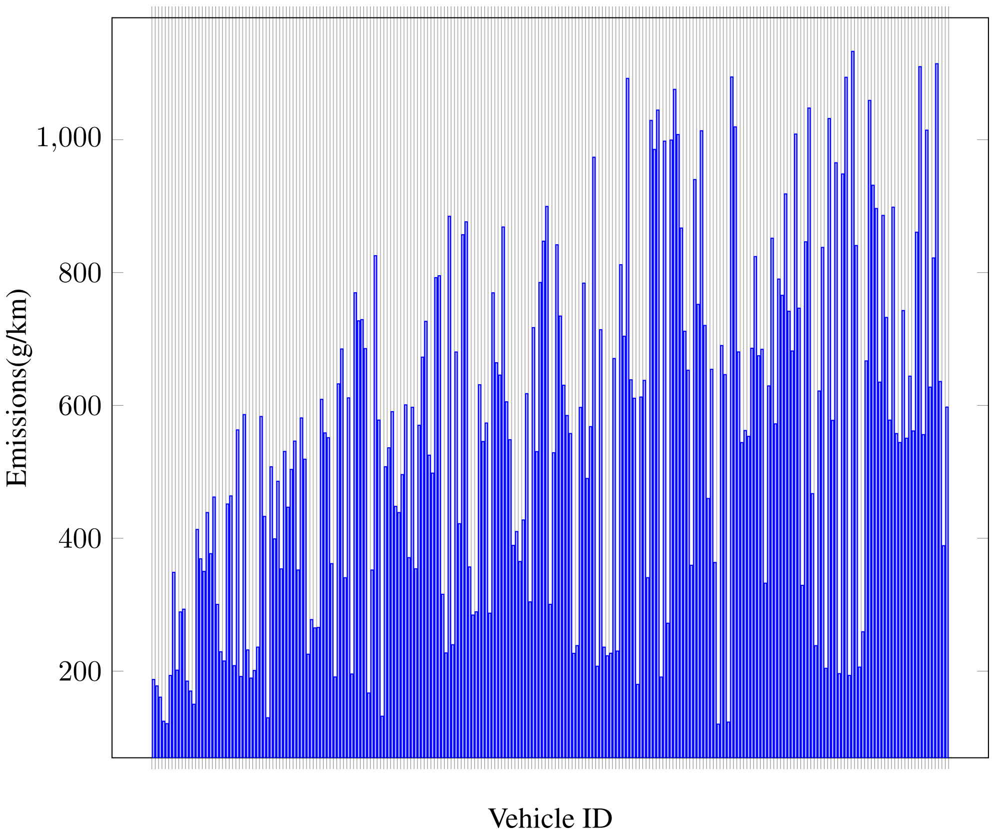
Both graphs of simulation #1 show the first 103 vehicles that entered their corresponding simulation. Within the first 103 vehicles range, the VANET model resulted in fewer emissions. However, neither simulations were able to finish. Thus the results are not comparable.

5.4.2 Simulation run #2

In simulation #2, all the relevant data is scaled by 50%.

Baseline

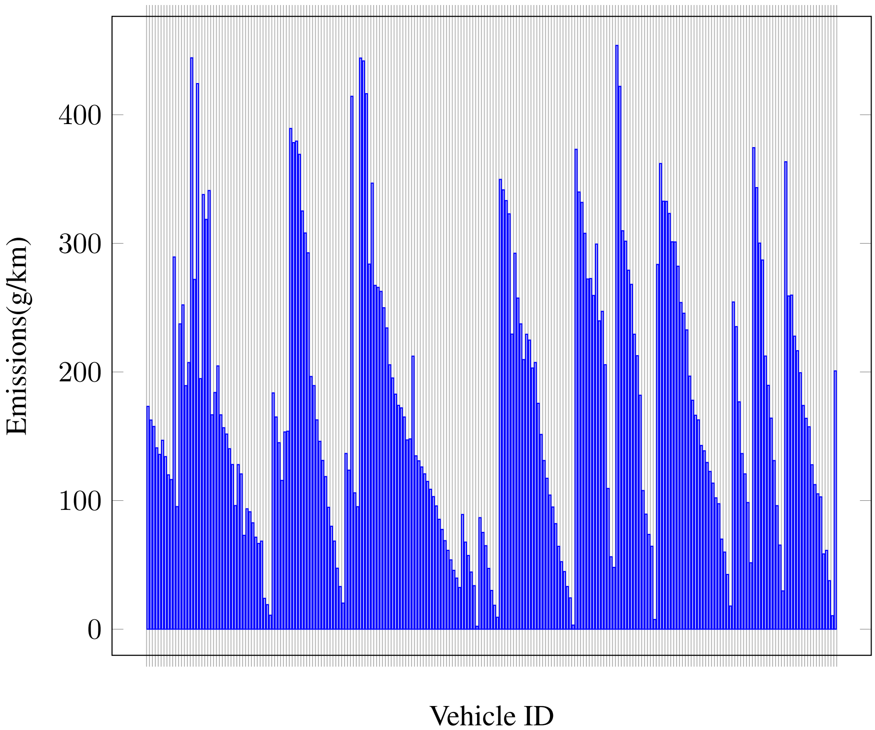
- Progress: 53%
- Time taken: 9 days 12 hours
- Events processed: ~400 million
- Machine: University VM
- Traffic Data: 29th April 2016 - 9:00am
- Parking Lot Data: 27th February 2017 - 9:00am
- On-Street Initial Population: 95% Occupied
- Parking Duration Scale: 50%



Average Emissions: 561.198626609g/km

VANET

- Progress: 10%
- Time taken: 4 days 9 hours
- Events processed: ~17 million
- Machine: University VM
- Traffic Data: 29th April 2016 - 9:00am
- Parking Lot Data: 27th February 2017 - 9:00am
- On-Street Initial Population: 95% Occupied
- Parking Duration Scale: 50%



Average Emissions: 175.149905231g/km

Conclusion

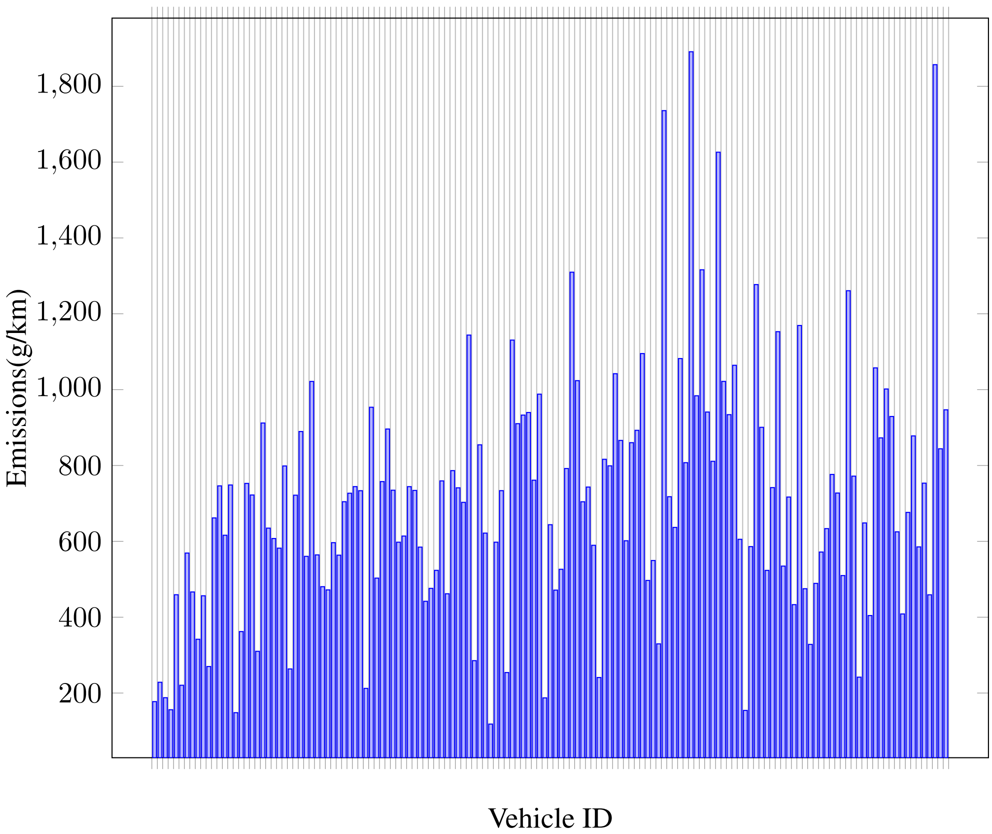
The gap between baseline and VANET models in simulation run #two are incomparable. The process took too long, and a decision was made to terminate the simulations. The simulation is then re-scaled and repeated for simulation #3.

5.4.3 Simulation run #3

In simulation #3, all the relevant data is scaled by 90%

Baseline

- Progress: 100%
- Time taken: 1d 10hr
- Events processed: ~7 million
- Machine: University VM
- Traffic Data: 29th April 2016 - 9:00am
- Parking Lot Data: 27th February 2017 - 9:00am
- On-Street Initial Population: 95% Occupied
- Parking Duration Scale: 90%

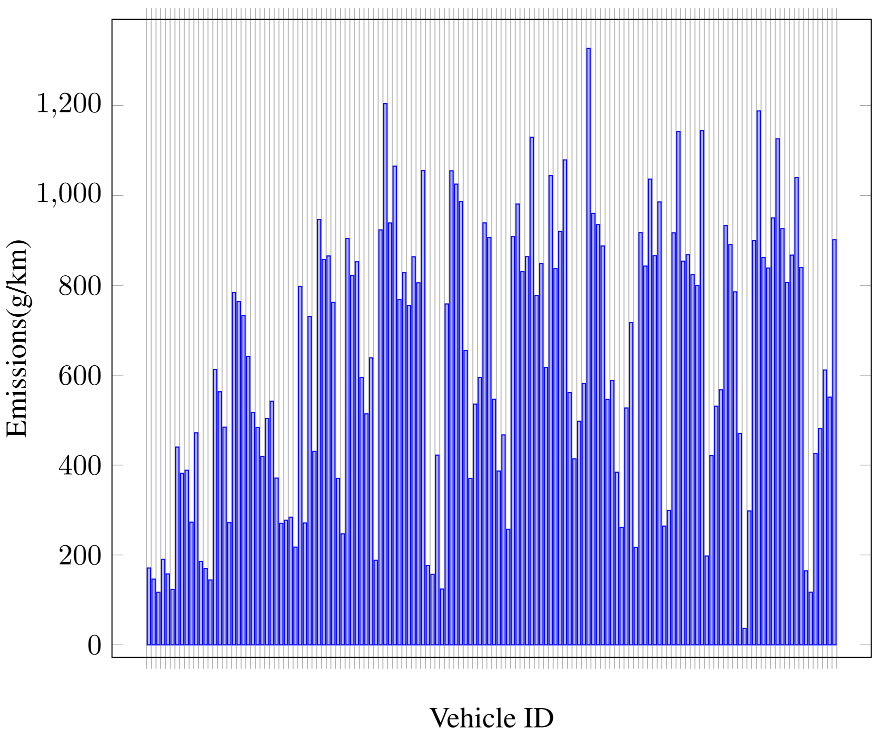


Average Emissions: 703.977383507g/km

Number of vehicles that had to re-route: 76 vehicles

VANET

- Progress: 100%
- Time taken: 1d 6hr
- Events processed: ~10 million
- Machine: University VM
- Traffic Data: 29th April 2016 - 9:00am
- Parking Lot Data: 27th February 2017 - 9:00am
- On-Street Initial Population: 95% Occupied
- Parking Duration Scale: 90%



Average Emissions: 639.881142556g/km
Number of vehicle that had to re-route: 64 vehicles

Conclusion

The results show the 146 vehicles, with their completed time through the simulation. The average emissions produced in the VANET model is observed to be less than that of the baseline model. As well as this, the number of vehicles that had to be re-routed is also less. Despite the fact that the results exhibit fewer vehicles required to re-route as well as fewer emissions produced, it should not be concluded that VANET is the solution to smart parking. Additional runs should be simulated at different traffic and parking levels.

The average of the baseline model is higher, with a handful of vehicles exceeding 1,400g/km. This may be due to the greater number of vehicles that had to re-route.

Additionally, it should be noted that the traffic data and parking lot data are on different dates. This is because the parking lot was not being recorded in 2016.

The Dublin real time parking lot site frequently contains parking lot that returns no data. Thus the dataset that I have accumulated over the six months, starting January 2017, contains several blank fields. I tried my best to find an hour that contains the most amount of data. An hours worth of data is split into 5-minute intervals. There were some gaps in the data, so I interpolated values to obtain a full set of parking data.

Chapter 6

Conclusion

6.1 Future Works

The primary considerations for future works regarding this dissertation are to undergo more simulation efforts. There are three main areas where additional work should be put into, these are explained in the sections below.

Evaluation on Different Dates

Identical parking and traffic data are used for all three simulations in this dissertation. For future works, evaluation should be done on different dates to avoid biased results. This consideration of unbiased results was already acknowledged as parking and traffic data was acquired externally. The traffic and parking datasets acquired externally span the course of one year, from January 2016 to December 2016.

An initial plan was to simulate more than one date. However, there was a naive expectation that the simulations would run within a week.

Evaluation Averaging

I realise that I have designed the simulation in a non-deterministic manner. The inputs to the simulation are constant. However, vehicles decide their final destinations in a non-deterministic way. For this reason, the evaluation comparison between one specific VANET model with a baseline model is not entirely accurate.

In future works, along with additional evaluations on different dates as outlined above. An aggregation of each VANET simulation scenario can be averaged and compared to an average of all the baseline simulation scenarios.

Simulation Optimisation

The computational power required to run the simulations is very high. To define a region of interest to simulate is regarded as one of the top solutions in easing the computations required for a simulation to run. However, given that this dissertation is based on Dublin Inner City, it is not possible to make the simulation region of interest any more granular.

In my design of the VANET model, the vehicles are inserted into the simulation solely from roads. A future alteration could be to insert vehicles from parking areas too. In the current implementation, it takes an extended period to simulate the first vehicle to leave a parking spot. This is due to vehicles only being inserted from the roads. This could be avoided; the simulation could start when a vehicle leaves a parking spot by inserting vehicles from parking areas from the beginning. In this way, the initial process of waiting for vehicles to fill the city can be avoided.

6.2 Reflection

Smart parking technology has its limits. The cost of deployment for smart parking systems can be substantial, especially when parking sensors are required to be installed in every known parking spot location. Additionally, a system that oversees these sensors is also required for the deployment of a such a system. The undeniable costs of deployment may deter governments from introducing this system into cities. This is part of the motivation behind exploring various parking space sensing technologies to compile an updated list of alternative sensing solutions.

Sensing parking spaces are one side of the coin, the other side is to introduce a robust system to disseminate the data efficiently and effectively. One of the core related works examined in section 2.2.2 forms the basis of exploring futuristic solutions for data dissemination. Notably, VANET is an increasingly popular field. With the recent introduction of autonomous vehicles, it would be highly unlikely that VANET would not have a major role in the development of self-driving vehicles in the future.

Concerns are raised regarding the computational power required on OBUs of vehicles. This specific field is only starting to mature, as the considerations put forward regarding inter-vehicular communications has not yet been made a reality. Despite this, considerations have already been explored regarding how a VANET architecture should be formed. The questions raised is, whether inter-vehicular communications should be solely dedicated to vehicles on the road, or should RSUs act as gateways to a public cloud that serves information to vehicles that support networking, or should there be a hybrid cloud model to satisfy both ends as we head into uncharted territories.

As outlined in the introduction to this dissertation, main motivations to smart parking are to minimise drivers from cruising around looking for spaces. From an environmental perspective, this is vital to sustain good air quality in urban districts. The European Union (EU) have provided targets for the year 2020 for all EU members. One of those targets is a 20% reduction of non-emission trading scheme sector emissions on 2005 levels (Pereira et al., 2005). However, according to the Environmental Protection Agency (EPA) of Ireland (Gas & Projections, 2017), by 2020, Ireland is projected to be 4% - 6% below 2005 levels. This is very low in comparison to the requirement of 20% by 2020. Although it does not look hopeful for Ireland to reach its targets by then, it would help to contribute towards the goal in any way possible, achieved or not.

This concludes this dissertation. Thanks for reading.

References

Amato, G., Carrara, F., Falchi, F., Gennaro, C., Meghini, C., & Vairo, C. (2017). Deep learning for decentralized parking lot occupancy detection. *Expert Systems with Applications*, *72*, 327–334. doi: 10.1016/j.eswa.2016.10.055

ANPR SmartParking. (2017). Retrieved from `https://www.smartparking.com/automatic-number-plate-recognition-anpr`

Brezmes, T., Gorricho, J. L., & Cotrina, J. (2009). Activity recognition from accelerometer data on a mobile phone. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *5518 LNCS*(PART 2), 796–799. doi: 10.1007/978-3-642-02481-8{_}120

Cappiello, A., Chabini, I., Nam, E., Lue, A., & Zeid, A. (2002). A Statistical Model of Vehicle Emissions and Fuel Consumption. *Intelligent Transportation Systems, 2002. Proceedings.*(September), 801–809.

Cardiff SmartParking. (2017). Retrieved from `https://www.smartparking.com/keep-up-to-date/press-releases/cardiff-city-council-set-to-unveil-europe-s-first-citywide-deployment-of-bay-sensor-technology`

Cho, J., Park, J., Baek, U., Hwang, D., Choi, S., Kim, S., & Kim, K. (2016). Automatic parking system using background subtraction with CCTV environment international conference on control, automation and systems (ICCAS 2016). In *2016 16th international conference on control, automation and systems (iccas)* (pp. 1649–1652). doi: 10.1109/ICCAS.2016.7832520

CNR-EXT. (2017). Retrieved from `http://claudiotest.isti.cnr.it/park-datasets/CNR-EXT/models/`

CronTab Documentation. (2017). Retrieved from `https://help.ubuntu.com/community/CronHowto`

data.gov.ie — Ireland's open data portal. (2017). Retrieved from `https://data.gov.ie/data`

Dokur, O., Katkoori, S., & Elmehraz, N. (2016). Embedded system design of a real-time parking guidance system. In *2016 annual ieee systems conference (syscon)* (pp. 1–8). Retrieved from `http://ieeexplore.ieee.org/document/7490653/` doi: 10.1109/SYSCON.2016.7490653

DUAROUTER. (2017). Retrieved from `http://sumo.dlr.de/wiki/DUAROUTER`

Dublin Parking Zone Tariffs. (2017). Retrieved from `http://www.dsps.ie/zones_map.pdf`

Eltoweissy, M., Olariu, S., & Younis, M. (2010). Towards autonomous vehicular clouds: A position paper (Invited paper). *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering*, *49 LNICST*, 1–16. doi: 10.1007/978-3-642-17994-5{_}1

Gas, G., & Projections, E. (2017). *EPA 2017 GHG Emission Projections Report Ireland's Greenhouse Gas Emission Projections EPA 2017 GHG Emission Projections Report Overview of Ireland's Greenhouse Gas Emission Projections* (Tech. Rep. No. April). Retrieved from `http://www.epa.ie/pubs/reports/air/airemissions/ghgprojections/EPA_2017_GHG_Emission_Projections_Summary_Report.pdf`

Gavin, K. (2008). *Bay-Specific Parking Guidance Information System Installed At Dundrum Town Centre* (Tech. Rep.). Retrieved from `http://www.agkdisplays.com/wordpress/wp-content/uploads/2013/02/Dundrum-Article.pdf`

Gerla, M., Lee, E.-K., Pau, G., & Lee, U. (2014). Internet of vehicles: From intelligent grid to autonomous cars and vehicular clouds. *2014 IEEE World Forum on Internet of Things (WF-IoT)*, *46*, 241–246. doi: 10.1109/WF-IoT.2014.6803166

Guille, C., & Gross, G. (2009). A conceptual framework for the vehicle-to-grid (V2G) implementation. *Energy Policy*, *37*(11), 4379–4390. doi: 10.1016/j.enpol.2009.05.053

Gupta, S., & Upadhyaya, V. (2016). Automated vehicle detection using optical fiber communication. In *2016 ieee sensors* (pp. 1–3). doi: 10.1109/ICSENS.2016.7808495

Hussain, R., Son, J., Eun, H., Kim, S., & Oh, H. (2012). Rethinking Vehicular Communications: Merging VANET with cloud computing. *CloudCom 2012 - Proceedings: 2012 4th IEEE International Conference on Cloud Computing Technology and Science*, 606–609. doi: 10.1109/CloudCom.2012.6427481

JOSM. (2017). Retrieved from `https://josm.openstreetmap.de/`

Kianpisheh, A., Mustaffa, N., Limtrairut, P., & Keikhosrokiani, P. (2012). Smart Parking System (SPS) architecture using ultrasonic detector. *International Journal of Software Engineering and its Applications*, *6*(3), 51–58.

Kiess, W., Rybicki, J., & Mauve, M. (2007). On the nature of Inter-Vehicle Communication. *Communication in Distributed Systems (KiVS), 2007 ITG-GI Conference*, 1–10. Retrieved from `http://ieeexplore.ieee.org/xpl/articleDetails.jsp?tp=&arnumber=5755516`

Kopeck, J., & Domingue, J. (2012). PARKJAM: Crowdsourcing Parking Availability Information with Linked Data (Demo). *N/A*. doi: 10.1007/978-3-662-46641-4

Krajzewicz, D., Erdmann, J., Behrisch, M., & Bieker, L. (2012, 12). Recent Development and Applications of {SUMO - Simulation of Urban MObility}. *International Journal On Advances in Systems and Measurements*, *5*(3), 128–138.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet Classification with Deep Convolutional Neural Networks. *Advances In Neural Information Processing Systems*, 1–9. doi: http://dx.doi.org/10.1016/j.protcy.2014.09.007

Kuhn, T. S. (1970). *The Structure of Scientific Revolutions* (Vol. II) (No. 2). doi: 10.1119/1.1969660

Lee, S., Yoon, D., & Ghosh, A. (2008). Intelligent parking lot application using wireless sensor networks. *2008 International Symposium on Collaborative Technologies and Systems*, 48–57. doi: 10.1109/CTS.2008.4543911

Lin, X., Lu, R., Zhang, C., Zhu, H., Ho, P.-H., & Shen, X. (2008). Security in vehicular ad hoc networks. *IEEE Communications Magazine*, *46*(4), 88–95. Retrieved from `http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=4481346` doi: 10.1109/MCOM.2008.4481346

Mailing List for SUMO. (2017). Retrieved from `https://sourceforge.net/p/sumo/mailman/sumo-user/`

Mehmood, A., Ahmed, S. H., & Sarkar, M. (2017). *Cyber-Physical Systems in Vehicular Communications*. Springer. doi: 10.4018/978-1-5225-0773-4.ch015

Milanés, V., Villagrá, J., Godoy, J., Simó, J., Pérez, J., & Onieva, E. (2012). *An intelligent V2I-based traffic management system* (Vol. 13) (No. 1). doi: 10.1109/TITS.2011.2178839

Millard-Ball, A., Weinberger, R. R., & Hampshire, R. C. (2014). Is the curb 80% full or 20% empty? Assessing the impacts of San Francisco's parking pricing experiment. *Transportation Research*

Part A: Policy and Practice, *63*, 76–92. Retrieved from http://dx.doi.org/10.1016/j.tra.2014.02.016 doi: 10.1016/j.tra.2014.02.016

Miller, H. J., & Shaw, S.-L. (2001). *Geographic Information Systems for Transportation*. Oxford University Press.

Na, K., Kim, Y., & Cha, H. (2009). Acoustic sensor network-based parking lot surveillance system. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *5432 LNCS*, 247–262. doi: 10.1007/978-3-642-00224-3{_}16

Ono, S., Kagesawa, M., & Ikeuchi, K. (2002). A probe car for parking-vehicle detection by using laser range sensor. In *Intelligent vehicle symposium, 2002. ieee* (Vol. 2, pp. 322–327). doi: 10.1109/IVS.2002.1187972

Pala, Z., & Inanc, N. (2007). Smart parking applications using RFID technology. In *Rfid eurasia, 2007 1st annual* (pp. 1–3). doi: 10.1109/RFIDEURASIA.2007.4368108

Panayappan, R., & Trivedi, J. (2007). VANET-based approach for parking space availability. *Proceedings of the fourth ...*, 75–76. Retrieved from http://dl.acm.org/citation.cfm?id=1287763 doi: 10.1145/1287748.1287763

Parking Meter Dataset. (2017). Retrieved from https://data.gov.ie/dataset/parking-meters-location-tariffs-and-zones-in-dublin-city

ParkPnp. (2015). Retrieved from https://parkpnp.com/

Pereira, C. S., Luís, O., & Quelhas, G. (2005). *Overview of Europe 2020 targets* (Vol. 1; Tech. Rep. No. April).

PKLot. (2017). Retrieved from http://web.inf.ufpr.br/vri/news/parking-lot-database

RFID SmartParking. (2017). Retrieved from https://www.smartparking.com/technologies/rfid-solutions

Robert C. Hampshire. (2011). *Smart Parking.* Retrieved from http://eldigital.bcn.cat/es/barcelona-despliega-el-primer-smart-parking-en-las-corts_107139.html

Schlote, A., King, C., Crisostomi, E., & Shorten, R. (2014). *Delay-tolerant stochastic algorithms for parking space assignment* (Vol. 15) (No. 5). doi: 10.1109/TITS.2014.2304356

Scrapy - Python Crawler. (2017). Retrieved from https://scrapy.org/

Sensors SmartParking. (2017). SmartParking Limited. Retrieved from https://www.smartparking.com/technologies/in-ground-vehicle-detection-sensors

SFMTA. (2011). *San Francisco Park (SFPark).* Retrieved from http://sfpark.org/

Shoup, D. C. (2006). Cruising for parking. *Transport Policy*, *13*(6), 479–486. doi: 10.1016/j.tranpol.2006.05.005

Shriver, A. (2016). *Understanding the Block-Level Price Elasticity of On-Street Parking Demand : A Case Study of San Francisco ' s SFpark Project* (Doctoral dissertation). doi: 10.13140/RG.2.1.2046.8089

Sugiyamal, Y., Fukui, M., Kikuchi, M., Hasebe, K., Nakayama, A., Nishinari, K., ... Yukawa, S. (2008). Traffic jams without bottlenecks-experimental evidence for the physical mechanism of the formation of a jam. *New Journal of Physics*, *10*. doi: 10.1088/1367-2630/10/3/033001

SUMO. (2008). *NETCONVERT.* Retrieved from http://sumo.dlr.de/wiki/NETCONVERT

Suykens, J. A. K., & Vandewalle, J. (1999). Least Squares Support Vector Machine Classifiers. *Neural Processing Letters 9*, *9*(3), 293–300. doi: 10.1023/A:1018628609742

Ucar, S., Ergen, S. C., & Ozkasap, O. (2016, 12). Security vulnerabilities of IEEE 802.11p and visible light communication based platoon. In *2016 ieee vehicular networking conference vnc* (pp. 1–4). doi: 10.1109/VNC.2016.7835972

Varga, A., & Hornig, R. (2008). AN OVERVIEW OF THE OMNeT++ SIMULATION ENVIRONMENT. *Proceedings of the First International ICST Conference on Simulation Tools and Techniques for Communications Networks and Systems*. doi: 10.4108/ICST.SIMUTOOLS2008.3027

Verroios, V., Efstathiou, V., & Delis, A. (2011). *Reaching available public parking spaces in urban environments using ad hoc networking* (Vol. 1) (No. 1). Retrieved from http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=1443594 doi: 10.1109/MDM.2011.49

Villanueva, F. J., Villa, D., Santofimia, M. J., Barba, J., & Lopez, J. C. (2016). Crowdsensing smart city parking monitoring. *IEEE World Forum on Internet of Things, WF-IoT 2015 - Proceedings*, 751–756. doi: 10.1109/WF-IoT.2015.7389148

Wang, H., & He, W. (2011). A reservation-based smart parking system. *2011 IEEE Conference on Computer Communications Workshops, INFOCOM WKSHPS 2011*, 690–695. doi: 10.1109/INFCOMW.2011.5928901

Want, R. (2006). An Introduction to RFID. *IEEE CS and IEEE ComSoc*, 25–33.

Westminster SmartParking. (2013). Retrieved from `https://www.smartparking.com/keep-up-to-date/press-releases/smart-parking-secures-landmark-westminster-city-council-contract-for-its-real-time-bay-sensor-parking-solution`

Whaiduzzaman, M., Sookhak, M., Gani, A., & Buyya, R. (2014). A survey on vehicular cloud computing. *Journal of Network and Computer Applications*, *40*(1), 325–344. doi: 10.1016/j.jnca.2013.08.004

Xu, B., Wolfson, O., Yang, J., Stenneth, L., Yu, P. S., & Nelson, P. C. (2013). Real-time street parking availability estimation. In *Proceedings - ieee international conference on mobile data management* (Vol. 1, pp. 16–25). doi: 10.1109/MDM.2013.12

Appendix

Appendix A

On Friday, 29th April 2016. Each approach represents each route entering that junction.

Time	Approach 1	Approach 2	Approach 3	Approach 4	Approach 5	Approach 6
01:00	63	70	114	46	71	364
02:00	59	42	65	20	25	211
03:00	32	20	40	16	12	120
04:00	31	29	41	19	11	131
05:00	18	24	39	15	60	156
06:00	44	50	61	21	47	223
07:00	74	114	265	87	103	643
08:00	135	271	354	110	184	1054
09:00	150	348	341	82	169	1090
10:00	194	315	294	84	187	1074
11:00	155	252	285	63	166	921
12:00	149	248	282	81	163	923
13:00	156	265	331	90	156	998
14:00	171	255	288	90	161	965
15:00	139	280	325	81	178	1003
16:00	157	300	340	88	155	1040
17:00	207	272	310	94	150	1033
18:00	207	296	289	88	115	995
19:00	146	216	341	89	118	910
20:00	163	221	304	79	154	921
21:00	161	172	232	72	159	796
22:00	133	127	190	54	142	646
23:00	113	112	147	63	129	564
24:00	91	87	145	55	93	471

Appendix B

Spaces available on Monday, 27^{th} of February 2017. Each row separated in two minute intervals.

PN	IL	JR	AR	MA	AB	TH	CC	SE	DW	TR	GR	DR	BT
168	940	741	298	357	274	217	115	35	183	255	779	367	357
161	936	733	296	353	274	217	111	34	180	255	776	365	355
161	936	733	296	353	274	217	111	33	180	255	776	365	355
161	936	733	296	353	274	217	111	32	180	255	776	365	355
147	933	722	294	347	269	216	107	31	173	247	759	359	353
138	930	716	293	343	266	215	107	30	172	245	755	353	353
138	930	716	293	343	266	215	107	30	172	245	755	353	353
138	930	716	293	343	266	215	107	30	172	245	755	353	353
129	920	707	292	338	262	215	103	29	177	242	753	350	351
129	920	707	292	338	262	215	103	29	177	242	752	350	351
129	920	707	292	338	262	215	103	29	177	242	746	350	351
121	918	699	291	336	261	215	100	28	178	238	743	346	350
121	918	699	291	336	261	215	100	28	178	238	732	346	350
112	910	691	288	330	257	212	99	28	178	236	728	340	349
112	910	691	288	330	257	212	99	28	178	236	728	340	349
112	910	691	288	330	257	212	99	28	178	236	728	340	349
105	909	686	287	325	256	211	96	24	177	230	717	339	348
105	909	686	287	325	256	211	96	24	177	230	717	339	348
105	909	686	287	325	256	211	96	24	177	230	717	339	348
98	901	681	285	318	257	209	92	21	174	228	709	335	347
91	895	671	283	308	254	208	90	19	171	224	699	334	346
91	895	671	283	308	254	208	90	19	171	224	699	334	346
91	895	671	283	308	254	208	90	19	171	224	699	334	346
83	885	662	279	304	249	208	86	18	165	223	688	326	343
83	885	662	279	304	249	208	86	18	165	223	688	326	343
83	885	662	279	304	249	208	86	18	165	223	688	326	343
68	873	650	279	300	247	208	85	13	155	223	682	314	341
68	873	650	279	300	247	208	85	13	155	223	675	314	341
64	866	647	275	295	247	208	83	10	153	218	669	311	340
64	866	647	275	295	247	208	83	10	153	218	669	311	340

PN: Parnell, IL: ILAC, JR: Jervis, AR: Arnotts, MA: Marlborough, AB: Abbey, TH: Thomas, CC: Christchurch, SE: Setanta, DW: Dawson, TR: Trinity, GR: RCS, DR: Drury, BT: Brown Thomas

Appendix C

Date	Amount	Zone	Customer
15/11/2016 11:50	1.60	Red	Driver 1
07/03/2016 13:04	4.35	Yellow	Driver 5
21/06/2016 13:23	1.45	Yellow	Driver 6
16/11/2016 08:58	3.87	Yellow	Driver 8
11/11/2016 12:51	2.00	Red	Driver 10
19/01/2016 15:20	1.45	Yellow	Driver 11
30/01/2016 15:19	2.42	Yellow	Driver 12
07/01/2016 11:40	1.20	Red	Driver 13
21/06/2016 11:47	1.60	Red	Driver 13
14/01/2016 12:47	1.69	Yellow	Driver 13
30/03/2016 12:59	0.97	Yellow	Driver 13
25/05/2016 10:04	1.93	Yellow	Driver 13
25/07/2016 11:01	2.90	Yellow	Driver 13
24/10/2016 11:18	1.93	Yellow	Driver 13
22/11/2016 12:51	1.45	Yellow	Driver 13
06/01/2016 10:57	1.45	Yellow	Driver 14
14/09/2016 11:51	2.90	Yellow	Driver 14
24/05/2016 14:04	1.21	Yellow	Driver 15
08/10/2016 14:34	0.97	Yellow	Driver 16
24/10/2016 13:52	2.17	Yellow	Driver 17
24/02/2016 12:21	2.40	Red	Driver 21
01/06/2016 15:00	1.20	Red	Driver 24
16/05/2016 11:10	2.90	Yellow	Driver 25