Development and Evaluation of Simulation Models for Shared Autonomous Mobility-on-Demand Systems

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Development and Evaluation of Simulation Models for Shared Autonomous Mobility-on-Demand Systems

PhD Dissertation

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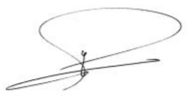
11 January 2019

Author's Declaration

The work in this dissertation contains no material, which has been accepted for the award of any other degree in any other university or institution. The author affirms, to the best of his knowledge, that this dissertation contains no material previously published or written by another person, except as acknowledged in the text.

Farid Javanshour



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Successful research never comes to fruition without collaboration. This work is the outcome of a three-year team effort and cooperation. My PhD journey has accomplished its goals, thanks to the technical, financial and intellectual assistance of many people over the course of this arduous path. Without their valuable support and involvement, this study would have never achieved its goals.

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Abstract

Autonomous Mobility-on-Demand (AMoD) systems hold great promise for addressing urban mobility challenges and realizing sustainable transport solutions in the world's large and rapidly growing cities. The key concept behind these systems is that they utilise fleets of shared self-driving vehicles to respond to customer demands in real-time, making them a more cost-effective alternative to privately-owned vehicles. Furthermore, and due to the reduced cost of operating these fleets, which do not need a human driver, they are increasingly being promoted as an alternative mode of public transport with the potential to reduce the number of vehicles on the road through car- and ride-sharing.

This PhD dissertation presents the development of a microscopic agent-based simulation approach to investigate the performance of AMoD systems in the context of a case study in Melbourne, Australia. The model developed in this research is the first agent-based AMoD model in the literature that simulates traffic flows using complex lane changing, car following, and gap-acceptance algorithms, while also implementing a real-time optimum rebalancing algorithm to redistribute the idle autonomous vehicles within the network.

Unlike currently available agent-based traffic simulation platforms, this model is capable of simulating the empty-vehicle-running of self-driving vehicles. This feature of the model is particularly important because the success of these shared fleets will rely largely on optimising the fleet size and minimising the number of empty runs to manage costs.

This research also explores the relationship between fleet size and induced Vehicle-Kilometres Travelled (VKT) in AMoD systems, finding a strong quadratic relationship between these two characteristics. This relationship always holds irrespective of the amount of travel demand.

Further, the results obtained and presented in this thesis provide an insight into a set of trade-offs between different fleet sizes and rebalancing time-steps. The simulation runs show that an AMoD system can reduce the current fleet size by 84%, while still meeting the same demand. It, however, comes at a cost of more VKT. This increase in VKT is 77% and 29% for the scenarios in which vehicles are used as car-sharing and ride-sharing systems respectively. These results suggest that the scale of potential benefits of AMoD systems, as reported in the current literature, has generally been overstated. The main reasons for this over optimism has also been identified and explored in detail.

The thesis also proposes a new method to take into account the effects of travel demand patterns on the performance of AMoD systems, concluding that the impact of this phenomenon on their efficiency is not trivial. Variation in travel demand patterns, however, does not affect the general quadratic relationship found in this study.

The model suggests that deploying an AMoD system during peak hours between suburbs and city centres would not be successful in meeting travel demands in a timely manner and would likely lead to more congestion on the roads. The discussions and findings of this dissertation could also be used by governments in preparing their future transport agendas.

List of Publications

Journal papers:

1. Javanshour, F, Dia, H and Duncan, G (2018). "Investigation of the transport implications and performance of shared autonomous mobility on-demand systems." Journal of transportation research part A: policy and practice (Under-review)

2. Javanshour, F, Dia, H and Duncan, G (2018). "Exploring the performance of autonomous mobility on-demand systems under demand uncertainty". Transportmetrica A: Transport Science. 1–24, https://doi.org/10.1080/23249935.2018.1528485

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2. Dia, H., Javanshour, F and Panwai, S. (2017). "Simulation-based assessments of smart mobility strategies" Network design and optimisation for smart cities, University of Florida, USA.

Conference papers:

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3. Dia, H and Javanshour, F. (2017). "Autonomous shared mobility-on-demand: Melbourne pilot simulation study." Euro Working Group on Transport (EWGT) conference, 5-7 September, Istanbul, Turkey.

4. Dia, H and Javanshour, F. (2016). "Modelling the impacts of autonomous shared mobility systems." ITS world congress, 10-14 October 2016, Melbourne, Australia.

5. Dia, H., Hill, J and Javanshour, F. (2016). "Autonomous mobility-on-demand: A review of recent literature." ITS world congress, 10-14 October 2016, Melbourne, Australia.

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Abbreviations

ABS: Australian bureau of statistics

AMoD: Autonomous mobility on demand systems

API: Application-programming interface

ASGC: Australian standard geographical classifications

ATM: Automated teller machine

AV: Autonomous vehicles

BC: Base case

CACC: Cooperative adaptive cruise control

CAMPO: Capital area metropolitan planning organisation

CD: Census collection district

Cdf: Cumulative distribution function

CF: car following

CVIC: Cooperative vehicle intersection control

DGPS: Differential global positioning system

DRS: Dynamic ride-sharing

DTA: Dynamic traffic assignment

DUE: Dynamic user equilibrium

DZ: Dilemma zone

EV: Electrical vehicle

eVKT: Empty vehicle kilometres travelled

FCFS: First come first served

FIFO: First in first out

FS: Fleet size

FSM: Four step modelling

GDP: Gross domestic product

GPS: Global positioning system

HCM: Highway capacity manual

HVoT: High value of time

IoT: Internet of things

IPF: Iterative proportional fitting

ITF: International transport forum

Lidar: Light detection and ranging

LP: Linear programming

LVoT: Low value of time

MGI: Mckinsey global institute

MoD: Mobility on demand

NHTS: National household travel survey

NTRR: Net trip rate proportion

OD: Origin destination

OECD: Organisation for economic co-operation and development

OTS: Optimisation time-step

P2P: Peer-to-Peer

Pmf: Probability mass function

PT: Public transport

PTV: Public transport Victoria

PVS: Private Vehicle Sharing

RFID: Radio frequency identification

RTK: Real time kinematic

SAE: Society of automotive engineers

SDV: Standard deviation

TAZ: Traffic analyses zones

TDP: Travel demand pattern

TRL: Transport research laboratory

TSS: Transport simulation systems

UNRSC: United nations road safety collaboration

V2I: Vehicle to infrastructure

V2V: Vehicle to vehicle

V2X: Vehicle to X

VDF: Volume delay function

VISTA: Victorian integrated survey of travel and activity

VKT: Vehicle kilometres travelled

WHO: World health organisation

Chapter 1 : Introduction

This chapter provides an overview of the concept of Autonomous Mobility-on-Demand (AMoD) systems, which rely on disruptive technologies. Further, the challenges facing governments to create sustainable communities are outlined, followed by a discussion of the potential opportunities, which can be used to tackle the challenges in a timely fashion. The last two sections of the chapter detail the research aims, questions, and present the contributions of the present research.

1.1. Background

Disruptive transport technologies are introducing new opportunities for providing travellers and consumers with more options to meet their travel needs. These prospects are being facilitated by the convergence of a number of disruptive technologies, including autonomous driving and mobile computing, and the shared (collaborative) economy. Although some of these disruptions are still a few years away (e.g. autonomous vehicles), they have already started to shape a vision for a very different future. Autonomous vehicles (AVs) are expected to be introduced to urban roads within the next 5-10 years. Vehicles with varying levels of self-driving capability are already available to consumers today, and transition to full autonomous operation is expected to be gradual taking up to 20-30 years. The pace of change will depend in part on acceptance by consumers, regulators and the wider industries, which may be disrupted by the changes.

Shared AMoD systems, in particular, are a novel and transformative mode of transportation promoted as an alternative to privately-owned vehicles and aim at reducing carbon emissions as well as vehicle accidents. The principal challenge for researchers and practitioners, however, is to ensure they produce the same benefits as privately-owned vehicles while also reducing reliance on non-renewable resources, minimizing pollution, decreasing the need to construct new roads and parking spaces.

This research is fundamentally an investigation into the potential network impacts of deploying AMoD systems in an urban context. The insights obtained through these investigations will provide better guidance for AMoD fleet operators and policy makers, and will result in timely actions, a key element in providing an efficient transport system.

1.2. Urban mobility challenges

The reform of urban mobility remains one of the biggest challenges facing policy makers around the world. Today, more than half the world's population lives in towns and cities and the percentage is growing. By 2050, 70 percent of the world is expected to live in cities and urban areas. According to the McKinsey Global Institute (Dobbs *et al.*, 2011), only 100 cities currently account for 30 percent of the world's economy. New York City and London, together, represent 40 percent of the global market capitalization. In 2025, 600 cities are projected to generate 58 percent of the global Gross Domestic Product (GDP) and accommodate 25 percent of the world's population (Dia, 2017).

The MGI also expects that 136 new cities, driven by faster growth in GDP per capita, will make it into the top 600 by 2025, all from the developing world, 100 of them from China alone. The 21st century appears more likely to be dominated by these global cities, which will become the magnets of economy and engines of globalization. The problem is further compounded by ageing infrastructures, which in many cities are at a breaking point with governments' budgets for major infrastructure projects under increasing pressure.

Furthermore, according to the United Nations Road Safety Collaboration (UNRSC, 2016), it is estimated that 1.3 million people are killed on the world's roads each year. If left unchecked, this number could reach 1.9 million fatalities worldwide by 2020. The World Health Organization (WHO, 2015) has described road casualty figures as being of 'epidemic' proportions, with road-related trauma being the biggest single killer of those aged between 15 and 29. Over 90% of road crashes are associated with human error which imposes a hefty cost in relation to economic burden and human suffering (ITF, 2015b).

A number of studies reported in the literature also document evidence showing that the environmental footprint of traditional transport systems, and in particular private vehicles with combustion engines, is not sustainable (ITFd, 2010). Globally, the transport sector accounts for 27 percent of the world's total energy consumption, 75 percent of which is sourced from non-renewable fossil fuels. Australia's per capita CO_2 emissions are almost twice the Organization for Economic Co-operation and Development (OECD) average while transport contributes 14 percent of greenhouse gas emissions (Godfrey *et al.*, 2015).

Moreover, road traffic continues to account for around 80 percent of transport CO2 emissions and is estimated to reach 9,000 megatons per year by 2030 if the current mobility trends are not curbed (ITFd, 2010).

Pursuing conventional approaches and relying on building new infrastructure to respond to increased travel demands has so far met with limited success and has proven to be ineffective in meeting these challenges. New approaches are needed (Kane and Whitehead, 2018). The following sections deal with the challenges faced by cities in providing adequate transport to meet current and growing travel demands.

1.2.1. Soaring urbanisation and its transport implications

We live in an age where urban areas are considered popular places to live. The population of urban areas is on the rise (United Nations, 2014). In 2014, 54% of the world's population lived in urban areas, while this figure was only 3% two centuries ago (Godfrey *et al.*, 2015).

As shown in Figure 1-1, in 2007, for the first time in history, the global urban population exceeded the global rural population. This trend has since continued and it is expected that by 2050, 66% of the world's population will be residing in urban settlements.

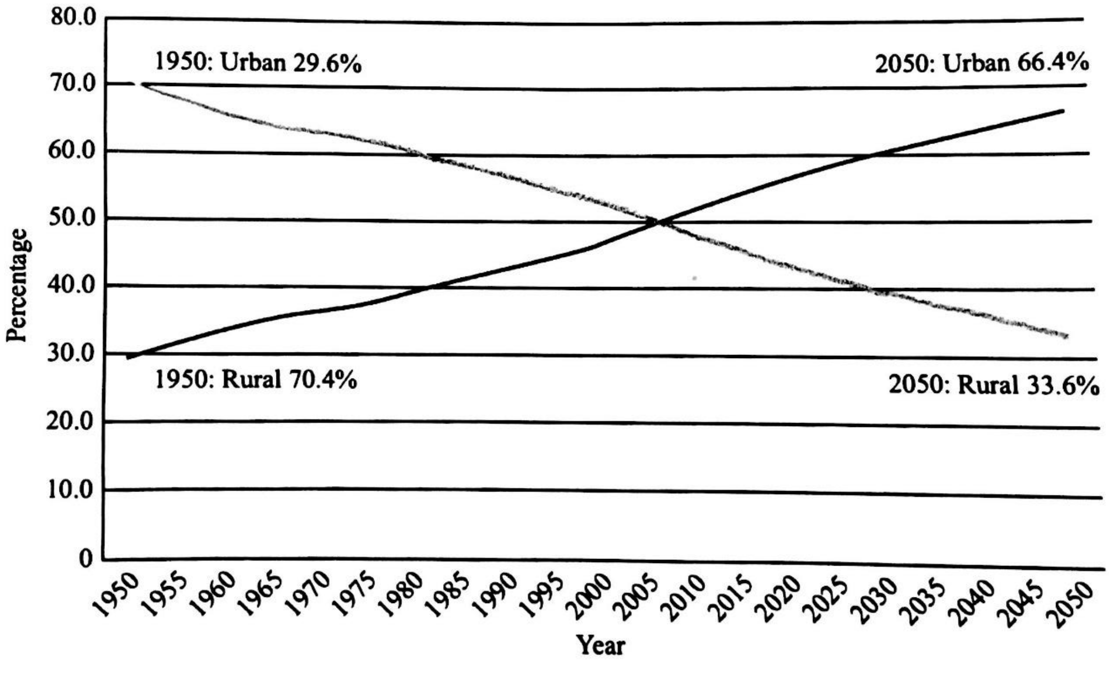


Figure 1-1: Percentage of the world population living in urban or rural areas 1950-2050 (Dia, 2017)

The urbanisation pace varies across the globe. Currently, Asia and Africa are predominantly rural, but they are urbanising more quickly than other parts of the world. The urban population growth rate in Asia and Africa are 1.5% and 1.1% per annum. The UN predicts that by 2050, urban areas will attract 2.5 billion people, with almost 90% of the increase happening in Asia and Africa. It also predicts that India, China and Nigeria will account for 37% of the projected growth of the world's urban population between 2014 and 2050. That is to say, by 2050, India is projected to add 404 million urban dwellers, China 292 million and Nigeria 212 million if the current trends persist (United Nations, 2014).

Rapid urbanisation has also increased the total number of mega-cities across the world. In 1990, the globe featured only ten mega-cities each with 10 million inhabitants or more. At the time, these cities were occupied by almost 153 million people, accounting for a bit less than 7% of the global urban population. In 2014, the number of mega-cities increased to 28 worldwide, accommodating almost 453 million people or about 12% of the world's urban population. By 2030, the number of mega-cities in the world is projected to rise to 41, each of which would be home to almost 10 million people or more (United Nations, 2014).

Until the end of the century, it is expected that the number of urban dwellers will grow by three billion (Seto *et al.*, 2012). The major part of this urban growth is expected to occur in small- and medium-sized cities, each with a million or fewer inhabitants. Many of the fastest growing cities in the world are relatively small urban settlements. Further, the fastest urbanisation pace is expected to occur in the developing world such as India (Godfrey *et al.*, 2015). Many villages in India have already transformed into urban areas in just one or two decades (Dia, 2017).

Rapid urbanisation will also change the way in which wealth is distributed across the world. Currently, only 600 urban centres are the producers of around 60% of the global GDP (Dobbs *et al.*, 2011). By 2025, it is estimated that 136 cities will join the top 600 wealthiest cities in the world. Around 100 of these cities will be within China and 13 within India. These top 600 cities are estimated to be producing 60% of the world's total GDP by 2025, with the top 100 cities alone contributing 35% of total GDP. The increase in wealth as a result of this expansion will occur mainly in developing nations and will enable more than one billion people to have high enough incomes to become significant consumers of goods and services by 2025. These consumers are expected to stimulate the global economy by contributing an extra $20 trillion a year in spending (Dobbs *et al.*, 2012).

Clearly, this rapid growth in urban population and wealth will translate into increased accessibility to jobs, services, and opportunities. For example, between 2000 and 2010, the world's urban population increased by roughly 650 million people. The International Energy Agency (IEA) estimates that urban passenger travel increased by nearly 3 trillion annual passenger kilometres during the same period (IEA, 2013). The IEA predicts that with the current trends, global urban passenger mobility will double by 2050 and increase as much as 10-fold between 2010 and 2050 in rapidly urbanising, fast-growing regions in Southeast Asia and the Middle East. This will have substantial implications for the global annual urban transport energy consumption, which by 2050 will increase by more than 80% over 2010 levels, despite improved vehicle technology and fuel-economy enhancements.

The global car fleet is also predicted to reach around 1.7 billion vehicles by 2030 because of rapid growth in urban population and wealth. This car fleet expansion will predominantly materialise in developing countries. The literature suggests that the total VKT per capita has plateaued or even decreased in developed countries (Bouton *et al.*, 2015).

1.2.2. Road crashes and injuries

Road traffic accidents claim nearly 1.3 million lives annually. The traffic fatalities worldwide lead to more than 3,000 deaths per day. This is the equivalent of 15 wide-body aircrafts, each with a capacity of 200 passengers, falling out of the sky every single day and killing everyone on board. Obviously, this wouldn't be accepted in air travel and it is disturbing that this trend is not yet curbed in road travel.

As shown in Figure 1-2, road traffic crashes remain the major cause of death among people aged 15-29 years. Road traffic trauma is also estimated to be the ninth leading cause of death across all age groups globally and is predicted to become the seventh leading cause of death by 2030 if the current trends continue. Most road accidents occur in low- and middle-income countries where the road infrastructure is not designed to international safety standards, and the levels of enforcement have not kept pace with the increasing vehicle use. In contrast, many developed countries have been successful in lowering road related injuries through providing high-quality infrastructure, improving the safety of vehicles, and introducing other wise interventions. For example, Figure 1-3 shows that in Australia, the annual road crash fatalities have declined from 2006 until 2015 at an average trend rate of 3.7% per annum (BITRE, 2016).

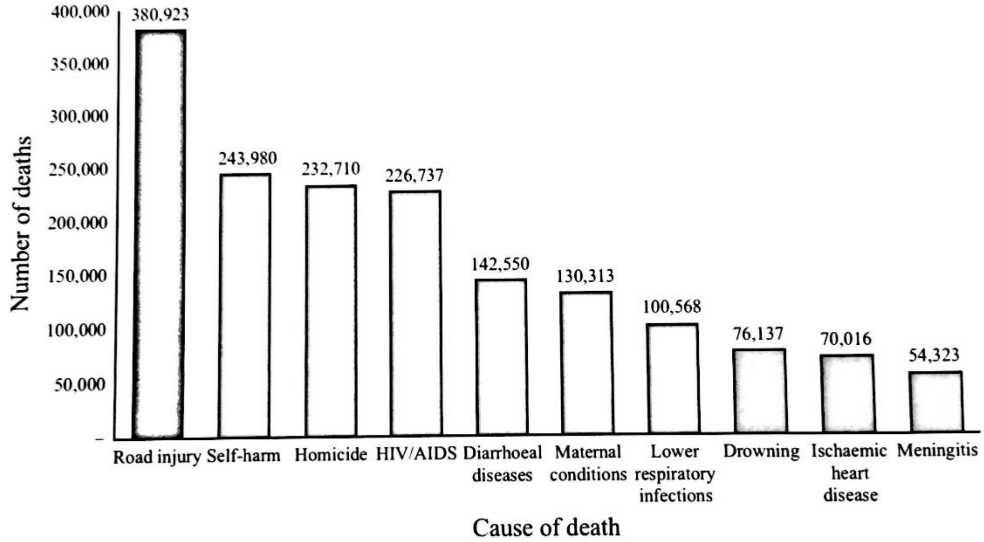


Figure 1-2: Top 10 causes of death among people aged 15-29 years (WHO, 2017)

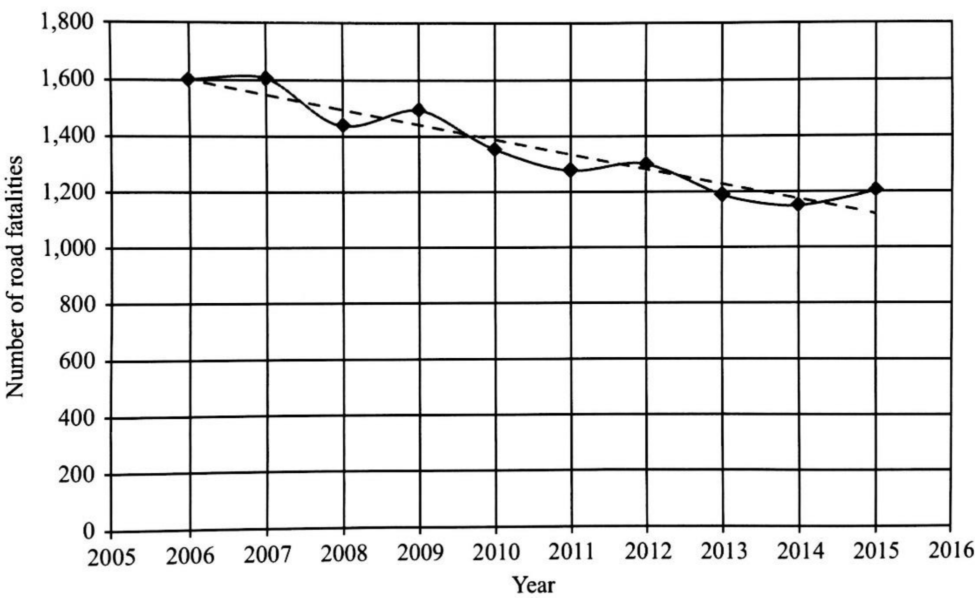


Figure 1-3: Annual road fatalities in Australia, 2006-15 (BITRE, 2016)

Traffic congestion and rising vehicle emissions ensued from the rapid growth in vehicle ownership, especially in developing countries, will result in higher rates of respiratory illnesses and other health problems.

In addition to the pain, suffering and unnecessary loss of life, road traffic crashes impose economic costs on nations. These costs are much higher in developing countries where the quality of the road infrastructure does not meet safety standards. Globally, it is estimated that road traffic deaths and injuries cost countries between 1% and 3% of their GDP, more than $500 billion each year globally (WHO, 2015).

Human error is responsible for 70-90% of motor vehicle crashes (NHTSA, 2015). A large proportion of these crashes could be avoided by using semi-automated and automated vehicles and there are currently very rapid developments aimed at removing humans, the key source of distraction and collision, from the driving equation by providing increasingly sophisticated technologies in vehicles.

1.2.3. Traffic congestion

Traffic congestion imposes a considerable cost on society by contributing to travel delays and environmental emissions. Lost productivity and wasted time are other costs imposed on urban communities by congestion.

The economic costs of congestion include the opportunity cost associated with the lost time spent in congestion and the financial costs associated with sitting in traffic, such as fuel consumption (Downs, 2005). In the United States, the cost of congestion in American cities has reportedly reached $160 billion in 2014 (Schrank *et al.*, 2015). The European Union estimates that congestion costs the community 1% of GDP (EC, 2011), whereas in Asia, it is estimated to cost the Asian economies around 2-5% of GDP (ADB, 2016). Traffic congestion in some of the world's mega-cities like Egypt's Cairo is also estimated to cost the country 3.6% in GDP, with the annual cost of congestion estimated at $7,972 million USD in 2010 (Downs, 2005). In Australia, the cost of congestion is estimated to have climbed from $12.8 billion in 2010 to around $16.5 billion in 2015 (BITRE, 2016).

It is not clear whether these costs will continue to climb in the future given the growing momentum on the provision of public transport and active transport, and the more recent evidence of peak-car phenomena, which has seen the total kilometres of travel per capita decline in recent years (Dia, 2017).

Congestion on a global scale has grown by 13% since 2008, with Australia being no exception to the trend (TomTom, 2016). Australia's population is projected to increase by 6.4 million people until 2031. The four major cities Perth, Melbourne, Sydney, and Brisbane are expected to absorb 5.9 million people from this projected population growth. This will exacerbate current congestion costs which have been estimated at around $16.5 billion in 2015, having climbed from $12.8 billion since 2010.

1.2.4. Emissions

The transport sector consumes half of the world's oil and is one of the key contributors to global air pollution (ICCT, 2012). As illustrated in Figure 1-4, in 2010, 25% of greenhouse gas (GHG) emissions were released by the energy sector, 24% from agriculture and other land use, 21% by industry, 14% by transport and 6.4% by the building sector (IPCC, 2014).

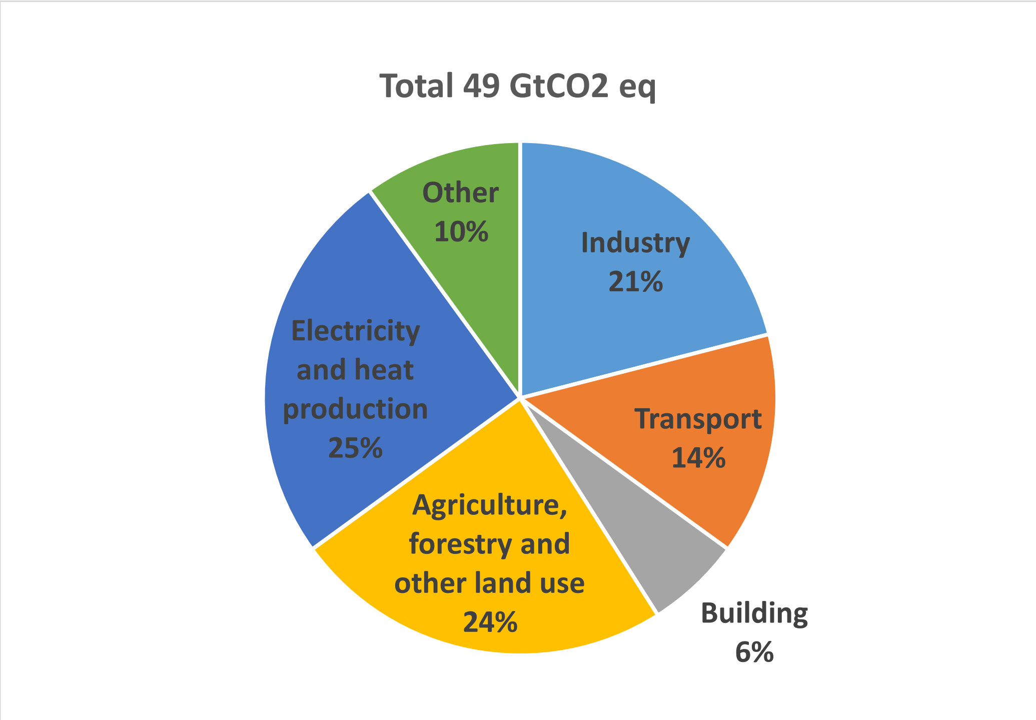


Figure 1-4: Total global anthropogenic greenhouse gas (GHG) emissions by economic sector (gigantic of CO2-equivalent per year) in 2010 (IPCC, 2014)

Emissions from transport have been shown to be growing more rapidly than those from other anthropogenic activities (Righi, Hendricks and Sausen, 2013). In the time period 1990-2007, the EU-15 CO_2-equivalent emissions from land transport comprised 74% of the global CO_2 emissions from all transport activities (Eyring *et al.*, 2010; Uherek *et al.*, 2010). This growth is expected to continue in the future, due to increasing world population, economic activities and related mobility (Righi, Hendricks and Sausen, 2013). In the year 2000, there were roughly 625 million passenger light-duty vehicles (PLDVs) around the world (IEA, 2013). By 2010, this number had reached nearly 850 million PLDVs. Modelling by the International Council on Clean Transportation (ICCT, 2012) predicts a doubling of the world's motor vehicle population over the next 20 years.

Modelling by the International Transport Forum, using a carbon dioxide equivalent measure, projects that transport emissions will grow by 9 $GtCO_2eq$ by 2030and increase by a further 110% above 2010 emissions levels by the year 2050. These forecasts underscore the importance of current and future policies that target a reduction in oil consumption and GHG emissions from the transport sector.

The effects of growing travel demand and increasing shifts to private motorisation are particularly evident in urban areas in developing countries. Motorised vehicle traffic has significant adverse effects on environmental quality and health. The IEA expects global travel (in terms of passenger and freight-tonne kilometre) to double by 2050 and corresponding transport energy use and emissions to increase 70% between 2010 and 2050, despite expected vehicle technology improvements. Global motorised vehicle stock is expected to double, and subsequent roadway occupancy levels are projected to increase as much as six fold in some countries (IEA, 2013).

Globally, modelling forecasts a threefold increase in both fuel demand and CO_2 emissions for the period between the years 2000 and 2030 (Uherek *et al.*, 2010). The modelling also showed that emissions of CO_2 from land transport and shipping accounted for 13% of the total anthropogenic CO_2 warming (year 2005).

In addition to long-lived greenhouse gases, ground-based vehicles also emit aerosol particles as well as a wide range of short-lived gases, including also aerosol precursor species (Forster *et al.*, 2007). Atmospheric aerosol particles have significant impacts on climate, through their interaction with solar radiation. In populated areas, they also effect air quality and human health (Pope and Dockery, 2006; Forster *et al.*, 2007).

Transport also accounts for half of the global oil consumption and nearly 20% of world energy use, of which approximately 40% is used in urban transport alone (IEA, 2013). The IEA expects that increased mobility will impose new challenges and anticipates urban transport energy consumption to double by 2050, despite ongoing vehicle technology and fuel-economy improvements. Attention to urgent energy-efficiency policies will be required to mitigate associated noise, air pollution, congestion, climate and economic impacts, all of which can cost countries billions of dollars per year (Dia, 2017).

1.2.5. Ageing assets and the infrastructure investment gap

Inadequate or poorly performing infrastructure are other challenges facing governments around the world. The lack of well-maintained and resilient transport infrastructure impedes the economic growth of countries. The problem is even further compounded by governments' tight budgets.

This problem is not exclusive to developing countries. From the United States through Europe to the emerging world, the backlog of projects includes upgrading existing assets and proposals for new projects to drive economic growth. Boosting transport infrastructure, which provides connectivity and ease of access to jobs and opportunities, is an urgent need in both developed and emerging nations.

Although governments and industry bodies agree that many cities across the globe suffer from an infrastructure deficit, there is no consensus on the magnitude of the global infrastructure gap. The World Economic Forum estimates a global need for $3.7 trillion in infrastructure investment each year, whereas only $2.7 trillion is annually invested, mostly by governments, around the world (Maier, 2015). The McKinsey Global Institute (Dobbs *et al.*, 2013) estimates the infrastructure gap at around $57 trillion over the next 14 years (up to 2030). This includes transport (roads, rail, ports and airports), power, water and telecommunications with transport collectively accounting for around 23.8 trillion (Figure 1-5).

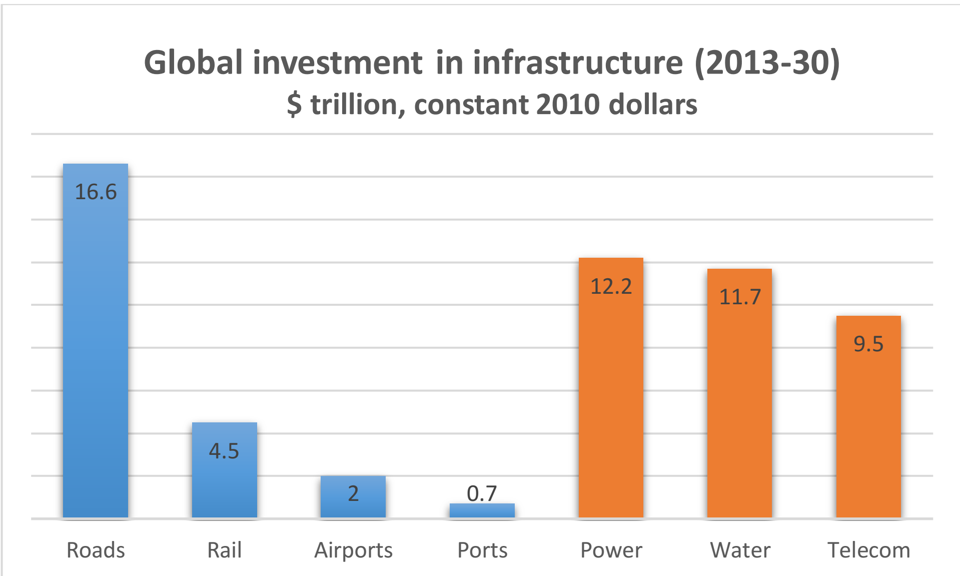


Figure 1-5: Demand for global infrastructure (2013-30) (Dobbs *et al.*, 2013)

This comes at a time when governments have only planned to invest around $37 trillion in all infrastructure assets over the same time period (Dobbs *et al.*, 2013). PwC estimates the gap at around $78 trillion in infrastructure needs and forecasts a need for capital project and infrastructure spending at more than $9 trillion per year by 2025, up from $4 trillion per year in 2012 (PwC, 2014)

Investment in infrastructure is hindered by various issues. In developed countries, obstacles are mainly public discomfort with privatised or partly privatised models, and governments taking measures to reduce debt amid fiscal constraints. In developing nations, the barriers are more about skills and economic capability. Countries that lack developed capital markets find it challenging to provide long-term finance and currency-exchange protections that investors require.

The global need for infrastructure is significant, particularly in emerging markets where the levels of service are not adequate, and connectivity is largely missing. Going forward, more emphasis needs to be given to the maintenance of existing assets and also to more deployment of technological solutions to enhance the performance of existing infrastructure while reducing reliance on building new assets. Future investments should also prioritise projects, which promote low carbon mobility including walking, cycling and public transport.

1.3. Opportunities

There is increasing recognition and acceptance that addressing transport issues through building additional road capacity is not sustainable and that it fails to fix traffic congestion or enhance mobility in cities.

Sustainable transport policies and intervention measures provide opportunities to meet the needs and demands of citizens and businesses in urban environments. Setting a city on a course towards sustainable transport requires a roadmap and a holistic vision, which incorporates different strategies to meet the demand for travel, including public transport and active policies. In recent years, technology has also played a big part in improving the performance of existing assets, thereby reducing the need for building additional infrastructure.

A sustainable transport system is one that meets the mobility and accessibility needs of the people while supporting the community's long-term social, environmental and economic goals and aspirations. The Centre for Sustainable Transportation at the University of Winnipeg in Canada offers a comprehensive definition (Dia, 2017):

A sustainable transportation system is one that accomplishes the following:

1. Allows the basic access needs of individuals and societies to be met safely and in a manner consistent with human and ecosystem health, and with equity within and between generations.
2. Is affordable, operates efficiently, offers choice of transport mode and supports a vibrant economy.
3. Limits emissions and waste within the planet's ability to absorb them, minimises consumption of non-renewable resources, limits consumption of renewable resources to the sustainable yield level, reuses and recycles its components, and minimises the use of land and the production of noise.

Sustainable transport and low carbon mobility are closely related and linked. Mobility is the total amount of travel that is undertaken on all modes of transport and relates to the physical movement from an origin to a destination (Baedeker, Kost and Merforth, 2014). When mobility is undertaken using motorised forms of transport, it results in harmful emissions of carbon and other pollutants. Transport, on the other hand, is broader than mobility and includes all modes of transport in addition to the supply of transport. For physical movement to take place, transport infrastructure needs to be supplied. Without the physical infrastructure, travel cannot happen. Infrastructure supply does not generate movement but allows it to take place. In this context, mobility can be seen as being situated between the demand for transport and the infrastructure that allows this demand to be realised (Dia, 2017).

Decision makers and leaders who run cities across the world are increasingly recognising the role of smart technologies in improving the efficiency of existing infrastructure and sweating of assets through better utilisation of the available infrastructure. These systems can significantly improve operations, reliability, safety, and meet consumer demand for better services with relatively small levels of investment. Cities are essentially made up of a complex network of systems that are increasingly being instrumented and interconnected, providing an opportunity for better infrastructure management. An Internet of Things comprising sensors, monitors, video surveillance, and radio frequency identification (RFID) tags, all communicate with each other to enhance infrastructure capability and resilience, capturing volumes of data. Through data mining, artificial intelligence and predictive analytics tools, smart infrastructure systems can help city managers monitor the performance of vital infrastructure, identify key areas where city services are lagging, and inform decision makers on how to manage city growth and make our cities more liveable.

1.4. Thesis objectives and research questions

The main objective of this research is to develop an agent-based simulation model, which investigates the transport network impacts of deploying shared AMoD systems could be possible. Detailed research questions within this study are as follows:

1. To what extent could AMoD systems reduce current transport fleet sizes?
2. What is the relationship between AMoD fleet sizes, empty Vehicle-Kilometres Travelled (eVKT), and waiting times of customers?
3. What is the relationship between rebalancing time-steps, fleet size, customer waiting times, and eVKT
4. What relationship exists between demand distribution within the network and generated eVKT?
5. To what extent could fleet size be reduced through encouraging more people into ride-sharing?
6. What benefits could be achieved in different levels of market penetration?

1.5. Statement of contribution

This research takes a new approach in terms of modelling techniques and algorithms compared to the current literature to investigate and quantify the transport network impacts of AMoD systems. This study develops a calibrated and validated model capable of predicting the possible effects of AMoD systems on current transport systems, and assists in the understanding of the latent behaviours of these systems which have been overlooked in the literature to date. The key findings and contributions of this research are as follows:

1. The benefits of AMoD systems have generally been overstated and shared AMoD systems might never be a sustainable transport solution as long as ride-sharing schemes and mass pubic transport systems have been dismissed.

2. Deploying shared AMoD systems during peak hours between suburbs and city centres is not an appropriate solution and could lead to more congestion.

3. This study is the first in the literature to quantify and discuss the elasticities of induced VKT within the network with respect to various fleet sizes and rebalancing time-steps.

4. A quadratic relationship between AMoD fleet size and induced VKT has been observed, which is independent of the amount of travel demand.

5. Although travel demand patterns can change the amount of induced VKT in the network, it never affects the general quadratic relationship between AMoD fleet size and VKT in the system.

6. A new measure, called Travel Demand Heterogeneity is introduced to assess the performance of AMoD systems from a different perspective. A method is also proposed to evaluate these systems taking into account the effects of demand heterogeneity.

1.6. Thesis Organisation

The rest of the thesis is structured as follows. In Chapter 2, a comprehensive review of the literature on AMoD systems with related case studies is provided. This chapter provides a detailed overview of the literature with identifying the gaps within it. Various definitions of available jargons in AMoD studies have also been provided in order to assist readers in comprehending the discussions.

Chapter 3 discusses the modelling approaches available in the literature and their pros and cons. This chapter deals with analytical models, macroscopic models and simulation models. The aim of this chapter is to show how various modelling approaches differ from each other and why the current research has chosen a simulation model.

In Chapter 4, the pilot study is described. The key purpose of this chapter is to examine the feasibility of the approach taken to carry out this PhD research. The pilot study has been undertaken within a small area in Melbourne and explored various AMoD scenarios to meet the goals of this chapter.

Chapters 5 and 6 deal with the main model developed for this research and discusses the results obtained from running a vast range of AMoD scenarios. These chapters discuss how necessary data were collected and used in the modelling process. A detailed description of the network deployed for this research, calibration and validation process and rebalancing algorithm has also been presented in these chapters. Simulation scenarios, assumptions and all the relevant investigations along with the achieved results have been extensively discussed in Chapter 5 and Chapter 6.

Chapter 7 presents all the findings of this research and discusses policy insights. Finally, Chapter 8 summarises the key findings of this doctoral research and discusses the future research directions.

Chapter 2 : Literature Review

This chapter provides an extensive review of the current literature on disruptive technologies, vehicle automation, and shared mobility on demand systems. Section 2.1 explains the notions of smart cities, smart mobility and disruptive technologies. It also expresses the available terminologies in this area. Section 2.3 discusses the meaning of vehicle automation, different levels of autonomy, their capital cost, regulation concerns, and some of the ramifications, which could result from these emerging technologies. Section 2.4 deals with some impacts of vehicle automation on transport networks and their contribution to traffic efficiency. Section 2.5 through 2.8 illustrate the concept behind AMoD systems and explains different forms of shared mobility systems. Section 2.9 reviews the available AMoD case studies in the literature and discusses their advantages and drawbacks. The chapter concludes with a summary of the literature review in section 2.10.

2.1. Smart cities and mobility

The concept of a smart city usually refers to a city that connects the social, physical, economic, and information infrastructure to create a vibrant urban environment that enhances access to services, places and economic opportunities, and improves the quality of life for its citizens (Dia, 2017).

The operation of urban infrastructure is becoming increasingly dependent on technology. As shown in Figure 2-1, the smart infrastructure paradigm includes a vast range of topics such as information technology, data mining, smart algorithms, and predictive analytics to improve the performance of infrastructure and services. This figure illustrates that technology is merely an enabler to achieve a city's desired objectives such as environmental sustainability, citizen well-being, and economic viability. To accomplish these objectives, cities need to harness the huge amounts of available data being produced by smart infrastructure. Then, these data should be mined and analysed to find their patterns and trends so that the optimisation and transformation of city services can be realised.

Smart cities would never materialise without providing their citizens with smart mobility services. These systems offer customers real-time and predictive information, enabling travellers to plan their journeys ahead, receive notifications of disruptions and avoid possible delays. Smart mobility services also enable customers to choose the travel mode that best suits their needs given their budget and the current traffic conditions within the network.

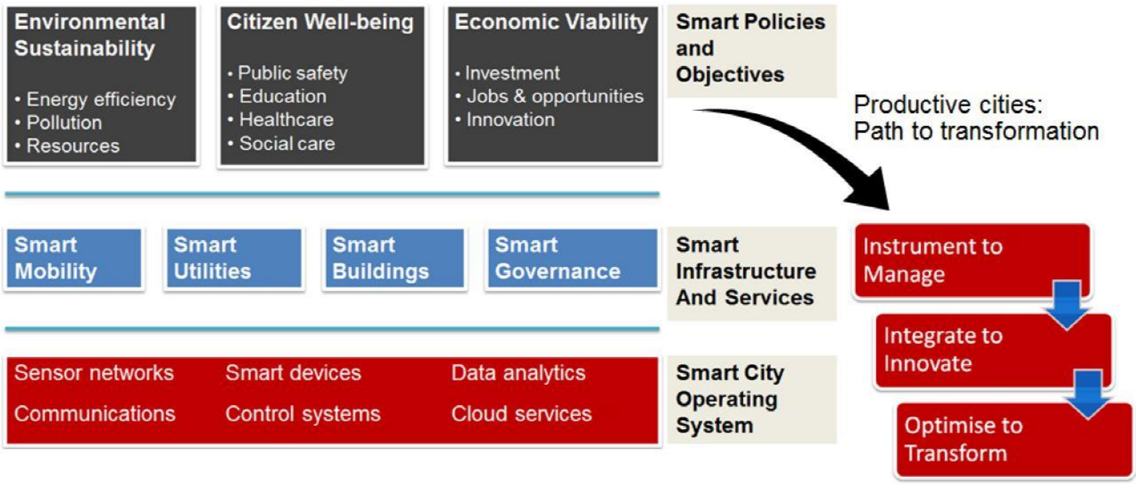


Figure 2-1: Smart cities model (Dia, 2017)

Figure 2-2 illustrates the key elements of a smart mobility model (Dia, 2017). As shown in this graph, developing models capable of predicting the performance of transport systems and the behaviour of travellers using these services is essential to for reliable smart mobility. Network management, control, and asset optimisation is extremely efficient in these systems as a result of having access to real time data and smarter algorithms. Low carbon mobility solutions, which will offer the mobility as a service (e.g. AMoD systems), will translate into smarter and more sustainable means of travel.

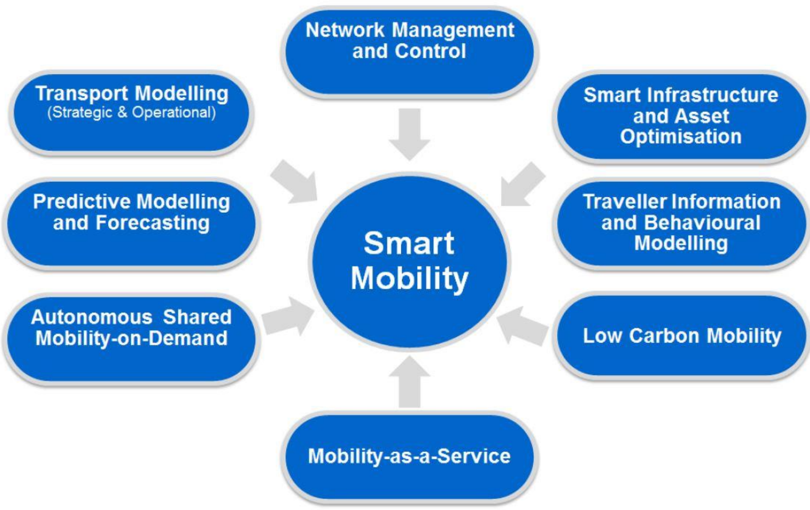


Figure 2-2: Smart mobility model (Dia, 2017)

2.2. Disruptive technologies

Disruptive forces are transforming the mobility landscape and providing consumers with more choices to meet their travel needs while reducing reliance on building additional infrastructure. Although some of these technologies are still a few years away (e.g. self-driving vehicles), they have already started to shape a vision for mobility transformation driven by a number of converging forces including autonomous vehicles, mobile internet, internet of things, cloud technology and vehicle electrification (Figure 2-3). This section provides more information on each of these elements.

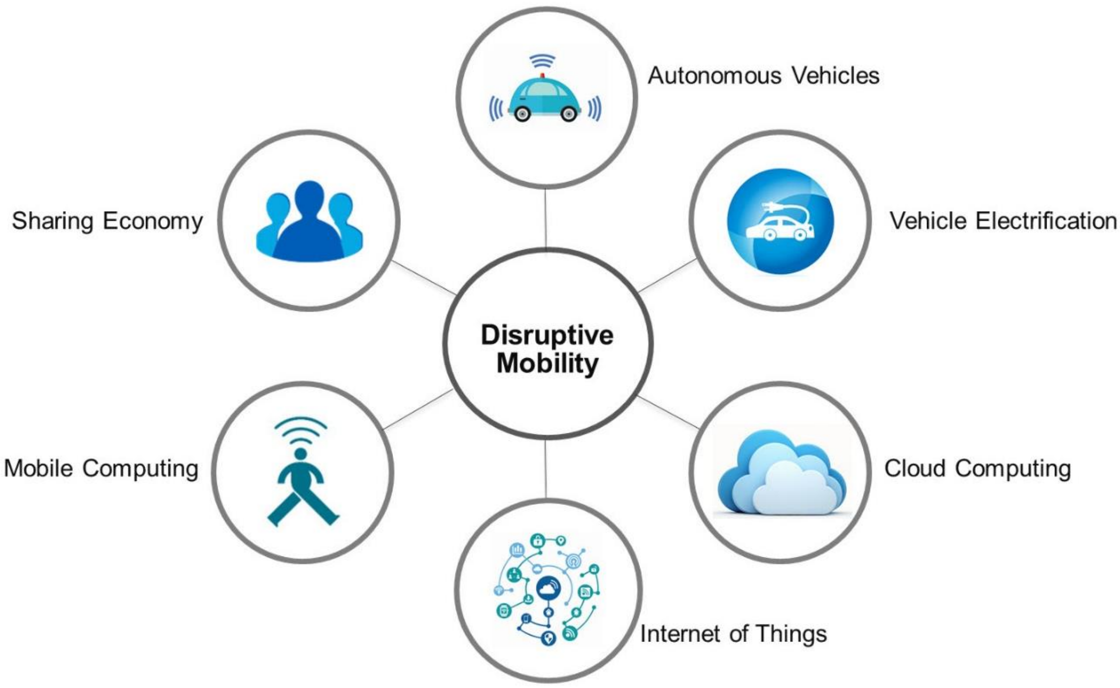


Figure 2-3: The disruptive mobility ecosystem (Dia, Javanshour and Hill, 2016)

2.2.1. Autonomous vehicles

An autonomous vehicle is one that can manoeuvre with reduced or no human intervention (Manyika *et al.*, 2013). The main contributions of these vehicles are a reduction in greenhouse emissions and a reduction in road car crashes. Each year, road crashes cause almost 1.24 million fatalities and between 20 to 50 million non-fatal injuries across the world (WHO, 2015), ninety per cent of which are caused by human error. Vehicle automation has a great potential to significantly decrease these numbers by removing the weakest link, the human driver, from the driving equation. Although reducing the number of people affected by car accidents is of great importance to the authorities, the main challenge is manufacturing vehicles that will replicate the good driving performance of humans (ITF, 2015b).

The convergence of sensor-based technologies and connected-vehicle communications is required to enable truly AVs (Bajpayee and Mathur, 2015). The term *connected vehicles* refers to the presence of devices in a vehicle that connect to other devices within the same vehicle and/or devices, networks, applications, and services outside the vehicle (Uhlemann, 2015). Fully autonomous vehicles deploying 3D cameras and other sensors, together with pattern recognition programs powered by artificial-intelligence knowledge to analyse the input signals, are able to move safely between other vehicles, obstacles and pedestrians from one place to a desired destination (Manyika *et al.*, 2013). These vehicles are also able to communicate with one another providing an appropriate condition to accrue the efficiency and safety benefits for commuters. However, designing coordination protocols that ensure safety while improving efficiency is challenging due to issues such as sensor range limitation, and reliability degree of wireless communication systems, which can result in errors such as lost messages (OHara *et al.*, 2015).

The key enabling technologies in developing the AVs are as follows:

- Lidar (Light Detection and Ranging): An optical remote sensing technology that measures distance to a target or other properties of the target by illuminating it with light.
- GPS (The Global Positioning System): a space-based satellite navigation system that provides location and time information anywhere on or near the earth.
- DGPS (Differential Global Positioning System): an enhancement to GPS that improves location accuracy from +/- 10 meters to about 10 centimetres.
- RTK (Real Time Kinematic): Navigation is based on the use of carrier phase measurements of the GPS, GLONASS, and/or Galileo signals where a single reference station provides real-time corrections.
- Digital maps: Digital mapping (also called digital cartography) is the process by which a collection of data is compiled and formatted into a virtual image (Silberg *et al.*, 2012).

Autonomous-drive technology is no longer a case of science fiction (Corwin *et al.*, 2015), and experts estimate that the circulation of highly automated vehicles in significant numbers on the roads will be likely by 2020 (Tannert, 2014), and might impact mobility to the same extent as smart phones impacted communication (Boesch and Ciari, 2015). Figure 2-4 illustrates a timeline for the introduction of driverless cars into the market by various car manufacturers up until 2030 during which the number of companies reaches from one (Tesla) in 2016 to at least ten in 2026.

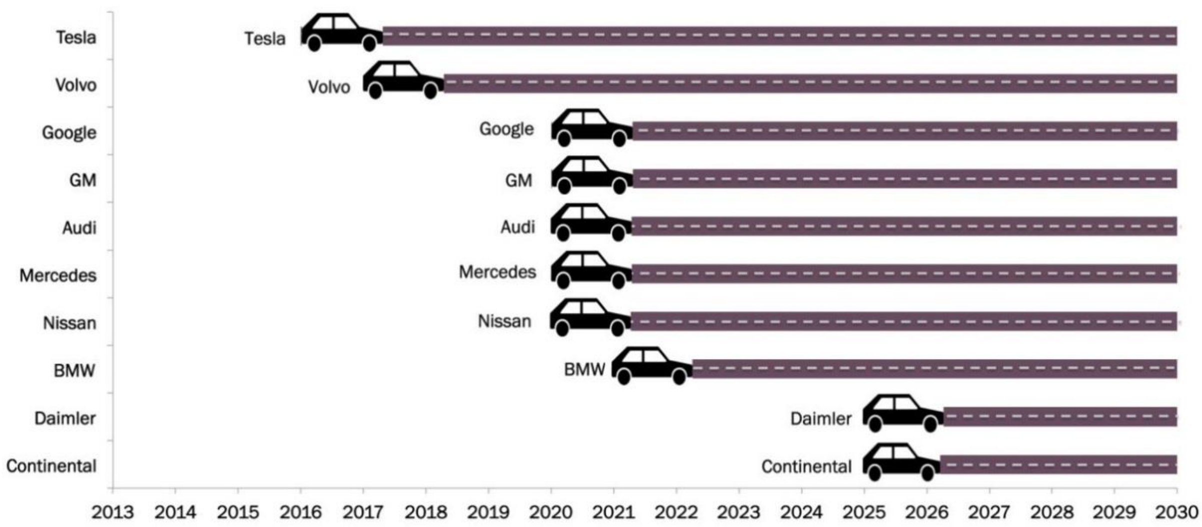


Figure 2-4: Autonomous vehicle release timeline by auto makers cited in (Hillier, Wright and Damen, 2015)

2.2.2. Mobile internet

Unlike the days when mobile phones had been just introduced and were considered a status symbol, smart phones have now become an essential part of people's lives, enabling the management of many tasks such as traveling or commuting through a vast range of applications supported by the ubiquitous Wi-Fi internet and GPS systems. The number of smart phone users is expected to exceed 2 billion in 2016 worldwide and reach 2.56 billion by 2018 (Emarketer, 2014).

Today, people are taking advantage of smart phones for their daily trips as well using a multitude of mobile apps for monitoring the traffic volume on roads, finding the arrival and departure time of public transport systems and choosing the shortest route to their destination. Moreover, smart phones are a great source from which to obtain real-time traffic information. Network-based solutions, which rely on the passive monitoring of data already being communicated in the mobile phone system, have the potential to provide network-wide travel time and origin–destination information Big Data (Rose, 2006).

Today's world has been swept up in an unprecedented amount of data- so-called Big Data- originating from social media, card readers, navigating systems and so forth. Every day, almost 2.5 quintillion bytes of data are created (Xindong Wu *et al.*, 2014) including tweets on various topics, people's comments about different issues on Facebook, daily money transfers and the number of vehicles travelling from one point to another by tracking them through GPS-enabled vehicles and smart phones etc.

Big Data refers to the amount of data that available technologies fail to store, manage and process efficiently and therefore demands the intervention of robust analytics along with powerful software and hardware tools (Kaisler *et al.*, 2013). The most fundamental challenge for Big Data applications is to explore the large volumes of data and extract useful information or knowledge for future actions (Xindong Wu *et al.*, 2014).

Harnessing such an extreme flow of data will benefit a multitude of sectors, including transport systems. Urban areas are equipped with many sensors and actuators, which collect information from different aspects of city dwellers' activities. Smart phones with built-in GPS systems can record and transmit their own trails. Transponders can be used to monitor the throughput at toll-booths, measure vehicle flow along a road or the number of empty spaces in a car park, track the progress of buses and trains along a route, and smart tickets can be used to track a passenger's travel. These instruments provide urban managers with abundant dynamic, well-defined and relatively cheap data on city activities, enabling them to undertake real-time analytics and establish adaptive management and governance systems (Kitchin, 2014).

2.2.3. Internet of Things

The Internet of Things (IoT) refers to the use of sensors, actuators, and data communication technology built into physical objects from roadways to pacemakers that enable these objects to be tracked, coordinated, or controlled across a data network or the Internet (Manyika *et al.*, 2013). IoT provides an IT-based infrastructure facilitating the exchange of "things" in a secure and reliable way. In other words, its function is to bridge the gap between objects in the physical world and their representation in information systems (Weber and Weber, 2010). IoT is a key element for intelligent transport systems powered by many sensors and actuators embedded in vehicles, pavements and traffic lights to exchange real-time information among one another to create a sustainable efficiency across the transport network.

2.2.4. Cloud technology

Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction (Mell and Grance, 2011). Cloud technology has the potential to disrupt entire business models, giving rise to new approaches that are asset-light, highly mobile, and flexible. Cloud technology allows the delivery of potentially all computer applications and services through networks or the Internet. With cloud resources, the bulk of computational work can be done remotely and delivered online, potentially reducing the need for storage and processing power on local computers and devices (Manyika *et al.*, 2013). Intelligent transportation clouds can provide services such as decision support, a standard development environment for traffic management strategies, and so on. With the support of cloud computing technologies, it is able to go far beyond other multi-agent traffic management systems, addressing issues such as infinite system scalability, an appropriate agent management scheme, reducing the upfront investment and risk for users, and minimizing the total cost of ownership (Li, Chen and Wang, 2011).

2.2.5. Vehicle electrification

Energy storage systems convert electricity into a form that can be stored and converted back into electrical energy for later use, providing energy on demand (Manyika *et al.*, 2013). Lit ion batteries are widely used in small applications, such as mobile phones and portable electronic devices. This type of battery attracts much interest in the field of material technology and others, in order to obtain high power devices for applications like electric vehicles and stationary energy storage (Iaz-González *et al.*, 2012).

2.3. Vehicle automation

The idea of assisting drivers in the process of driving to provide smoother, safe and appropriate driving patterns has always been of interest to scientists and car manufacturers. As a result, this has led to various advancements in vehicle automation from the automatic transmission, steering or parking technologies to AVs. In this section, current technologies and different levels of autonomy, fixed costs of available and future automated vehicles, as well as policy and regulation issues, will be discussed.

2.3.1. Technology and levels of autonomy

Automated vehicles engage state-of-the-art technologies such as Lidar, GPS and digital maps to sense their surrounding environment and act based on the retrieved information. Many of the key technologies, which guide the vehicles or even perform the driving task with minimal human intervention, are already in place. Other infrastructure developments, however, need more attention to accelerate the process of vehicle automation such as Vehicle-to-X connectivity (V2X), decision and control algorithms, and digital infrastructure (ITF, 2015a).

The Society of Automotive Engineers (SAE) has recommended a 5-level description of autonomy for on-road motor vehicles, which includes functional definitions for advanced levels of driving automation and related terms and definitions (SAE, 2016). These levels describe the percentage of human and machine intervention in the dynamic driving task ranging from Level 0 (no automation) up to Level 5 (full automation) (Figure 2-5).

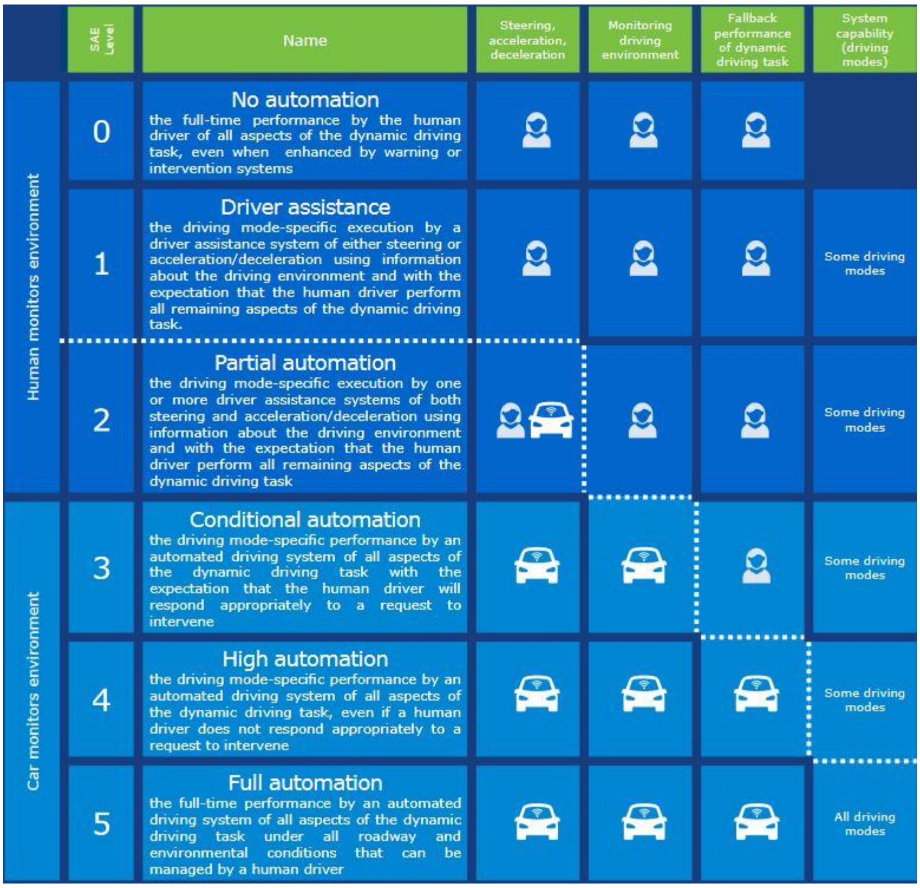


Figure 2-5: Levels of driving automation according to the Society of Automotive Engineers (ITF, 2015a)

2.3.2. Capital cost of autonomous vehicles

Driverless vehicles feature high-tech components, which make them prohibitively expensive and prevents them from gaining a sizable market penetration. LIDAR is one of these expensive components which acts like an eye for the driverless car. In 2014, an advanced Lidar system for AVs cost between $30,000 and $85,000 apiece (Shchetko, 2014). This price, however, could be cut by 90% in 2017 thanks to recent advancements in Lidar technologies (Amadeo, 2017). A study conducted by HIS Automotive (HIS, 2014) estimates that a driverless vehicle will cost $7,000 to $10,000 more than a similar human-driven car in 2025. This price, however, will drop by $5000 in 2030 and about $3000 in 2035.

There has also been growing government awareness to invest in this area with the Obama administration proposing spending $4 billion to accelerate autonomous- car technology over the next decade (Stoll, 2016). This will be of significant help for car manufacturers to keep the capital cost of their products low and will help facilitate large-scale market AV adoption. One of these companies to be successful in releasing affordable cars capable of driving themselves is Honda who prices this product at $20,440 (Stoll, 2016).

2.3.3. Regulation

Thanks to automation, the role of drivers in the driving process is gradually diminishing with new cars featuring automatic steering, cruising and lane-keeping technologies as well as cars with the full capability of driving themselves along with a manual driving mode. This trend has raised questions regarding the litigation and liability of drivers in the event of an accident and prompted regulators to rethink how they can move with the same pace as technological advancements in a manner that encourage this innovation.

The International Transport Forum (ITF, 2015a) recommends two types of approaches in regulating automated vehicles namely, the general method and the specific method. In the general method, a government modifies the current laws for traditional vehicles to make them compatible with automatic vehicles. In the specific method, on the other hand, a government enacts special rules for automatic vehicles and articulates exclusively which rules should be applied in the case of an accident.

There are currently various jurisdictions worldwide (e.g. Australia, United States, United Kingdom, France, Finland, The Netherlands) dealing with the regulation and on-road testing of AVs worldwide in order to provide an appropriate condition within the community which is necessary for a smooth transition from the current mobility systems to a fully automated environment.

2.4. Network impacts of vehicle automation

Vehicle automation and AVs are considered potential solutions for addressing road safety problems, boosting environmental conditions, and enhancing network throughput (Talebpour and Mahmassani, 2016) by providing more connectivity between vehicles and the infrastructure. Real-time data sharing between vehicles and the infrastructure could be realised through establishing a connected Vehicle-to-Vehicle (V2V), and Vehicle-to-Infrastructure (V2I) environment. Achieving system efficiency due to automation, however, might induce more travel demand and lead to more congestion in the network and affect land use patterns.

Connected vehicles and infrastructure can contribute to collaborative techniques to enhance the capacity of current transport networks and attenuate congestion levels. Cooperative Adaptive Cruise Control (CACC) systems are one of the achievements provided by a connected environment. Researchers in the Institute of Transport Studies at the University of California Berkley (Milanes *et al.*, 2014) suggest improvements in highway capacity and traffic flow stability through deploying a CACC system which was also tested on public roads to confirm its real performance. Another study conducted in this university (Shladover, Su and Lu, 2012) also suggests that freeway capacity-increase could be realised by deploying a CACC system with moderate-to-high market penetration rates.

Research shows that intersection traffic control could also benefit from connected environments. Lee and Park (2012) propose a Cooperative Vehicle Intersection Control (CVIC) system for a fully automated-vehicle fleet. The CVIC system removes the need to install traffic signals through establishing cooperation between vehicles and infrastructure thereby vehicles are able to pass through the intersection without a need to stop. They developed a simulation model representing a hypothetical four-way single-lane approach intersection under varying congestion conditions to evaluate the performance of their algorithm. The results suggested that not only stop delay could drop by 99% but also total travel time could be reduced by 33% by deploying the proposed CVIC system (Lee and Park, 2012).

Other research (Goodall, Smith and Park, 2013) develops a predictive microscopic traffic simulation algorithm fed with real-time data retrieved from connected vehicles. This algorithm optimises the traffic signal timing via receiving the present vehicles' positions, headings, and speeds. The results suggest that the proposed algorithm could improve the performance of the signalised intersection at low and mid-level volumes.

Given that this research only looks at the network impacts of vehicle automation, in this section, only studies of the same scope are discussed. For a comprehensive review of the implications of vehicle automation and connectivity, readers are referred to (Milakis, van Arem and van Wee, 2017).

2.5. Autonomous Mobility-on-Demand

In the past century, private cars have been the most popular mode of transport in urban areas by providing rapid, comfortable and door-to-door travels without confining consumers to a specific time-schedule. However, experts assert that the high dependency on oil; soaring traffic congestion and the ever-increasing demand for land to pave more roads and build new parking spaces make private cars an unsustainable mobility system for urban areas (Mitchell, Borroni-Bird and Burns, 2010).

In addition, according to the National Highway Traffic Safety Administration (2008), 93 per cent of road crashes are associated with human error. In addition, several studies summarised in (Salmon *et al.*, 2005) indicate that human error contributes to as much as 75% of all roadway crashes. The ageing of the population also poses a challenge to communities in terms of road safety. Figure 2-6 shows that by 2031, the percentage of the population aged 65 years and older will escalate to 23 percent equivalent or one in four Victorians. As shown in Figure 2-7, the relative risk of being involved in a casualty crash on Melbourne's arterial roads (per distance travelled) is around 1.5 times greater for drivers aged 60-74 years compared to drivers aged 40-49, and about 4.7 times for those aged 75 years and older.

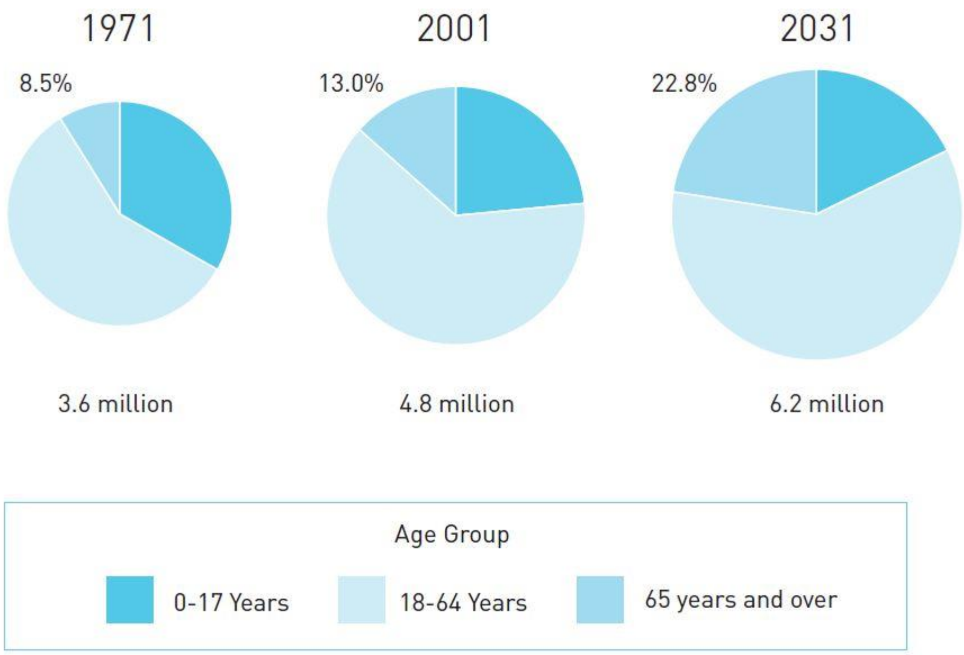


Figure 2-6: Population growth and age profile of Victoria's population, 1971-2031 (VISTA, 2016)

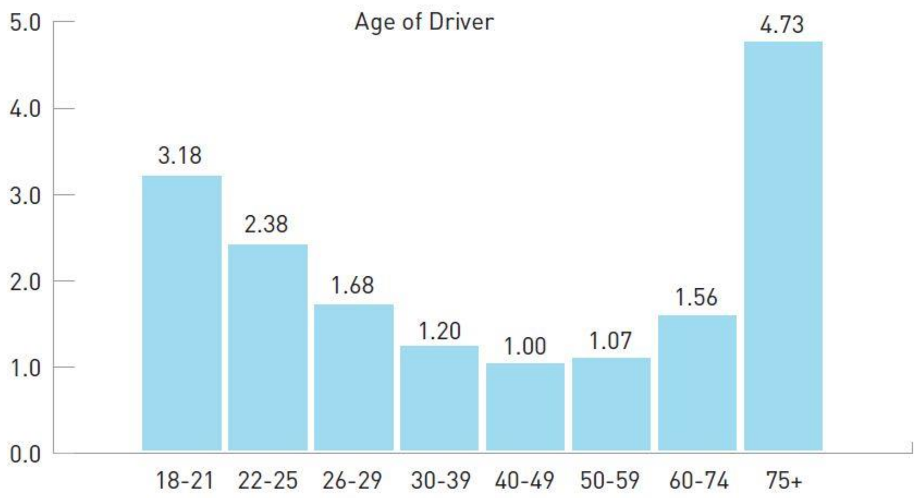


Figure 2-7: Relative risk of a driver being involved in a casualty crash by age group, Victoria 2001 (VISTA, 2016)

On the other hand, new research like Zipcar's annual millennial survey substantiate the claim that the younger generation is less keen to own a private car than their older counterparts as the popularity of new technologies like smart phones is growing. Further, more than half of all millennials say they would prefer public transit and car sharing systems to privately-owned cars (Zipcar, 2014). As shown in Figure 2-8, even in the United States where cars are greatly popular, ownership rates are declining, and drivers are driving less. Moreover, in most families, cars are underutilised commodities which cost an unnecessary amount of money. Private cars meet the mobility needs of families typically during peak hours and are usually used less than one hour a day (ITF, 2015c).

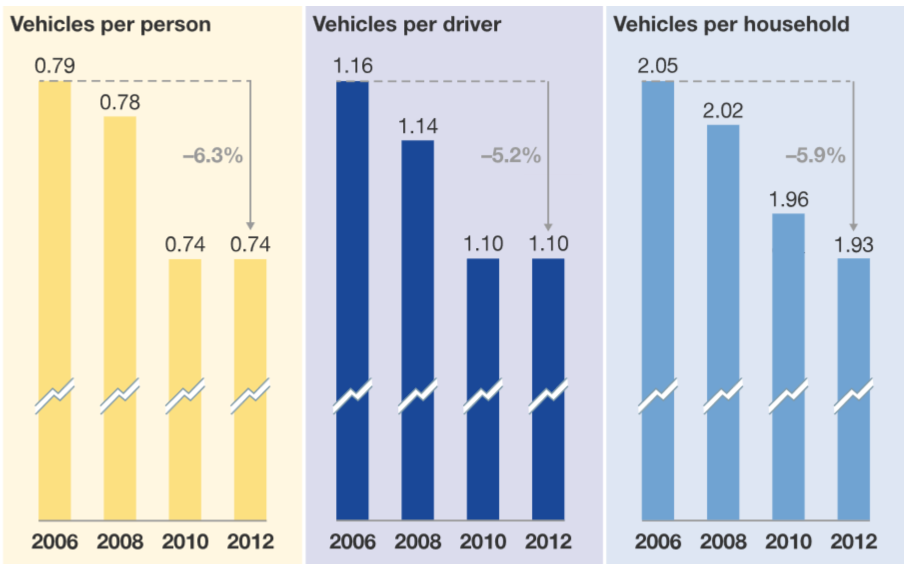


Figure 2-8: Vehicle ownership rates in USA (Bouton et al., 2015)

With the aforementioned issues in mind, exploiting one-way shareable electric vehicles in which electricity is produced through clean resources (e.g. wind turbines or solar systems), and vehicles are distributed at convenient locations across the urban area to enable travellers to pick them up them at short notice seems a promising way to decrease the overall number of private cars. This system, referred to as mobility-on-demand or MoD systems in the literature, is seen by many experts to be a sustainable solution to the problems of oil dependency, pollution, and parking lot sprawls (Zhang *et al.*, 2015).

Having assets (e.g. private cars) shared within a community could reduce the necessity to own them (Stephany, 2015). As shown in Figure 2-9, ubiquitous wireless internet networks could provide a suitable platform to enhance the accessibility of assets and promote the culture of sharing. This new business model would distribute the overall expenses of owning the asset within the community rather than placing the burden on a single individual.

Figure 2-9 illustrates that an appropriate shared system enabled with omnipresent internet technology that provides convenient services to consumers leads to a substantial increase in the utilization of assets.

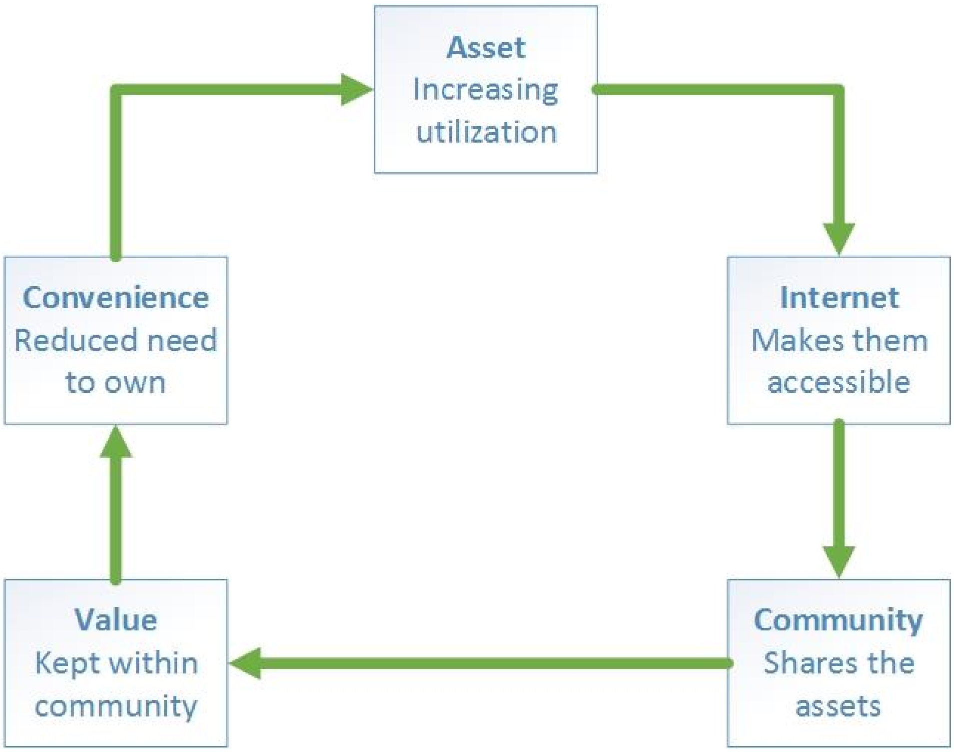


Figure 2-9: The sharing economy, increasing asset utilization (Stephany, 2015)

However, two dominant challenges are facing MoD systems. Firstly, due to the spatiotemporal nature of urban mobility, certain locations tend to be more popular destinations than others, which leads to unbalanced vehicle fleets. Secondly, MoD systems are not able to address increased traffic congestion directly. In actual fact, the need to rebalance vehicles creates additional trips that increases the overall mileage driven (Zhang *et al.*, 2015).

Emerging AMoD systems have a great potential for rebalancing trips (Chong *et al.*, 2012) and alleviating the drawbacks of MoD systems. For instance, robotic vehicles can rebalance themselves, autonomously monitor and recharge their batteries, and coordinate their actions at a system-wide level to optimize throughput. Furthermore, robotic vehicles would free passengers from the task of driving especially those unable or unwilling to drive, and boost the safety level of urban transport networks (Zhang *et al.*, 2015). However, the principal challenge for researchers is to ensure the same benefits of privately-owned cars in parallel with reducing private car ownership (Pavone, 2015). In addition, the security of these new systems will be an issue. For example, the security of AMoD systems against cyber-attacks was investigated in a recent study (Yuan, Thai and Bayen, 2016) where the authors proposed a tractable block-coordinate descent algorithm to compute attack strategies in the Manhattan road network.

Another challenge in deploying AVs is defining moral decision-making algorithms for them such as running over pedestrians or sacrificing themselves and their passengers to save pedestrians in a case where an automated system malfunctions. The results of a recent study (Bonnefon, Shariff and Rahwan, 2016) suggest that moral algorithms for AVs create a social dilemma.

Although people tend to agree that everyone would be better off if AVs were utilitarian (in the sense of minimizing the number of casualties on the road), these same people have a personal incentive to ride in AVs that will protect them at all costs. This study concludes that regulators will be faced with two difficulties: first, most people seem to disapprove of a regulation that would enforce utilitarian AVs; second, such regulation could substantially delay the adoption of AVs, which means that the lives saved by making AVs utilitarian may be outnumbered by the deaths caused by delaying the adoption of AVs altogether.

2.6. Ride-sharing

Ride-sharing refers to sharing rides between drivers and passengers with similar origins and destinations. Traditionally defined, ridesharing includes vanpooling and carpooling, which have been alternative transport options for decades. In vanpooling schemes, customers are clustered into groups of 7 to 15 people commuting together in one van, while in carpooling models, travelling clusters consist of fewer than 7 individuals. Shaheen et al., 2017, offer a very clever classification to clarify the difference between carpooling or vanpooling schemes and other emerging ride-sharing models. This article classifies carpooling and vanpooling systems as traditional ride-sharing models or for short ride-sharing, while emerging business models fall into the category of for-hire driver services. The following section discusses various types of for-hire driver models in detail.

2.7. For-hire driver services

In for-hire driver services, passengers request a ride through a mobile app installed on their phone. Unlike traditional ride-sharing, in these services drivers do not necessarily have the same origins and destinations as passengers. For-hire driver services are categorised into three distinct models: ride-sourcing, ride-splitting or pooling, and e-Hail services for taxis with medallions (Shaheen *et al.*, 2017). These models are explained thoroughly in the next sections.

For-hire driver services have their own weaknesses as well. Drawbacks include concerns about the safety and security of anonymous matching, as well as problems with stranded riders if they cannot find a match for the return trip. Additionally, program costs and financing, as well as overall program business models, must be considered. Costs include start-up and ongoing operations and staffing, marketing, incentives to participants, software and hardware for ride-share matching, and program monitoring and evaluation.

2.7.1. Ride-sourcing

Ride-sourcing services use mobile apps to match potential passengers with drivers. Using these apps, passengers can specify their desired point for pick up, final destination, time to be served, maximum time to be delivered, number of travellers and their favourite fare. Then, matching vehicles to riders is carried out by a server, which receives information and defines the routes (Santos and Xavier, 2015).

These emerging technologies are known by various terms by different stakeholders: ride-sourcing by transportation academics, Transportation Network Companies (TNC) by practitioners, and ride-hailing or ride-booking by the popular press (Shaheen *et al.*, 2017). Examples of these services include Lyft and Uber (specifically, UberX, UberXL, and UberSELECT), as well as specialised services for children and the older population. Ride-sourcing services usually implement surge-pricing schemes to charge their customers to incentivise more drivers to take ride requests.

Lift hero is a ride-sourcing company established to service elderly individuals and the disabled in the San Francisco Bay Area. Concierge is another company operated by Lyft to provide non-emergency medical transportation in New York City. HopSkipDrive facilitates rides for children either to or from school or afterschool activities. In this scheme, drivers are either mothers or those with a background in childcare. HopSkipDrive services the Los Angeles and San Francisco Bay areas. Ride-sourcing services are also promoted by many as a complementary system to the existing public transit systems and reduce parking demand (Winter *et al.*, 2016; Scheltes and de Almeida Correia, 2017).

2.7.2. Ride-splitting or pooling

Ride-splitting (pooling) is another type of for-hire driver service. Through this system, passengers not only share ride with other travellers with similar routes but also split the ride fare between each other. LyftLine and UberPool are examples of companies that offer ride-splitting services. LyftLine encourages passengers to gather at specific points in the city in order to smooth their operation and provide a more efficient system. In return for walking to pick-up points, customers are offered discounted fares. Similarly, UberPool launched Smart Routes, where customers can get a discounted fare starting at US$1 off the normal UberPool price in return for walking to a major arterial street. This strategy leads to drivers picking up their passengers faster.

Uber launched UberHOP in Seattle, Washington, and Toronto, Canada, an on-demand pooling service tailored for peak hours. This system pools more riders together and uses predetermined pick-up and drop-off locations. The closest drivers are sent to pick-up stations to service travel demand.

2.7.3. e-Hail services

The taxi industry has developed specific mobile apps known as e-Hail to avoid lagging behind ride-sourcing companies. These apps are maintained either by the taxi company itself or a third-party provider. Given the increasing popularity of e-Hail services in the US, various e-Hail apps have emerged recently across the country. Arro, Bandwagon, Curb, Flywheel, Gett, Hailo, and iTaxi, are some of these services. For instance, as of October 2014, Flywheel was used by 80% of San Francisco taxis (1450 taxis). This application has reduced taxi wait times to the same level as that of ride-sourcing services.

The Bandwagon app combines ride-splitting with e-Hail to facilitate taxi splitting. It matches taxi rides going in a similar direction and provides a platform for splitting the fare. Since Spring 2016, Bandwagon has operated at LaGuardia Airport and John F. Kennedy International Airport in New York City. In April 2016, the Gett app introduced a fare splitting feature for use in over 15,000 black cabs in London. Because regulated taxis charge static fares, e-Hail services also employ locally regulated taxi rates and do not implement surge pricing during periods of high demand, as ride-sourcing services often do.

The development of e-Hail apps has recently gained momentum with public bodies, taxi companies, and app developers forging partnerships. UpTop is an international taxi network developed by a partnership of IRU and the Taxicab, Limousine and Paratransit Association. UpTop has been partnering with app companies. More recently, it added Curb, The ride, and zTrip apps to its network, and it covers 500,000 taxis or 10% of all taxis worldwide.

2.8. Car-sharing

The car-sharing system, which emerged in Switzerland, dates back to 1948. It has expanded to approximately 1,100 cities worldwide, in 26 nations on five continents (Shaheen and Cohen, 2013; Lazarus *et al.*, 2018). Car-sharing is a service that provides members with access to a fleet of vehicles on an hourly basis. Members reserve a car online or by phone, walk to the nearest parking space, open the doors with an electronic key card, and drive off. They are billed at the end of the month for time and/or mileage (Millard-Ball, 2005).

To date, different studies have suggested the substantial role of car-sharing in diminishing the negative environmental and social impacts of private cars on urban areas worldwide. Table 2-1 summarises some of the results of these studies across Europe, North America and Australia. As shown in Table 2-1, thanks to deploying car-sharing systems, carbon dioxide emission and the number of privately-owned cars have decreased in all places and has had a considerable effect on convincing people to relinquish their private cars.

It is worth mentioning that according to the literature, high density areas are the best candidate to implement car-sharing systems as it implies more potential members within walking distance (1/3 miles) of a car-sharing vehicle (Barrios and Godier, 2014).

Table 2-1: Reported social and environmental impacts due to car-sharing (Shaheen and Cohen, 2013)

Impact	Europe	North America	Australia
Carbon dioxide emission reduction (Observed impact)	39 to 54%	27%	N/A
Number of private cars that a car-sharing vehicle replaces (sold or forgone purchase)	4-10 Cars	9-13 Cars	7-10 Cars
Sold vehicle due to car sharing	15.6 to 34%	25%	21.3%
Forgone vehicle purchase due to car sharing	N/A	25%	28.1%

There are three types of car-sharing systems namely, round trip car-sharing, one-way car-sharing, and personal vehicle sharing. The following sections discuss these business models in detail.

2.8.1. Round-trip car-sharing

In round-trip car-sharing, users make a reservation for a car through smart phones or the internet just before their desired time for travel and designate the start time and trip duration. In this system, users must pay for the entire time between trip commencement and returning the car to the point where it was first accessed. The vehicles are allocated to dedicated parking spots including off-street and on-street parking places. A professional car-sharing operator is usually in charge of this task. The main role of a car-sharing operator in this system is matching car owners with car seekers through an online platform. Zipcar is the largest provider of round-trip car-sharing services worldwide.

2.8.2. One-way car-sharing

One-way car-sharing, also known as point-to point or free-floating car-sharing, provides one-way journeys within a specified geographical zone with the advantage of being able to make the reservation only a few minutes ahead of the journey. In this system, contracts with authorities enable consumers to drop the cars at any place within the operating area without having to leave them in a specific parking place. These services are also recommended as a complement to public transport systems (Becker, Ciari and Axhausen, 2017).

The largest operator of point-to-point free-floating car sharing services worldwide is car2go. Some point-to-point car sharing systems are station-based (e.g. Autolib in France) in which cars start their journey from one station and end up in another one. This system is less flexible than free-floating system; however, consumers are still not required to return the cars to the first place (Vine, Zolfaghari and Polak, 2014).

One of the major problems in operating one-way car-sharing systems is vehicle fleet rebalancing. This challenge is caused by the spatiotemporal characteristic of travel demand, which makes some parts of the city more attractive than other areas. Upon arriving at the destination, customers leave the car in the street or designated station for shared-cars. If the area is popular, vehicles would accumulate there and be depleted in others. Thus, rebalancing idle vehicles is essential to maintain a specific quality of service within the area without causing further VKT.

Rebalancing traditional vehicles requires hired drivers to perform the task and requires well-defined rebalancing strategies to avoid the unbalancing of drivers themselves (Smith *et al.*, 2013). This problem, however, could be resolved for a fleet of shared AVs in which no driver is required to rebalance the system.

One-way car-sharing systems began in Europe in the 1970s. In 2012, one-way car-sharing expanded rapidly to seven countries worldwide. As of October 2014, there were 851,988 one-way car-sharing members globally, 372,466 of which were in Europe, 445,722 were in North America, 29,600 in Asia, 3,500 in South America, and 700 in Oceania. As of January 2015, 35.7% of North American fleets allowed one-way trips, and 30.8% of members had access to such fleets (Shaheen *et al.*, 2017).

Procotip was the first one-way car-sharing company, launched in Montpellier, France in 1971. It featured 35 cars with 19 stations. This company was forced to close down in 1973 due to operational and financial problems. Liselec launched in 1993 in La Rochelle, France with 50 EVs at seven stations. This company was successful and today, it has been rebranded as Yelmobile. Praxitele launched in 1997 as a last mile solution in Saint-Quentin-enYvelines, France. This one-way car-sharing company had 500 members and provided access to 14 stations, located in neighbourhoods, near offices, and at public transit stations. Praxitele ceased operations in July 1999 due to financial issues (Shaheen *et al.*, 2017).

In Japan, car manufacturers brought car-sharing systems into operation. In 1998, the Honda Motor Company deployed the Intelligent Community Vehicle System, which included both round-trip and one-way carsharing with connections to public transit. In 1999, the Toyota Motor Company launched the Crayon System in Toyota City, Japan. This company was made up of 50 EVs located at various places including public transit stations. Nowadays, these companies employ emerging technologies such as smart cards, automatic vehicle location, vehicle information and communication systems, and a management system for reservations and recharging (Shaheen *et al.*, 2017).

In the United States, one-way car-sharing services were first used as a supplement for public transit systems. In 1999, CarLink I launched at the Dublin/Pleasanton Bay Area Rapid Transit (BART) station in the East Bay of the San Francisco Bay Area. This scheme consisted of 12 cars transporting customers between the BART station and the Lawrence Livermore National Laboratory. Similarly, CarLink II was based at the Caltrain station in Palo Alto, California with 27 cars. Once CarLink II pilot came to an end, Flexicar took over the service in 2002. However, it stopped operations in 2003 due to concerns with cost recovery and its limited scale.

The Zero Emission Vehicle Network Enabled Transport (ZEV.NET) is another one-way car-sharing project piloted by the UC Irvine. This system, launched in 2002, provides trips between the Irvine Transportation Centre commuter rail terminal, four employers, and the UC Irvine campus. Its fleet is entirely comprised of EVs. More recently, 30 Toyota iQ EVs were added in March 2013, and the system still operates today (Shaheen *et al.*, 2017).

Since the 1970s, despite many successful one-way car-sharing projects (e.g. Yelomobile), some have ceased operations. The main reasons include economic viability (e.g. CarLink), underuse (e.g. Praxitele), and insufficient technology (e.g. Procotip). Early one-way car-sharing attempts established the foundation for existing car-sharing services today.

2.8.3. Personal vehicle sharing

Personal vehicle sharing (PVS) is another car-sharing model in which private vehicle owners rent their cars to customers. In this business model, the process of vehicle booking is facilitated by an authorised company usually through an online platform. There are four distinct models of PVS: (a) peer-to-peer (P2P) car-sharing, (b) hybrid P2P traditional car-sharing, (c) P2P marketplace, and (d) fractional ownership (Shaheen, Mallery and Kingsley, 2012).

- P2P car-sharing

In the P2P business model, privately-owned vehicles are available to members of a P2P company for a short period. In P2P systems, users are allowed to drop cars wherever needed, hence the operation area for these models is usually much wider than other car-sharing systems.

Getaround and Turo are examples of P2P car-sharing companies in the United States. Pricing and rental terms for these services are usually determined by owners. P2P operators charge a specific amount of money in return for facilitating the exchange and providing third-party insurance.

- Hybrid P2P-roundtrip car-sharing

In the hybrid P2P-roundtrip car-sharing model, individuals access vehicles by joining an organisation that maintains its own fleet, but it also includes private vehicles throughout a network of locations.

- P2P marketplace

The P2P marketplace enables direct exchange among individuals via the internet, including pricing agreements. Terms are generally decided among the parties of a transaction, and disputes are subject to private resolution.

- Fractional ownership

In the fractional ownership model, members subscribe to or sublease a vehicle owned by a third party. In this model, the customers bear part of the operating and maintenance expenses in exchange for being able to use this system. This system enables individuals to have access to vehicles, which might be unaffordable otherwise. Fractional ownership is typically used for luxury cars and recreational vehicles. This system is currently in its early stages and needs more time to evaluate whether it can compete with existing car-sharing systems. Examples of fractional ownership companies in the US are Curvy Road, Gotham Dream Cars, and CoachShare. In December 2014, Audi launched its Audi Unite fractional ownership model in Stockholm, Sweden. Audi Unite offers multiparty leases with pricing based on model, yearly mileage, and the number of drivers ranges from two to five. In February 2016, Ford launched a fractional ownership scheme in Austin, Texas that leases vehicles to self-organised groups of up to six people. Co-owners can reserve a vehicle, check on its status, exchange, exchange messages, make vehicle payments, and monitor their accounts via an app and in-vehicle device.

2.9. AMoD case studies

As discussed in section 2.5, AMoD systems are seen as holding great promise for addressing urban mobility challenges (Kornhauser *et al.*, 2013; Brownell and Kornhauser, 2014). In these systems, road safety is reported to be addressed through removing the main source of error, the driver, from the driving equation. By making cars electric, carbon emissions are reduced hence the environmental quality of cities is improved. Most importantly, by sharing cars, the cost per kilometre would ultimately be reduced to a level that is competitive with car ownership and could in the long-term result in a substantial reduction in the vehicle fleet sizes required to serve the mobility needs of city residents (RMI, 2016).

In recent times, the literature on AMoD systems has grown at a rapid pace. Each study investigates the impacts of these novel systems from various viewpoints such as their effects on capacity, travel cost, vehicle use, environmental issues and so forth (Bösch *et al.*, 2018). A comprehensive review of the literature on all these implications was provided in (Milakis, van Arem and van Wee, 2017). Given this study merely looks at the network impacts of shared AMoD systems, especially their effect on fleet size, and induced VKT, the literature review also focuses on articles of the same scope as the current study. This review is conducted in two sections: analytical and simulation models.

2.9.1. Analytical models

A case study conducted in Singapore (Spieser et al., 2014) provided analytical guidelines for the design of AMoD systems. They used a mathematical network-modelling framework known as the Jackson Network. This concept is discussed thoroughly in chapter 3, section 3.1.6 and 3.1.7.

The researchers used Singapore's household travel survey and taxi data to retrieve the travel demand and traffic characteristics. The results of their study showed that an AMoD system featuring a third of the current number of passenger vehicles could meet the same personal mobility needs of the population. However, the research assumed that the distances between origins and destinations are represented by Euclidean distances, which results in less realism around the network impacts of AMoD systems.

Zhang and Pavone (2016) presented a queuing-theoretical method for modelling and evaluating AMoD systems. Similar to the previous study, this research group also used Jackson network concepts for their investigations. They conducted the study in the context of a case study of New York City and showed that the current taxi demand in Manhattan can be met using only 70% of the current taxi fleet.

A recent study published in Nature (Vazifeh *et al.*, 2018) deploys an analytical approach to explore its AMoD scenarios. The model uses travel demand consisting of 150 million trips undertaken in New York City over the calendar year of 2011. It also utilised historical data to estimate travel times between the origins and destinations. The results of this research suggest a 30% reduction in fleet size compared to the current taxi fleet in New York City.

Another analytical study (Burns, Jordan and Scarborough, 2012) conducted cost analyses and measured potential savings due to deploying AMoD systems in comparison with traditional personal owned vehicles. The researchers also validated their analytical model against a simulation model. However, the amount of information provided by the authors regarding their simulation model is insufficient. In particular, the algorithms used for simulating the agents is unspecified.

The major drawback of all the studies reported in this section is that they underestimate induced VKT, a key decision variable in assessing the performance of AMoD systems, and the performance of these systems has only been assessed based on trip success rates and passenger waiting times.

2.9.2. Simulation models

Lisbon Study:

In a study conducted for the city of Lisbon in Portugal (ITF, 2015c), the authors developed an agent-based simulation model to explore the impacts of AMoD systems. They used 1.2 million trips to represent the travel demand based on the Lisbon travel survey and aggregated the demand to a grid of cells measuring 200 metres by 200 metres. The major finding of their study was that AMoD systems would meet the demand for travel using only 10% of the existing number of vehicles, if supported by a high capacity public transport system. Their study also suggested that this would be at a cost of 6% more VKT. Further, they showed that VKT could increase up to 89% if no ride-sharing is allowed, and the city lacks a high-capacity public transport system. It is not clear, however, how the authors performed the redistribution of empty vehicles to service the waiting customers. Moreover, they did not use a dynamic traffic model to simulate the variation of traffic conditions due to changes in current transport fleet size.

Austin Studies:

Researchers at the University of Texas (Fagnant and Kockelman, 2014) used MATSim[1] to model a non-realistic gridded city that includes a ten-mile by ten-mile square area, about twice the size of

1 MATSim is widely discussed in Chapter 3, section 3.3.3.1.

Austin city. They divided the whole area into 1,600 different zones, each of which represent a 0.25-mi-by-0.25-mi square area, and aggregated the travel demand into these cells. The results of this study indicated that each shared AV can replace around eleven conventional vehicles at the cost of adding 10% more travel distance compared to conventional trips. The temporal distribution of trips was based on National Household Travel Survey (NHTS) data, and the redistribution of empty vehicles was performed through a heuristic method. Another limitation in this study is that they used an average speed for the whole area during peak and off-peak periods based on 2009 NHTS data instead of having the speeds produced by a traffic simulation model.

The authors also conducted other research (Fagnant, Kockelman and Bansal, 2015) to quantify the potential impacts of the AMoD systems at low levels of market penetration. The MATSim model represented a 12-mile by 24-mile regional core area of Austin with link-level travel speeds which varied by time of day to take into account the changes in traffic conditions over the course of the day. A 100,000-trip subset was then randomly drawn, with 57,161 of these travellers having both origins and destinations with a centrally located 12-mile by 24-mile geofence.

The spatial distribution of demand was based on a zoning system introduced in the Capital Area Metropolitan Planning Organisation (CAMPO) in which the distribution of trip origins are at half-mile resolutions. As for the temporal distribution of demand, the authors used another city's travel survey data (Washington's household travel diaries) on the grounds that the Austin data's departure times seemed inaccurate.

The results of this study suggest that each shared AV could replace around nine conventional vehicles within the study area while maintaining an acceptable level of service, but adds up to 8% new VKT. Unlike their previous study (Fagnant and Kockelman, 2014), the authors in this case used MATSim estimated travel times to account for the dynamic nature of traffic flow.

The same researchers also leveraged the model developed for Austin to investigate the network impacts of AMoD systems with ride-sharing (Fagnant and Kockelman, 2016). The results suggested that a Dynamic Ride Sharing (DRS) system could reduce the empty VKT and had the potential to improve passenger satisfaction through decreasing waiting times. This study implemented a heuristic DRS method. There are other papers in the literature (Agatz *et al.*, 2010, 2011; Nourinejad and Roorda, 2016) which propose optimum DRS algorithms. However, these algorithms have only been tested using an optimisation studio called CPLEX and therefore, future works in this area could implement them in an agent-based simulation framework to test the performance of optimum DRS methods in a dynamic environment as well. Greedy DRS algorithms have also been proposed in the literature (Shuo Ma, Yu Zheng and Wolfson, 2013) to investigate the efficiency of these systems.

Another study (Levin et al., 2017) conducted in Austin city developed a simulation model in Java and showed that shared AMoD systems could increase current congestion levels. They suggested that implementing these systems without dynamic ride-sharing schemes would not prove sustainable.

Chen et al. (2016) developed an agent-based model for Austin which took into account the effects of electric vehicle charging infrastructure and vehicle range on the efficiency of the AMoD systems. Their research suggests that fleet size is highly dependent on the charging characteristics of the system. In addition, they concluded that a shared AMoD system could serve 96-98% of trips with average passenger wait-times between 7 and 10 minutes. However, this system induced 7-14% more VKT.

Finally, Liu et al. (2017) evaluated AMoD systems for a region, located in Austin defining four different fare levels for shared AVs. They developed a model in MATSim and deployed discrete choice models (Chen and Kockelman, 2016) to model travellers' travel preferences. Their AMoD model suggests a 7.8% to 14.2% increase in VKT. However, ride-sharing was allowed in their scenarios.

Zurich Study:

Boesch et al. (2016) conducted a study in Zurich to investigate the required fleet sizes for different levels of demand. The travel demand for the study included 3.6 million trips. The authors investigated the relationship between AV fleet sizes for different levels of demand ranging from 1% to 10%. They concluded that the relationship between served demand and required fleet size is nonlinear and the ratio increases as demand grows. Further, their study found that if the customers accepted waiting times of a maximum 10 minutes, the current fleet size could be reduced by up to 90% even without empty vehicle redistribution. The study, however, did not redistribute the idle vehicles to service the waiting customers, and used static rather than dynamic travel demands.

Stockholm:

Researchers at the university of KTH (Burghout, Rigole and Andreasson, 2015) developed a simulation AMoD model to explore the efficiency of these systems for the city of Stockholm.

Their study revealed that a fleet of shared AVs without ride-sharing, which is 92% smaller than the current private vehicle fleet, can completely meet the travel demand while inducing 24% more VKT.

Berlin Study:
Berlin is another city for which performance of AMoD systems has been investigated using MATSim. The results of this research (Bischoff and Maciejewski, 2016a) show that the current private vehicle demand (1.1 million cars) in Berlin could be met by only 100,000 AVs. However, their AMoD model suggests that the empty rides are less than 10% in the city. This study also believes reducing the service area enhances the efficiency of the system.

New York Studies:
The New York study (Shen and Lopes, 2015) introduced the Expand and Target algorithm, which was integrated with three different scheduling strategies for dispatching AVs. The study also implemented an agent-based simulation platform and empirically evaluated the proposed approaches using the New York City taxi data. The experiment results demonstrated that the algorithms significantly improved the passengers' experience by reducing the average passenger waiting-time by around 30% and increasing the trip success rate (i.e. the number of trips can be serviced without exceeding the customer-waiting time threshold) by around 8%.

In another study (Alonso-Mora et al. 2017), the authors investigated the effects of AMoD systems using AVs with different capacities and ride-sharing capabilities via dynamic trip-vehicle assignment. The research proposed a highly scalable optimal algorithm, which was experimentally validated using New York City taxi data and information from a shared vehicle fleet with a capacity of up to ten passengers. The results of their study showed that a fleet of 3,000 AVs with a capacity of four passengers could serve 98% of taxi rides, which are currently served by over 13,000 single occupant taxis. This article, however, does not report on the induced VKT in the system.

The review of the current literature indicates that although these studies show that replacing the current person trips with shared AMoD systems would result in more VKT, there is no consensus on the degree of the expected increase. ITFa (2015) suggests that a shared AMoD system without any ride-sharing has the potential to serve all demand at the expense of 89% more VKT. However, (Fagnant and Kockelman, 2014), (Fagnant, Kockelman and Bansal, 2015), (Bischoff and Maciejewski, 2016a) and (Chen, Kockelman and Hanna, 2016) estimated this increase between 7% to 14%. Boesch et al (2016), on the other hand, suggested that 90% of trips could be met using a shared AMoD system without induced VKT provided that passengers accepted waiting times up to 10 minutes.

2.10. Chapter summary

This chapter started with an elaboration of the concepts of smart cities and mobility. Then, vehicle automation, disruptive technologies, and their main constituents were explained. Further, some applications of these technologies in different urban contexts were provided to show how smart mobility could improve the efficiency of our cities. This chapter also illustrates concepts of AMoD systems, ride-sharing, car-sharing and their various forms.

The final section of this chapter provided a comprehensive review of the available AMoD case studies in the literature. This chapter categorises these case studies into two distinct groups namely, analytical models and simulation models.

Analytical models, which are based on the method proposed by James R. Jackson in 1957 (Jackson, 1957), utilise mathematical techniques to model transport networks. The main drawback of analytical models is their reliance on quite unrealistic assumptions such as disregarding the effects of congestion in the network. Although using such models could have been justifiable back in the time when powerful computers did not exist, deploying them to answer today's transport questions does not make sense.

One of the analytical models was developed for Singapore (Spieser *et al.*, 2014) in which researchers showed a fleet of AMoD system could meet the same travel demand as today using only a third of the current number of passenger vehicles. Another analytical model (Zhang and Pavone, 2016) also suggests that an AMoD system could meet the current taxi demand in Manhattan using only 70% of the current New York taxi fleet.

Neither of these models, however, explored the effects of AMoD systems on VKT. Further, they assumed Euclidean distances between their origins and destinations rather than utilising the real road network, which ultimately led to less realism.

There are also many simulation models in the literature which have suggested AMoD systems could meet the current demand using much fewer vehicles than that of today at the expense of an increase in VKT.

Many studies suggest very small potential increases in VKT, ranging from 6% to 14% (Fagnant and Kockelman, 2014; Fagnant, Kockelman and Bansal, 2015; Bischoff and Maciejewski, 2016b; Boesch, Ciari and Axhausen, 2016; Chen, Kockelman and Hanna, 2016; Liu et al., 2017). The Stockholm study (Burghout, Rigole and Andreasson, 2015) also predicts a 24% increase in VKT when AMoD systems are operational. However, studies such as (ITF, 2015c; Levin *et al.*, 2017) suggest AMoD studies could translate into high induced VKT in the system.

Various other simulation models also exist (Shen and Lopes, 2015; Alonso-Mora *et al.*, 2017) which, although having shown the potential impact of AMoD services on reducing the current private vehicle fleet size, they do not report on the amount of increase in VKT.

Chapter 3 : Modelling Approaches: Selection of Suitable Frameworks for the Evaluation of Technology-Driven Transport Initiatives

Supply modelling in transport engineering endeavours to put forward concepts, methods, and algorithms to provide a platform where investigating the performance and implications of various transport scenarios becomes feasible. Transport supply modelling (also known as transport network modelling) techniques always try to trade-off the accuracy of models with computational efficiency. This trade-off is mainly determined by the scope of the project at hand, availability of data, and budget constraints.

Initially, transport supply modelling techniques were heavily based upon mathematical algorithms and concepts and far simplistic assumptions to provide a tractable solution. This category of modelling is known as the analytical modelling approach.

The advent of computers suitable for use in personal offices at an acceptable price led to the rise of new modelling tools that were much more sophisticated than their analytical counterparts, and could remove many of the simplifying assumptions, which was the case in analytical models. These models are known as simulation models and provide a more realistic representation of transport networks, an essential component for producing reliable outcomes.

Section 3.1 provides a comprehensive discussion of analytical models, their underlying concepts and limitations. Section 3.2 deals with macroscopic models also known as static methods. Section 3.3 illustrates simulation models, agent-based simulation and associated packages as well as their advantages and limitations. A summary of all modelling approaches is presented in section 3.4.

3.1. Analytical models

This section discusses the Jackson Network concept, which have been used as an analytical modelling tool in many studies attempting to analyse AMoD systems. The limitations of this method has also been outlined.

3.1.1. Jackson networks

In practice, an arrival will pass through various queues rather than passing only one queue. For instance, a transport network is made up of several road segments that can be modelled as various queues in which vehicles have to wait to pass a node (intersection). Generally, some simplifying assumptions should be made to overcome the quite difficult nature of the queuing networks. One of these networks is called Jackson networks, first put forward by J. R. Jackson in 1957 (Jackson, 1957).

A network of queues is called a Jackson network if the following conditions are satisfied,

1. All outside arrivals at each queuing station in the network must follow a Poisson process
2. All service times must be exponentially distributed
3. All queues must have unlimited capacity
4. When a job leaves one station, the probability that it will go to another station is independent of its history, and of the location of any other job (Markovian property).

The first three conditions represent the assumptions made for an $M/M/s$ queue. The fourth condition implies that in such systems, real-time decision-making is not possible. For instance, in a transport network, if a road segment becomes congested, the new arrivals do not switch to the route with the highest level of service, rather they choose a random route according to some probability distribution.

It has been proved by (Jackson, 1957) that when a system holds these conditions, each queue can be analysed as separate queues by the equations discussed earlier in this chapter and the results can be aggregated at the end.

To illustrate how these discussions can be deployed to analyse different networks, consider a system with v parallel processing stations that feed a final packaging station j as shown in Figure 3-7.

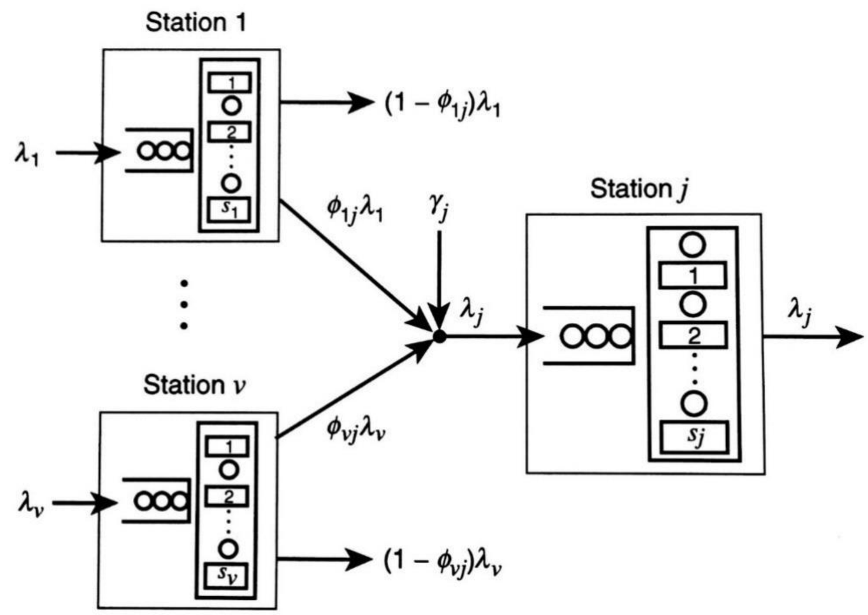


Figure 3-1: Two-stage queuing network (Jensen, P and Bard, J, 2003)

In this system, each station receives input from only an external source and a fraction of its output goes to station j, while the remainder leaves the system. Station j receives inputs from outside the network at a rate of γ_j as well as from the v processing stations with probability $\phi_{ij}, i = 1, 2, \ldots, v$. In other words, if the flow rate through station i is λ_i, then the flow rate into station j is the sum of all these sources.

$$\boldsymbol{\lambda_j = \gamma_j + \sum_{i=1}^{v} \phi_{ij}\lambda_i} \qquad \textbf{Equation 3-1}$$

In this example, the steady-state probability distribution for the number at each station and Little's law discussed for the $M/M/s$ model can be used, provided that all the external arrival processes and all the service processes are Poisson. Note that steady-state results are only valid for queues with unlimited capacity, Poisson input and service processes, and independent transfer probabilities ϕ_{ij}.

To compute the input rate to each queuing station, let λ_i denote the total input to station i. Assuming that input to the station equals output, it can be stated that the total output from station i is λ_i as well. Given that the input to any station i must equal the input from outside the system plus any output from the other stations routed to i, for an arbitrary network with m stations, the general relationship can be written as follows,

$$\boldsymbol{\lambda_i = \gamma_i + \sum_{k=1}^{m} \phi_{ki}\lambda_k \qquad i = 1, 2, \ldots, m} \qquad \textbf{Equation 3-2}$$

In this equation, γ_i is the rate of arrival at station *i* from outside the network and ϕ_{ki} is the probability that the output from station *k* will be routed to station *i*. The system of m linear equations given by this formula can be solved to determine the net input rate λ_i for each station.

Let Φ be the $m \times m$ probability matrix that describes the routing of units within a Jackson network, and let γ_i denote the mean arrival rate of units going directly to station *i* from outside the system. Then

$$\boldsymbol{\lambda} = \boldsymbol{\gamma}(\mathbf{1} - \boldsymbol{\Phi})^{-1} \qquad \textbf{Equation 3-3}$$

where $\gamma = (\gamma_1, \dots, \gamma_m)$ and the components of the vector λ denote the arrival rates into the various stations that is λ_i is the net rate into station *i*.

After the net rate into each node is known, the network can be decomposed and each node treated as if it were an independent queuing system with Poisson input.

3.1.2. Limitations

As discussed in the previous section, analytical models established on queuing theory are mainly restricted by various limitations attempting to turn these models into a tractable solution. The most prominent analytical model that has been manipulated to represent transport networks is called Jackson networks, discussed previously in this chapter.

Jackson networks are limited by the constraints obliging the transport modellers to resort to very unrealistic assumptions, discussed as follows,

1. First constraint: *All outside arrivals at each queuing station in the network must follow a Poisson process.*

The Poisson process assumes a constant rate of occurrence for a specific random variable such as passenger arrival times. That is, it assumes passengers arrive at a constant rate to a taxi station over a specific course of time (or simulation time). In other words, it fails to capture the time-variant nature of arrival rates which happens in real life, thereby leading to less realism.

2. Second constraint: *Service times are exponentially distributed.*

Exponential distributions assume constant expected times between various events of a random variable. For instance, if a random variable is the time a vehicle needs to traverse a road segment (i.e. service times), an exponential distribution will assume the expected travel time required to pass that road segment is always the same for all vehicles regardless of the volume of traffic on that road. This feature is also referred to as the memoryless property of an exponential distribution.

In simple terms, this constraint disregards the congestion effects on a real transport network. Moreover, the study shows that travel times on a transport network do not follow an exponential distribution (Chalumuri and Yasuo, 2014).

3. Third constraint: *All queues must have unlimited capacity*

In Jackson models, each road segment is modelled as a queue starting from a node that represents the intersection. This constraint implies that the capacity of a specific road segment is infinite and can take as many vehicles as arrives at that road segment. In reality, a specific road has a limited capacity exceeding which will result in queue spillback affecting the capacity of the following road segment as well.

4. Fourth constraint: *When a job leaves one station, the probability that it will go to another station is independent of its history and of the location of any other job*

This constraint rules out the real-time decision-making process entirely. That is, in a transport network context, if a road segment becomes congested, the new arrivals would not switch to the route with the highest level of service, rather they choose a random route according to some probability distribution.

In addition to the limitations discussed in this chapter, another simplifying assumption that Jackson networks make is the fact each queue (a queue of vehicles on a road segment, or a queue of customers waiting at a taxi rank in a transport network context) can be analysed as separate systems and the results can be aggregated at the end.

It is a very coarse assumption that rules out the interactions of different components of a system with each other. As (Barcelo, 2010) states, a system is a collection of entities that act and interact together toward the accomplishment of some logical end. Wholes cannot be reduced to the sum of their part, and a system is more than the mere sum of its parts.

3.2. Macroscopic models

Macroscopic models (also known as aggregate or static models) represent the dynamics of traffic flow regarding their analogy with fluids. These models consider the spatiotemporal evolution of the macroscopic variables, volume q(x, t), speed u(x, t), and density k(x, t) in order to explore the behaviour of transport systems (Barcelo, 2010).

Fundamental relationships between traffic flow parameters are speed-sensity, speed-flow, and flow-density relationships, called the Greenshield's models, which are shown in Figure 3-8. It should be noted that the slope of any line drawn from the origin of the speed-flow curve to any point on the curve represents density. Similarly, the slope of any drawn line from the origin of the flow-density curve to any point on the curve represents speed.

It is clear from Figure 3-8 that flow rate is zero when density is either zero (no vehicle is on the road) or maximum (Jam density (D_j) in which the number of vehicles is more than the road capacity). For the zero density condition, speed is equal to S_f (speed for the free flow condition in which traffic flow is unaffected by upstream or downstream conditions) and should be considered as a theoretical amount and is selected by the first driver.

Figure 3-8 illustrates that flow and density increase from zero in parallel as speed declines constantly over this period up to a point called road capacity. This condition is shown as optimum speed , So (often called critical speed), optimum density, Do (sometimes referred to as critical density), and maximum flow Vm (HCM, 2010).

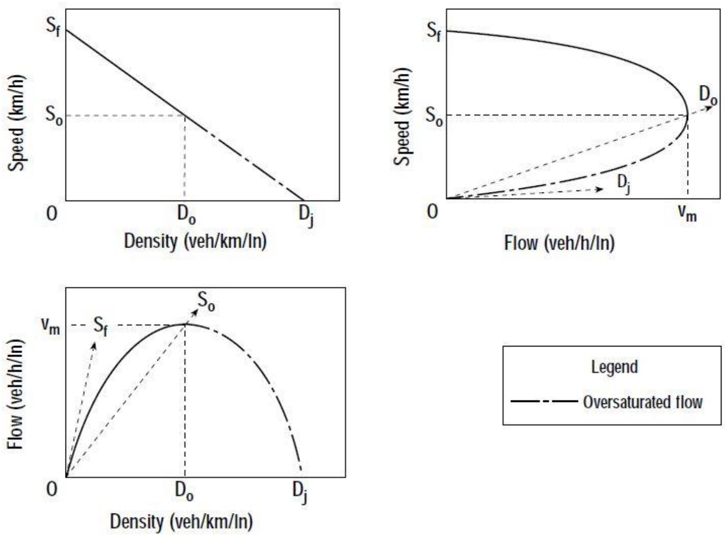


Figure 3-2: Relationships between speed, density, and flow rate (HCM, 2010)

Macroscopic models are appropriate for analysing large-scale areas such as an entire city, where realizing the minor interactions between entities does not affect the final results of simulation. For instance, in a metropolitan area, the overall effects on the transport network due to obstructing one arterial route in order to perform some essential maintenance can be examined by developing a macroscopic model which provides a sound insight into how traffic characteristics alter on neighbouring suburbs. Examples of macroscopic simulation models are Visum (PTV Visum, 2017) and Aimsun (TSS, 2017).

Some of the most significant characteristics of macroscopic models are as follows,

1. Macroscopic models describe the most important properties of traffic flows, such as the formation and dissipation of queues, shock waves etc.
2. They enable the determination of average travel times, the mean fuel consumption and emissions in relation to traffic flow operations.
3. These models are generally deterministic and less sensitive to small disturbances of input (TUD, 2014).

The application of macroscopic models is extensive and ranges from signal optimization models (Chen and Chang, 2014), traffic flow predictions (Abadi, Rajabioun and Ioannou, 2014) to assessing the environmental impacts of traffic management methods (Uzunova and Djemai, 2014).

For example, the study by (Uzunova and Djemai, 2014) incorporated a macroscopic traffic simulation model in combination with a CO_2 emission model to investigate the effect of traffic control on CO_2 emissions for a case study situated downstream on a toll plaza. This study proposes a general conceptual framework for evaluating the CO_2 emissions on the highways, depending on the driving speed and the density on the road. The macroscopic lighthill, Whitham and Richards's model, was utilised to model the toll plaza traffic flow, which uses the Greenshield's function method and is presented by a non-linear hyperbolic partial differential equation.

This study proved that improved traffic flow does not necessarily result in lower vehicle emission. In other words, traffic control strategies can have a constructive impact on CO_2 emissions provided that they ensure high density and high velocity on the highways. In contrast, if traffic control strategies end up with low density and high velocity or high density and low velocity on highways they will lead to high CO_2 emissions.

3.3. Simulation models

With the advent of more powerful computers, transport modellers are provided with novel tools whose capabilities goes beyond that of traditional analytical models, which were merely based upon simplistic and sometimes unrealistic assumptions.

Simulation provides a platform for studying the behaviour of specific real-world systems in various circumstances in a simple and economical manner. Most of the subsequent effects due to any modification in a system can be assessed in a computer without any need to establish high-cost experiments in the field which is also impossible in some cases. In other words, simulation is a technique which permits the study of complex systems such as transport networks in the laboratory rather than in the field. Some reasons why simulation methods are utilised, especially in the transport modelling domain are as follows:

a) Simulation provides a condition in which gathering the data in a systematic way becomes possible thereby the study of traffic characteristics and operation become much more possible.

b) The simulation of complex traffic operations clarifies the importance degree of different variables and how they relate. This may lead to significant analytic formulations.

c) Simulation is a method to test the authenticity of analytical solutions (Drew, D, 1968).

One of the powerful aspects of transport simulation tools is their ability to represent the dynamic nature of supply and demand processes, a key feature in all stochastic systems. The dynamic propagation of traffic flow within the network, varying traffic control strategies such as traffic signals, various capacity of links within a day, and the effects of public transport systems on traffic flow are examples of various phenomena that can easily be modelled and explored in simulation models.

Transport simulation models fall into two categories, namely, microscopic and mesoscopic models. These classifications are based on the way the traffic simulation models treat the traffic flow. Sections 3.2.1 and 3.2.2 discuss these models in more detail. Section 3.2.3 illustrates the notion of agent-based modelling and describes the related programs, MATSim and Commuter. MATSim is an agent-based simulation tool that has been widely used in the literature by many researchers to investigate the behaviours of AMoD systems. This section provides more details on the algorithms that MATSim and Commuter deploy and their associated limitations.

3.3.1. Microscopic models

Microscopic simulation models consider each vehicle through the network and apply its interaction with other vehicles and road infrastructure. In other words, microsimulation models are dynamic, stochastic and discrete time modelling techniques that simulate the movement of individual vehicles based on car following, lane changing and gap acceptance algorithms that are updated several times every second (NSWG, 2013). Additionally, given microscopic models can better capture the dynamic nature of traffic flow, analysing the small part (e.g. intersection, merging ramps etc.) of a large network utilizing microscopic simulation models can lead to more precise results.

Generally, vehicle-behaviour models can be divided into car-following, lane-change, and route-choice models. The car-following model describes the breaking and accelerating patterns as a result of the interaction between the driver and the following vehicle as well as other objects such as speed limits, road curvature, etc. The lane-changing model determines when a driver should change lanes based on the driver's preferences, speed of the following vehicle, a sufficiently large gap in the adjacent lane, etc. The route-choice model describes how drivers determine which path to take from their starting location to their destination, and how they react to traffic and route information along the way (Burghout, Koutsopoulos and Andréasson, 2005).

Demand in microscopic models is determined in two ways. The first method is to designate the traffic flow entering the network in combination with the percentage of vehicles that turn left, right or go straight for each intersection approach. The second method is to divide the entire modelled network into different zones and define the number of vehicles that intend to travel from each zone to others using an origin-destination (OD) matrix (Burghout, Koutsopoulos and Andréasson, 2005).

Microscopic models have a great capability to analyse a specific part of a whole transport network (e.g. merging ramps, signalized intersections, roundabouts, etc.) in considerable detail. For example, the effect of a bus stop on the capacity of an intersection, signal timing optimization or the delays which are being experienced by each type of vehicle due to a cross walk can be investigated exploiting a microscopic model. Moreover, microscopic models can be used to assess the emission of green-house gases due to transport activities (EC, 2009). Another advantage of microscopic simulation models is their ability to interact online with external real time applications, as for example SCOOT, SCATS, Real-Time Ramp Metering, or actuated systems (TSS, 2017). Examples of microscopic simulation models are Vissim (PTV Vissim, 2017), Paramics (Paramics,

2017) and AIMSUN (TSS, 2017). However, microscopic simulation models have their own shortcomings, including high sensitivity to input parameters and geometric properties as well as a cumbersome calibration and validation process due to the many parameters that are part of the microscopic model (Burghout, Koutsopoulos and Andréasson, 2005).

Many studies have dealt with transport issues utilizing microscopic models. For instance, Alterawi and Yousif (2014) developed a micro simulation model to examine complex drivers' behaviour at shuttle-lane urban roadwork where one lane of a single carriageway road is closed while leaving the other for use by both directions in an alternating way. The model development for this study is made up of two parts. The first part defines a car following (CF) model calculating the acceleration/deceleration rates of successive vehicles with respect to their leader. To develop the CF model, the authors took into account used by previous studies with some modifications to account for the driver's compliance at the TTSs and the effects of a dilemma zone (DZ). In the second part, the behaviour of a driver approaching an SL roadwork zone is modelled inspired by the available concepts in normal signalized intersections. Moreover, the compliance of a driver with TTSs in terms of responding to the presence of DZ was examined. The study which was based on real observations collected from six SL road works within Greater Manchester, UK, divided drivers into four categories given their intention to cross the red light as follows,

Category 1—DZ: Drivers choose to cross during amber/red light due to the presence of a DZ.

• Category 2—DZ follower: Drivers choose to follow a leader that crossed during amber/red light due to the presence of a DZ.

• Category 3—Group violations: Drivers choose to violate the red light due to frustration/long waiting time caused by microwave vehicle detector failure.

• Category 4—Single violation: Drivers choose to violate the red light because of the available opportunity of a gap in traffic.

All parts of the microscopic model were tested using real data collected from site observations, and the calibration and validation of the model led to acceptable results (Alterawi and Yousif, 2014).

3.3.2. Mesoscopic models

Mesoscopic models refer to mathematical models for the movement of clusters or platoons of vehicles, incorporating equations to indicate how these clusters interact (HCM, 2010). Mesoscopic models lie between macroscopic and microscopic models aimed at decreasing the computational burden of microscopic models for calibration and validation in parallel with shrinking gaps of macroscopic models. In general, under the mesoscopic traffic flow, models should be understood as models where traffic flow is described with a high level of detail, but at the same time, flow behaviour and flow interaction are presented at a low level of description (Savrasovs, 2011). Aimsun, DYNAMIT, DYNEMO and DYNASMART are some examples of mesoscopic simulation models (Boxhill and Yu, 2000). The main application area of mesoscopic models is where the detail of microscopic simulation might be desirable but infeasible due to a large network, or limited resources available to be spent on the coding and debugging of the network (Burghout, Koutsopoulos and Andréasson, 2005).

Different programs incorporate varying techniques for defining mesoscopic models. Programs such as CONTRAM (Leonard, 1989) receive input demand as a time-sliced Origin-Destination matrix and divide them up into a stream of small packets which are routed independently (Taylor, 2003). The speed for each packet on any road is derived from a speed-density function, which is special for that link. However, the lane changes and acceleration/deceleration of vehicles is not modelled (Burghout, Koutsopoulos and Andréasson, 2005).

Another mesoscopic model called DYNAMIT (Ben-Akiva, 1996) simulates driver-behaviour at a disaggregate level while OD matrix estimation and prediction take place at an aggregate level. In this model, a deterministic queuing model and a speed model are utilised to capture traffic dynamics (Ben-akiva *et al.*, 1998).

Exploiting mesoscopic models can aid researchers cope with transport challenges. As an example, Li et al. (2015) developed a mesoscopic model to simulate the dynamics of vehicles on an urban expressway network under variable speed limit strategies. This study took the Jinan expressway network as a case study, which is the main traffic artery of this city, and focused on finding the discipline of traffic jam propagation and characteristic congestion propagation to seek a solution to ease traffic congestion by a variable speed limit method. The results of the simulation showed that the variable speed limit strategy can improve the traffic condition of an area where there is an accident which causes traffic jams on the traffic network (Li, Fu and Dang, 2015).

3.3.3. Agent-based simulation

All traffic simulation programs regardless of their traffic flow models (microscopic or mesoscopic), are described as agent-based packages. However, the key difference between agent-based simulation tools is the fact that in some of them, such as Vissim or Aimsun, only vehicles are considered to be agents, whereas in others such as MATSim or Commuter, individual travellers are also considered agents. In other words, in the former type, only vehicles' information can be retrieved while in the latter, travellers' information can also be generated.

Tracking individual travellers within the simulation framework enables software to store the travel information of each customer moving from one point to another across the transport network. This information can be customer waiting times at taxi stations, or the success rate of a transport system in servicing customers in time. In particular, models that evaluate AMoD, car-sharing or ride-sharing scenarios need to have access to individual travellers' information in order to gain a realistic insight into the performance of the proposed transport system.

MATSim is one of the most famous agent-based programs and is capable of tracking travellers within transport network. This program, however, suffers from some significant limitations, which led the current research team to choose a different agent-based program called Commuter. The following sections illustrate MATSim and Commuter in detail along with their limitations.

3.3.3.1. MATSim

MATSim (Multi-Agent Transport Simulation) is an open-source agent-based simulation platform tailored for large-scale scenarios. This has been realised through stripping down the model's features such as deploying a very simple queue-based approach to represent the traffic flow within the network rather than using very complex car-following and lane-changing models.

Each agent in MATSim repeatedly optimises its daily activity schedule while in competition for space-time slots with all the other agents in the model. This is based on a co-evolutionary algorithm and is analogous to the dynamic route assignment technique with some additional choice dimensions such as departure-time and mode-choice models.

In MATSim, initial demand is based on the daily activity chains of the populations involved in the study area and is derived from empirical data through sampling or discrete choice modelling. As shown in Figure 3-9, this initial demand is optimised individually by each agent through a process known as MATSim loop or MATSim cycle.

In MATSim, each person has a number of daily plans, which are scored through simulation and calculate the performance of each plan. In other words, every agent initially selects a plan and executes that plan through simulation. At the end of the simulation, if the agent finds that the chosen plan incurred a penalty (e.g. arrived late at workplace), the agent chooses another plan for the next day. This process is referred to as re-planning (Horni, Nagel and Axhausen, 2016).

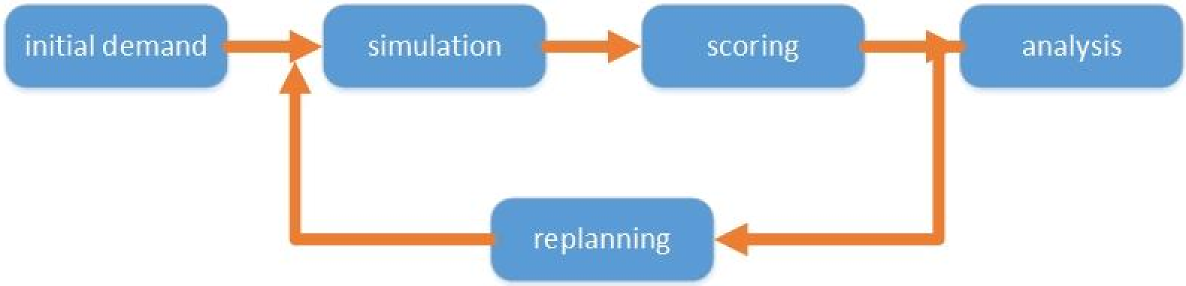


Figure 3-3: MATSim loop, sometimes called the MATSim cycle (Horni, Nagel and Axhausen, 2016)

a. MATSim Traffic Flow Model

As MATSim is developed to model large-scale scenarios, it utilises a computationally efficient queue-based approach. In this model, cars queue up in front of the intersection and new entrants to the link are added to the end of the waiting queue. This method disregards the state of traffic on the link itself and analyses traffic flow looking only at the intersections. In other words, in this method, traffic is either flowing freely on the links or cars are queuing up in front of the next intersection and waiting for the car in front of them to move. Travel time is equivalent to the time needed to travel down the street at free speed. That is, when a car enters a link, it keeps traveling at free flow speed as long as it confronts a queue where it must stop as long as the preceding cars move forward. This model accelerates the simulation process by reducing the amount of information processed by the program by virtue of disregarding the fine-grained stop-and go interactions between following vehicles (Charypar, Axhausen and Nagel, 2007).

MATSim uses an event-driven simulation approach in which information regarding a link is processed whenever a car enters or leaves a link (i.e. an event occurs) as opposed to the time-step based approaches that store the information in every time-step.

The inefficiency of time-step approaches become visible when flow density is very low on a link such as during off-peak periods or at nights. During these periods, the program has to conduct many computations for empty links, which will translate into a slower simulation process.

Event-based approaches, on the other hand, process the links whenever they enter or leave them. That is, the computational effort is proportional to the traffic load, and the most computational time is spent where traffic flow is maximal and almost no time is spent where the traffic network is empty (Charypar, Axhausen and Nagel, 2007).

b. MATSim's Co-Evolutionary Algorithm

In MATSim, each person represents a species with a specified daily plan. A co-evolutionary algorithm co-evolves different species regarding their attributed plans, and people compete to optimise their plans, taking into account the interactions between various agents (Figure 3-10). Note that this equilibrium is more than traditional traffic flow equilibria, which ignores activities.

The main difference between evolutionary and co-evolutionary algorithms is that the evolutionary algorithm results in system optimum as optimisation is conducted using a global fitness function, whereas the co-evolutionary algorithm leads to user equilibrium since optimisation is realised in terms of individual scoring functions, and within an agent's set of plans.

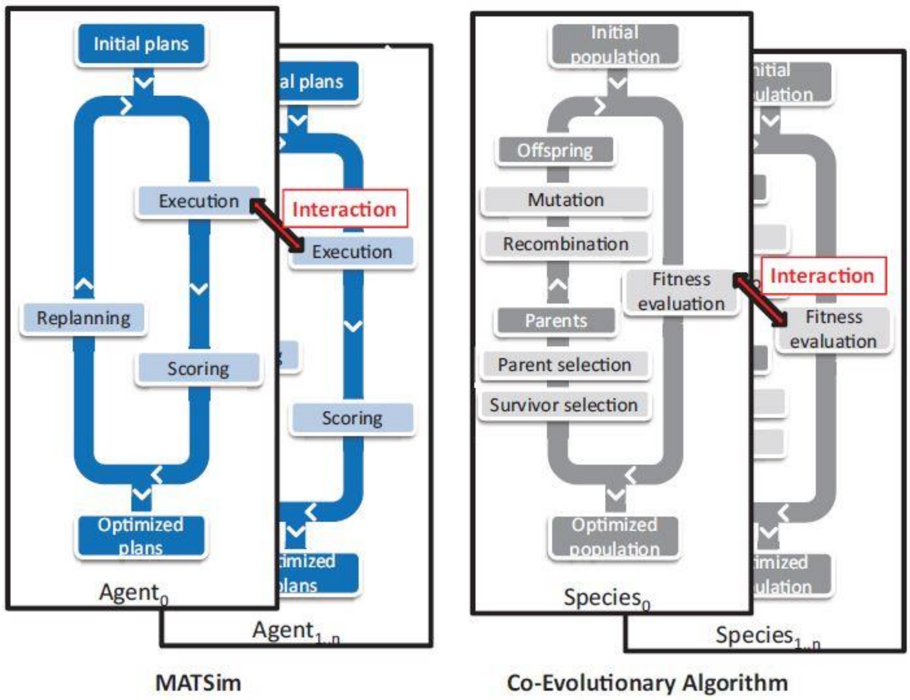


Figure 3-4: The co-evolutionary algorithm in MATSim (Horni, Nagel and Axhausen, 2016)

c. Score and Utility

As previously discussed, in MATSim, agents learn by executing multiple plans in the simulation environment and scoring them accordingly. Scoring is a central component of MATSim and only solutions with the highest score will survive. That is, if an agent's plans exceed the maximum number of plans he or she is allowed to have, MATSim will remove the plan with the lowest score from the agent's memory.

The performance of the plans is selected by the agents at the end of simulation. Some may prefer a congested car trip, others may prefer a crowded but affordable trip by public transit, while others may prefer using a bicycle even in bad weather. To replicate this, MATSim uses random utility models for the score, as discussed in (Ben-Akiva and Lerman, 1985).

MATSim's basic scoring function was formulated by (Charypar and Nagel, 2005) in which the utility of a plan S_{plan} is computed as the sum of all activity utilities $S_{act,q}$ plus the sum of all travel dis-utilities $S_{trav,mode(q)}$.

$$\boldsymbol{S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)}} \quad \textbf{Equation 3-4}$$

where N is the number of activities, and Trip q is the trip that follows activity q. For more information regarding the scoring functions, refer to (Horni, Nagel and Axhausen, 2016).

3.3.3.2. Commuter

The agent-based simulation program used for this research is called Commuter. To build a model in Commuter, one needs to start by constructing the network objects which define the surfaces on which the agents move, such as lanes and intersections for road vehicles, tracks for trains and trams, and walking surfaces for pedestrian movement.

After defining the required objects to represent the network, mode-change areas need to be specified within the model. For instance, a parking area represents a mode change from driving to walking or vice versa. Mode-change locations supported in Commuter are as follows:

- Parking areas on-street, in bays, and off-street and in single-story or multi-storey lots;
- Public transit stands for buses, trams, and trains;
- Drop-off areas applying to private vehicles and taxis;
- Pick-up areas for private vehicles and prearranged collection points, and

- Taxi ranks.

Parking bays can be defined on either side of a street with bays parallel to the direction of traffic flow or perpendicular.

a. Demand definition in Commuter

The next stage in developing a model in Commuter is designating travellers' origin points and also their destinations, when people are to be directed. For directed cases, Commuter uses OD matrices similar to other vehicle-oriented simulation programs with the difference that the areas refer to places that might not be accessible by vehicles. This feature adds some interesting functionalities into the modelling system such as the capability of defining a multi-story building specifying the base and ceiling for each area (Duncan, 2010).

In Commuter, demand consists of three components, namely, demand division, profiles, matrices (directed) or origin volumes and splits (undirected).

A demand division defines a group of types and assigns a proportion to each type, with the proportions summing to 100 percent (e.g. 30% of people travel to the city centre, 40% travel to the northern suburbs, and 30% travel to the eastern suburbs). The demand division is then associated with a demand matrix or origin volume.

A profile can be utilised to specify the demand distribution over time using different demand release rates into the model during different terms, say peak periods or off-peak periods. A profile has a term, defining start time and end time, a number of intervals, and a weight for each interval, specified as a percentage. The weights for all intervals must sum to 100%. For example, in a motorway model with a term of 08:00 to 09:00, automated traffic count data is used to determine the profile of the northbound traffic released from the motorway South zone. This data shows:

• 800 vehicles 08:00 to 08:15;

• 2000 vehicles 08:15 to 08:30;

• 800 vehicles 08:30 to 08:45, and

• 400 vehicles 08:45 to 09:00.

The total number of northbound vehicles in the modelled period is 4000. The profile applied to the South zone would have a term of 08:00 to 09:00, interval of 4, and demand release percentages of:

20% (08:00 to 08:15)

50% (08:15 to 08:30)

20% (08:30 to 08:45)

10% (08:45 to 09:00)

If defining the directed demand in such a way as to assign predefined origins and destinations to each person is of interest, this demand can be entered into the model as a two-dimensional table known as an OD matrix. In commuter, each matrix can be for people, vehicles or freight. A person matrix generates people from each area who can choose any available transport mode to their desired destination. A vehicle matrix releases vehicles into the model in which mode change is not possible. Vehicle OD matrices can be used to generate background traffic where no mode switch is required. Freight is modelled as an agent in Commuter with no walk speed, the freight has a route choice and moves along moving walkways and on available modes of transport (Duncan, 2013).

Once the origin and destination areas are defined, the model builds a routing decision tree to each possible destination from every possible origin. This routing tree uses all available mode choice segment as its branches. The routing tree is based on cost and each person has a behaviour type that assigns costs to time, distance, and price (Duncan, 2010).

Another method for defining demand in Commuter is called undirected demand in which a one-dimensional origin volume and a set of splits are to be specified in the program. The origin volume specifies the number of people or vehicles to be released from each area or zone, respectively. The splits are used for route assignment at each route choice location – for example at intersections or walkway junctions. Undirected demand can be used for smaller networks to speed up the demand building process. When using undirected demand, it is important to recognise that each person or vehicle does not have a destination while travelling through the network; it discovers its destination only when it arrives. Each route choice location automatically creates a split object that, by default, assigns an equal proportion of all incoming traffic to each of the available exit options. At a 4-way intersection, an incoming agent has a choice of left, right or straight ahead, and the default split object will stochastically assign the agent to one of those exits, each with equal probability of 1/3.

The split function is very simple; if more complex routing rules are required, then the route choice tool allows rules to be created that assign the exit (left, ahead, right) based on origin area, agent type, sign settings, etc. The outcome of a route choice rule can be a single exit or a stochastic distribution across multiple exits, similar to a split (Duncan, 2013).

b. Behavioural definitions in Commuter

Another valuable function of Commuter is assigning different behaviours that define which modes of transport (walking, driving, riding, etc.) a person can take to get to the desired destination. For instance, if a person has been assigned behaviours called Can Walk, Can Drive, Can Ride, he can start his trip walking from his home to his own car and drive it to the train station and park it there and take a train to his final destination. Different behaviours available in Commuter are as follows,

- Can Walk: True if a person with this behaviour can use walking as a mode of travel in the model;
- Can Drive: True if a person with this behaviour can drive to a parking zone or a transition zone in the model;
- Can Ride: True if a person with this behaviour can take public transport;
- Can Taxi: True if a person with this behaviour can take a taxi, if taxis are available. Even if this is true, the cost of taking a taxi will still be taken into account in the calculation of the lowest-cost route to the destination. Setting this to false will rule out the option of taking a taxi.
- Can Cycle: True if a person with this behaviour will cycle, and a cycle vehicle type exists
- Can Be Dropped Off: True if a person with this behaviour can be dropped off at a designated drop-off zone. This implies that this person has a car and driver available to drive them to their destination, thus will not need to spend money on parking. This may often be the cheapest option for travelling to a destination with pay parking, but in many cases only a small fraction of the population will have a car and driver available to them.
- Will Be Picked Up: True if a person of this behaviour will be picked up at a designated pick-up zone. If this flag is true, then no other mode will be considered (apart from walking from the origin to the point of pick-up).

c. Traffic flow in Commuter

As for car-following modelling, Commuter proposes three popular models, namely, the Gipps, Wiedemann, and Fritszche models. The Gipps model is used by default, being the simplest of three to calibrate. Users can also define their own car-following algorithms by deploying the Application Programming Interface (API) tool provided by Commuter to enable user-defined extensions.

To investigate the feasibility of Commuter creating a model and running it successfully within a reasonable time to produce results suitable for analysis, Duncan (2010) conducted a study based on Edinburgh Airport, United Kingdom. The study area consists of two ODs for people (areas) one representing the city, the other representing the airport concourse for check-in and arrivals. There are seven different transport modes available for travellers as follows,

1. **Train:** People use a train to get to the airport
2. **Taxi:** People take a taxi to get to the airport
3. **Drop-off:** People have someone to drop them off at the airport
4. **Short-term parking:** People use their own private car to get to the airport and use short-term parking to park their cars
5. **Medium-term open-air parking:** People use their own cars to get to the airport and park their cars in the medium-term open-air parking.
6. **Medium-term multi-story parking:** People use their own cars to get to the airport and park their cars in the medium-term multi-story parking.
7. **Long-term parking:** People use their own cars to get to the airport and park their cars in the long-term multi-story parking.

Six travellers are defined with various behaviours and value of times, and the desired modes are chosen based on their behaviours and the cost of travel.

The model simulated a 4-h morning peak period (06:00 to 10:00am) in an average time of just under 25 minutes. A total of 5335 trips were generated, consisting of 4400 person trips, 845 vehicle-only trips, and 90 public transit trips.

Ten repeated runs with the same input and random seed produced identical results, and when a couple of small network geometry variations were introduced, the variations observed in some key measurements (total travel time and total distance travelled) were not significant. Thus, the model showed excellent repeatability.

In conclusion, the pilot study was successful in that it illustrated that it was possible to model all people in a transport network from origin to destination through a number of mode-changes. Moreover, as shown in Figure 3-11 and Figure 3-12, Commuter provides an appropriate visual platform which allows analysts and even non-experts to well-grasp the interactions between different agents and also the mode-switching of travellers within the network. To date, Commuter has been utilized to investigate several real transport networks in different cities such as Tokyo, Perth, Shanghai (Azalient, 2013).

Further, Commuter enables analysts to explore the environmental effects of vehicles in terms of the amount of exhaust emissions (CO2_NO_PM10) they produce when the number of standard engines is defined. Commuter uses some standard definitions of engines retrieved from the UK Transport Research Laboratory (TRL). However, using the local emission values in order to define the available environmental models of a region is also possible in Commuter (Duncan, 2013).

Figure 3-5: Taxi rank in the model where people change mode from walking to passenger (Duncan, 2010)

Figure 3-6: Shuttle bus stopping to pick up passengers from long-term parking area (Duncan, 2010)

3.3.3.3. Advantages and limitations

MATSim uses a queue-based approach to simulate traffic flow within the network to reduce computational burden (Horni, Nagel and Axhausen, 2016). Therefore, it does not capture the complex car following and lane changing effects and results in reduced model resolution. Another limitation of MATSim is that simulating empty self-driving vehicle-kilometres-of-travel (VKT) (i.e. those vehicles travelling on the road network searching for a customer or needing to travel to service a particular demand) is not possible. MATSim, therefore, only estimates the empty VKTs (eVKT) through unrealistic assumptions in which the AVs are moved virtually between stations based on Euclidean distances from origins to destinations (Boesch, Ciari and Axhausen, 2016), and not on the physical road links. It is worth noting that these limitations are the state of MATSim at the time of writing this dissertation.

On the other hand, Commuter deploys a microscopic traffic flow model, which leads to a more realistic propagation of traffic in a network. Further, Commuter is able to simulate the movement of empty AVs within the network, which helps modellers obtain a better insight into the impact of these empty travels on traffic conditions. However, in Commuter, unlike MATSim, demand can only be introduced at an aggregate level by a demand matrix. This means dynamic destination choice is not possible in Commuter, and people can only head towards a destination ordered by a demand matrix. Added to this, the high resolution of Commuter's traffic flow model prevents it from modelling large areas on a typical PC.

3.4. Chapter summary

This chapter outlines the available supply modelling techniques along with their limitations and divides them into three groups: 1. analytical models, 2. macroscopic models and 3. simulation models.

Although analytical models implement computationally efficient methods to analyse transport systems, their reliance on simplistic assumptions results in a less realistic perspective. Their main limitations include disregarding the effects of congestion and dynamic route choice on traffic conditions in a network as well as modelling transport networks using Euclidean distances.

Macroscopic models use more realistic algorithms and assumptions to evaluate transport systems in comparison with analytical models. Although macroscopic models similar to analytical models implement static methods to assign traffic to the network, their algorithms, to some extent, can capture the effects of congestion on the performance of transport scenarios. Moreover, macroscopic models use real transport networks for their evaluations as opposed to analytical models. Macroscopic models are usually used for strategic planning where detailed traffic flow characteristics do not play a crucial role.

Simulation models can be differentiated according to their traffic flow models and are categorised into two groups: 1. microscopic models and 2. mesoscopic models. Microscopic models use more complex traffic flow models than mesoscopic ones. Although microscopic models give transport modellers a better understanding of traffic conditions on roads, their high resolution does not allow large areas to be modelled on a typical office computer.

All simulation models are agent-based. However, the definition of agent differs in each model. The first group of agent-based simulation models only provide users with information on vehicles travelling within the network, while the second group in addition to vehicle data, records travellers' information and provides them at the end of the simulation.

Given the objectives of the current PhD research, an agent-based simulation model with the latter features would be more helpful. MATSim is one of the most well-known agent-based simulation tools with this characteristic. However, it is not able to simulate empty AVs travelling in the network to pick up customers. Added to this, MATSim's traffic flow model is not able to take into account the interactions between vehicles as it utilises a mesoscopic model. Given the current research aims for exploring the network effects of AMoD systems, implementing a microscopic model which is capable of replicating interactions among vehicles would make more sense. Further, as none of the current AMoD studies in the literature have looked into these systems at a micro level, it would be useful to analyse AMoD systems from this new perspective as well.

With respect to all the aforementioned shortcomings of MATSim, Commuter was chosen as the modelling platform in this research. Commuter uses a microscopic traffic flow model and is able to simulate the empty travels of AVs. That is to say, Commuter produces a more realistic traffic flow in comparison with MATSim. However, modelling large areas in Commuter using a typical PC is not possible due to its more detailed traffic flow models.

Chapter 4 : Pilot Study- Exploration of the Feasibility of Agent-Based Simulation for AMoD Studies

This chapter describes the initial steps undertaken to commence the research process and obtain the knowledge necessary to establish a reliable test bed. The remainder of this chapter is organised as follows. Section 4.1 describes the study area, and sections 4.2 through 4.6 discuss six different scenarios and the simulation results associated with each of them. Finally, section 4.7 offers the concluding remarks for the pilot study.

4.1. Pilot study area

To develop a proof-of-concept, a pilot study is conducted on a real transport network located in Melbourne (Figure 4-1). The pilot explores the feasibility of using Commuter for this project. It also helps to develop a better understanding of the capabilities of the tool and the various functionalities required to enable the investigation of a vast range of AMoD scenarios across a much larger study area.

The study area is located in Stonington and covers an area equivalent to 6 km^2 (Figure 4-1). It features 11 signalised intersections, and 10 arterial roads. Travel demand is aggregated into nine distinct areas representing the ODs for the travellers (Figure 4-2). Travellers enter the model according to a stochastic approach from these areas. Note that no public transport is modelled in the pilot study area, and the whole traffic flow contains only private vehicles.

Travel demand in this model is based on Victorian Integrated Survey of Travel and Activity, which will be discussed in detail in chapter 5. VISTA provides a detailed image of Victorian household travel. All members of surveyed households are asked to fill in a travel diary for one specified day of the year. The survey administered in a similar way to the Census, with survey staff dropping off and picking up the self-completed travel diaries. VISTA helps the government in making better transport and land-use decisions. The survey is conducted in Greater Melbourne, Geelong and some regional centres (VISTA, 2016).

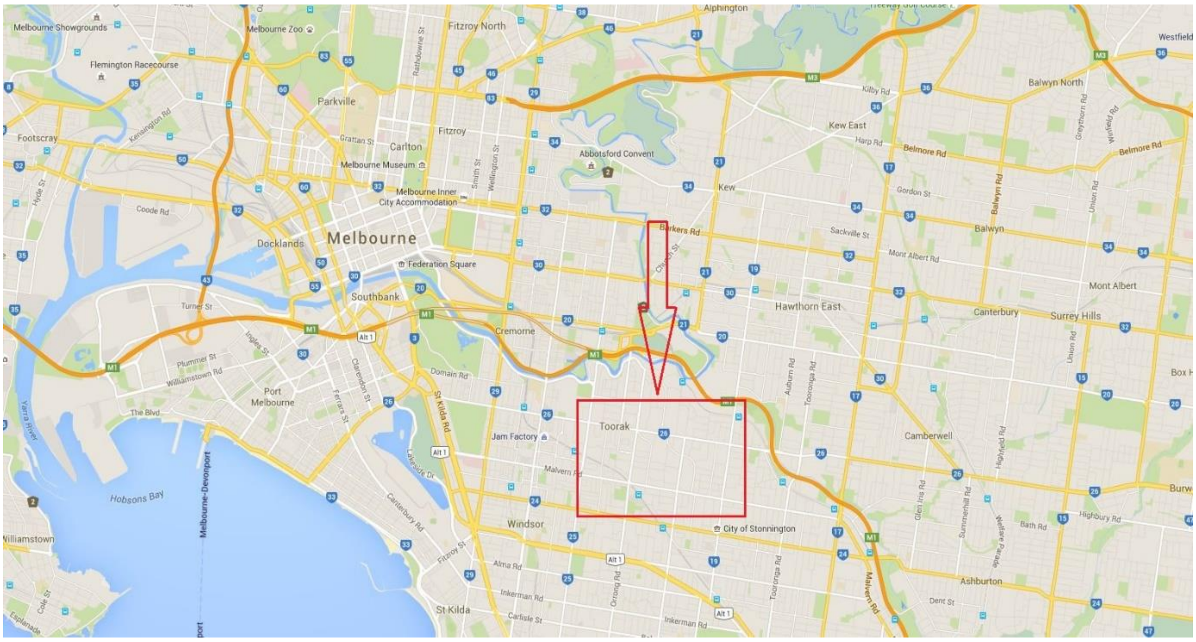


Figure 4-1: Pilot study area

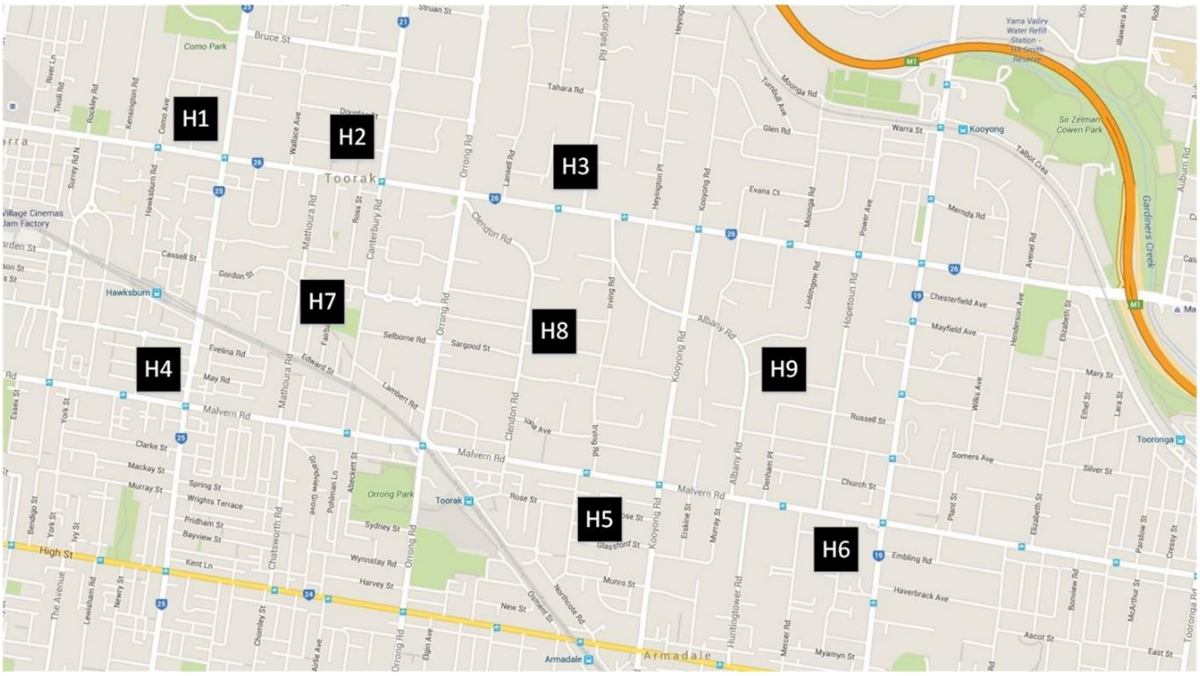


Figure 4-2: Origins and destinations in the pilot study area

4.2. Scenario 1: autonomous shared mobility with zero passenger waiting times

A base case (BC) scenario and a scenario using a simple AMoD system (AMoD1) were developed in Commuter. In the BC scenario, all trips are undertaken during the AM-Peak (7am-9am) using private cars. Table 4-1 describes the demand distribution among different ODs. The information in Table 4-1 assumes single-occupant vehicles and shows a BC scenario with a total number of 2,136 privately-owned vehicles. Assuming an area of 16.8 square meters is needed (on average) to accommodate every single private vehicle at the destination, it is estimated that these vehicles will require an area of around 35,885 square meters as parking lots in the proximity of destinations.

In the autonomous shared mobility scenario (AMoD1), it is assumed that privately-owned AVs and shared AVs with capacities ranging from two to four people are available to replace all private vehicle travel. This scenario also assumes that passengers will have a vehicle immediately available for their travel and that their waiting times are zero. This scenario was investigated as it represented the closest conditions to owning and driving a private vehicle, which is immediately available to travellers. Twenty-five percent of travellers were assumed to be using privately-owned AVs, and the other seventy-five percent were assumed to travel in groups of two, three or four. In both cases, passengers are picked up and dropped-off at their destinations by the AVs. After dropping their passengers off, the privately-owned AVs head back to their starting point (Home) and wait for further instructions from their owners. The self-driving shared cars, on the other hand, are typically owned by a commercial fleet company, which directs the vehicles to nearby waiting areas where they wait for further instructions.

An initial analysis of the autonomous mobility scenario (Table 4-2) shows that people travelling in groups and being dropped-off by the AVs results in both a decreased number of required vehicles (more than 40% compared to the BC) and parking space (around 58% compared to the BC). This frees up a substantial amount of land and space, which can be used for different purposes. However, the simulation also shows that the total VKT by the AVs increased by around 29% because the vehicles needed to reposition according to the heuristic rebalancing method will be described in Section 4.4 . This increase is largely due to the privately-owned vehicles, which were assumed to return to their point of origin. Finally, it is assumed in the analysis that no public parking space is needed for the privately-owned cars because they wait at home rather than in a public parking space.

Table 4-1: Total number of trips between different ODs during AM-peak (07:00-09:00am)

Origin \ Destination	H7	H8	H9	Total
H1	100	120	89	309
H2	147	90	126	363
H3	125	100	109	334
H4	160	100	140	400
H5	120	160	100	380
H6	110	120	120	350
Total	762	690	684	2,136

Table 4-2: Comparative evaluation of base case and AMoD1 scenarios

Scenario name	Number of vehicles on the road network	Mean VKT travelled (Km)	Parking space required (m2)
Base Case – human-driven single-occupant vehicles (BC)	2,136	4.04	35,885
Autonomous mobility scenario (AMoD1)	1,217	5.20	15,238
Percent difference between BC and AMoD1	43% decrease	29% increase	58% reduction

4.3. Scenario 2: Autonomous shared mobility with maximum 5-minute passenger waiting times

This scenario comprises the same origins and destinations as the first scenario within the study area shown in Figure 4-1 with a different demand matrix (Table 4-3).

In the BC scenario, it is assumed that all trips originate from home (where required on-street parking space is zero assuming all vehicles are parked on-site) and travel toward destinations where off-street parking is also available. All trips are assumed to be undertaken during the period 07:00-09:00am using single-occupant traditional privately-owned vehicles (therefore, the waiting time for travellers is zero).

Table 4-3: Total number of trips between different ODs during AM-peak (07:00-09:00am)

Origin\ Destination	H1	H2	H3	H4	H5	H6	H7	H8	H9	Total
H1							50	60	68	178
H2							78	40	47	165
H3							64	60	68	192
H4							70	65	70	205
H5							80	75	80	235
H6							50	84	90	224
H7	50	43	50	60	40	35				278
H8	30	50	45	35	25	45				230
H9	40	56	36	70	80	70				352
Total	120	149	131	165	145	150	392	384	423	2,059

In this second scenario (AMoD2), the waiting times for passengers are assumed to be longer than in AMoD1. This reflects situations in which the AV needs some time to travel to the customer's location. The only constraint is that the waiting times should not exceed 5 minutes. It is assumed that all ODs have at least one taxi rank in close proximity and one drop-off lane at their destinations. In this scenario, an AV picks up customers at the taxi rank, and as soon as it drops off the customers, the vehicle proceeds to the nearest taxi rank where it is needed to meet the maximum 5 minutes waiting constraint defined by the system. The following section explains the methodology used to determine the required initial AMoD fleet size and a heuristic rebalancing strategy to reduce the empty travel and idle times for AMoD vehicles.

4.4. Determination of fleet size and rebalancing strategy

The goal is to find the minimum number of AMoD vehicles required to meet the same demand as the BC scenario such that passengers do not wait more than 5 minutes for their pick-up vehicle. To achieve this, the area (3km x 2km) is divided into two equal blocks of 1.5km by 2km (Figure 4-3).

The first challenge is to determine the initial number of AMoD vehicles which should be fed into the taxi ranks. To this end, the difference between the number of generated and attracted trips is calculated for each origin. If the number of outgoing vehicles exceeds the number of in-coming AMoD vehicles, this number is chosen as the initially required number of vehicles for the origin at the start of the simulation. For the first simulation run, no AMoD vehicles were allocated to the origins in which the number of attracted trips was greater than the generated ones. The premise is that as the trip attraction rate for these areas is higher, AMoD vehicles leaving other areas with greater trip generation rates will have enough time to arrive at these taxi ranks. Then, vehicles are released into the model within 30 minutes and afterwards no new vehicles are generated and the fleet size remains fixed until the end of the simulation time (07:00-09:00am). This period at the start of simulations (e.g. 30 minutes in our model) is referred as "Warm-up" time within the literature. The warm-up time allows us figure out the approximate fleet size suitable to meet travel demand.

After the first run, the waiting times for all passengers are calculated and the number of initial AMoD vehicles for the taxi ranks where passengers experience waiting times more than 5 minutes within the first 30 minutes of the simulation are increased proportional to the length of waiting times. This process is repeated until all traveller's waiting times are less than 5 minutes during the first 30 minutes of the simulation period. Thereafter, attempts are made to reduce the waiting times by rebalancing the AMoD vehicles between various taxi ranks rather than generating new vehicles to meet the demand.

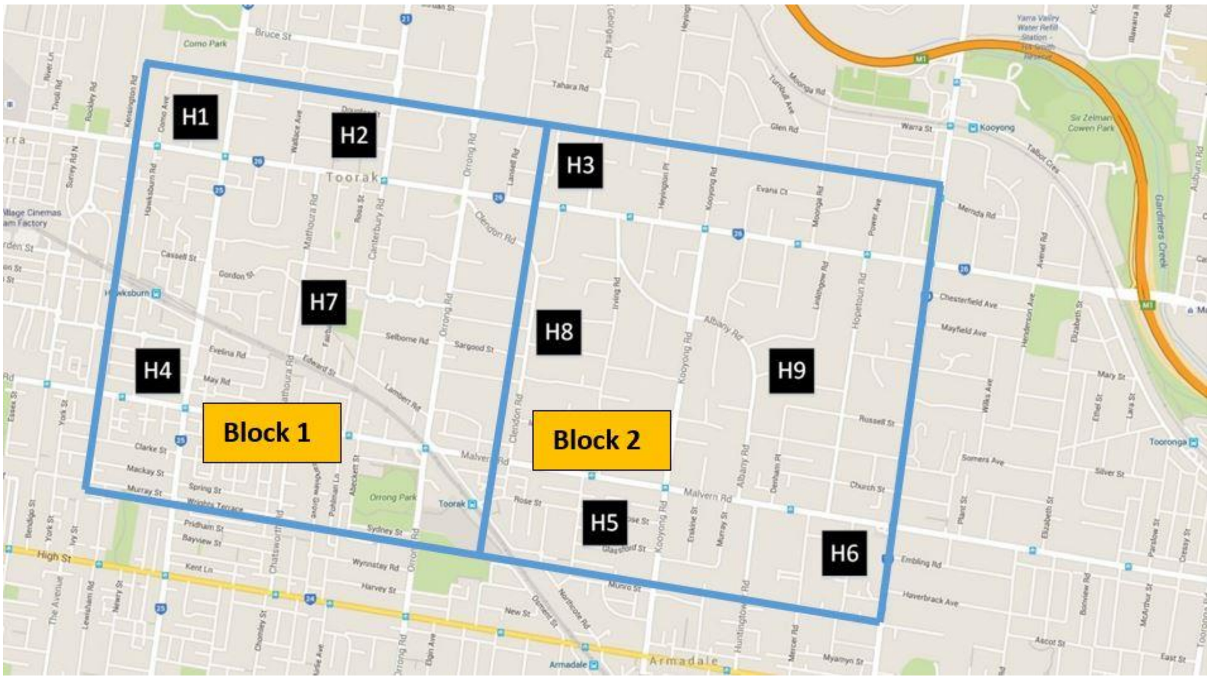


Figure 4-3: The pilot area divided into two equal blocks, namely block 1 and block 2 for AMoD rebalancing purposes

The waiting times for each taxi rank over the simulation period are recorded and the periods during which waiting times are longer than 5 minutes are identified. The waiting times in excess of 5 minutes are reduced by redirecting the AVs parked in the areas with waiting times less than 3 minutes (i.e. the areas with the surplus AVs) within the same block. An iterative process is undertaken until all waiting times are under 5 minutes within the same block. This is repeated for Block 2 and this process repeats until the waiting times for all passengers across the whole network falls to below 5 minutes.

The results, shown in Table 4-4, illustrate that deploying the AMoD system leads to a dramatic decrease in not only the total number of vehicles required to meet the demand (88% compared to the base case scenario) but also the required parking space (83% compared to base case scenario) at the expense of a 10% increase in the total VKT incurred by empty AVs repositioning themselves to better serve the demand at the taxi ranks. This demonstrates that the same demand can be met using only 12% of the total number of vehicles required in the BC scenario with an average waiting time of 1 minute and a maximum waiting time of 4 minutes (lower than the 5-minute constraint).

Table 4-4: Comparative evaluation of base case and AMoD2 scenarios

Scenario name	Number of vehicles on the road network	Total VKT (Km)	Parking space required (m2)
Base case – human-driven single-occupant vehicles (BC)	2059	4660.38	34591
Autonomous mobility scenario 2 (AMoD2)	247	5204.16	6048
Percent difference between BC and AMoD2	88% decrease	10% increase	83% reduction

To sum up, as shown in Table 4-5, using the AMoD system results in a significant reduction in both the number of vehicles on the road (43% in scenario 1 and 88% in scenario 2), and the required parking space (58% in scenario 1 and 83% in scenario 2) at the expense of a less significant increase in the total VKT (29% in scenario 1 and 10% in scenario 2).

Table 4-5: Comparative evaluation of base case and AMoD scenarios

Scenario name	Reduction in number of vehicles	Increase in the total VKT	Reduction in required parking space
Scenario 1 (AMoD1) compared to base case (BC)	43%	29%	58%
Scenario 2 (AMoD2) compared to base case (BC)	88%	10%	83%

4.5. Scenarios 3-5: Autonomous shared mobility with car-share and ride-share mode choice preferences

In Scenario 2, a homogeneous population of travellers is assumed where all travellers have identical mode-choice preferences and use only car-sharing with single-occupant AVs to reach their destinations. In reality, the value of travel time is generally distributed heterogeneously across individuals within a population, and according to time of day and trip purpose (Brownstone and Small, 2005; Cirillo and Axhausen, 2005). It is therefore expected that the preference for car-sharing versus ride-sharing will differ between travellers based on the increased travel time required to ride-share.

In this section, we explore the effects of travel cost on mode choice behaviour of four categories of travellers. These are travellers with a high value of time (HVoT) who choose car-sharing systems (single-occupant AVs with zero waiting time for passengers). This necessitates that a sufficient number of AVs are available all the time to serve these customers (at a premium cost). Travellers with a low value of time (LVoT), on the other hand, share their ride with other passengers using AVs with capacities of 2, 3 and 4 people. For the ride-sharing system, it is assumed that travellers need to wait until a vehicle is available. After dropping their passengers off, vehicles available for HVoT customers stay at the taxi rank to pick up other customers even if there is no current demand. Vehicles servicing LVoT customers may relocate to other taxi ranks if there is a need. The same rebalancing system used in Scenario 2 is utilized for rebalancing the empty vehicles in these scenarios.

To develop a better understanding of the impacts of mode choice preferences, three scenarios are simulated in which the proportion of ride-sharing travellers varies between 40% and 90%, as shown in Table 4-6. The simulation results are reported in Figure 4-4. As expected, the results show marked reductions in the total number of vehicles, total VKT traveled and parking space requirements when more people choose to ride-share instead of car-share. For example, the results show that the total number of required vehicles increased by 132% (from 273 in AMoD3 to 632 in AMoD5) as a result of a 50% decrease in the proportion of ride-share travellers (from 90% to 40%). However, the number of vehicles in AMoD5 is still substantially lower (69% less) than the BC.

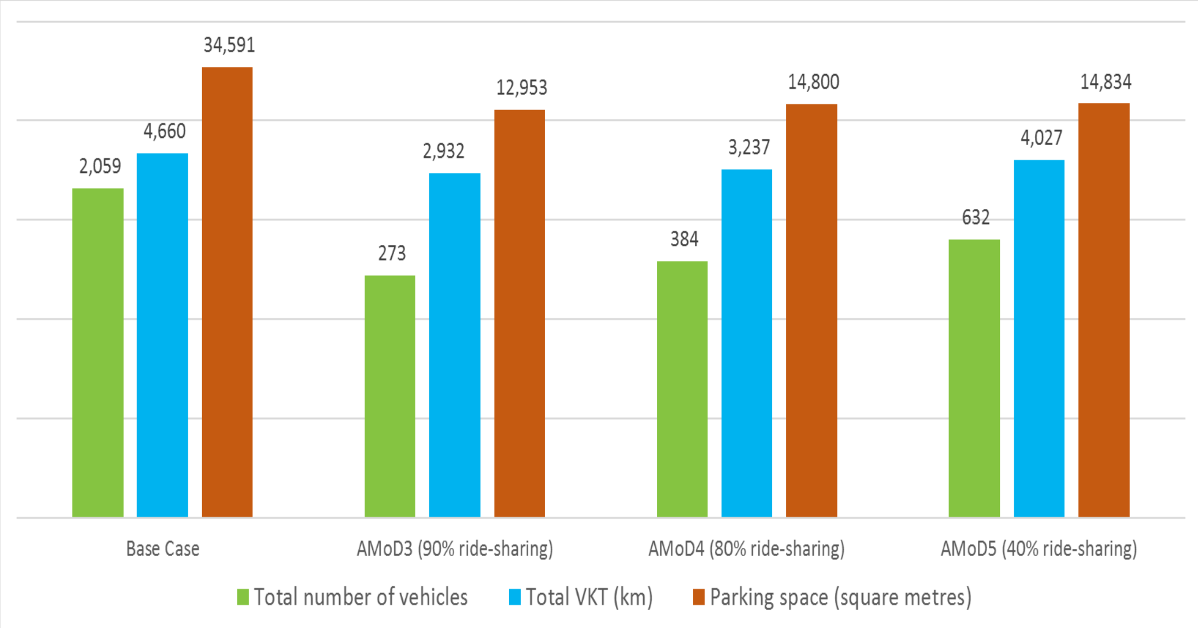


Figure 4-4: Impacts of variable proportions of ride-share and car-share

Table 4-6: Proportions of ride-share and car-share travellers in scenarios AMoD 3-5

System	Car-sharing (For travellers with HVoT)	Ride-sharing (For travellers with LVoT)		
Scenario \ Capacity(person)	1	2	3	4
AMoD3	10%	30%	30%	30%
AMoD4	20%	20%	30%	30%
AMoD5	60%	0%	20%	20%

A comparison of the results for AMoD5 and BC also suggests that shifting 40% of the population to autonomous on-demand ride-sharing will result in a 70% decrease in the total vehicle fleet size (from 2059 to 632); 14% reduction in the total VKT (from 4,660 to 4,027) and 57% reduction in the required parking space.

Table 4-7 provides some additional insights. For example, a comparison of AMoD5 and BC shows that the same demand for travel can be met using only 31% of the total number of AVs required in the BC, with an average passenger waiting time of 4 minutes and a maximum waiting time of 12 minutes.

Table 4-7: Mean and maximum waiting times

Scenario	Proportion of ride-sharing travellers	Percentage of vehicles compared to BC scenario	Passenger mean waiting time (minutes)	Passenger maximum waiting time (minutes)
AMoD3	90%	13%	3	10
AMoD4	80%	19%	2	10
AMoD5	40%	31%	4	12

4.6. Scenario 6: Autonomous shared mobility supported by public transport

One of the major drawbacks of AMoD systems is the need to rebalance empty vehicles on a regular basis to minimize empty travel. Public transport (PT) systems in the form of on-road buses or rail have the potential to minimize such negative effects by moving large numbers of people around a city more efficiently (Kelly and Zhu, 2016). To explore the impacts of AMoD when supported by a PT system, the same ODs and travel demand as Scenario 2 (Table 4-3) are used to run a simulation scenario, which includes AMoD and bus services. The AMoD is assumed to have single-occupant passengers with an average passenger waiting time of 3 minutes (maximum 10 minutes). A bus service is defined in the simulation with 10 min frequency to transport customers across the network. Each bus is defined to have a maximum capacity of 48 passengers. It is assumed that all ODs have at least one taxi rank in close proximity, and at least one drop-off lane at their destinations. The AMoD vehicle picks up the customer at the taxi rank and after dropping the passenger off, the vehicle proceeds to the nearest taxi rank where it is needed. The rebalancing of vehicles to ensure the passenger waiting times is as small as possible was undertaken in the same way as scenario 2. The operation of the PT service in Commuter includes the designation of stops, routes, schedules with departure times and service timetables.

Four scenarios are developed with different AMoD and PT user percentages. Note these percentages have been selected randomly without deploying any specific mode choice model. The results, shown in Table 4-8, indicate that shifting 30% to 70% of AMoD users to the public bus service results in an 8%-15% decrease in the total VKT of AMoD systems. Integrating AMoD systems with PT reduces the rebalancing burden of empty vehicles and leads to a decrease in total VKT.

Table 4-8: Comparative evaluation of fleet size and VKT for different PT scenarios

Scenario name	Number of shared vehicles	Total VKT (Km)
100% AMoD (0% PT)	115	6,190
70% AMoD (30% PT)	90	5,697
50% AMoD (50% PT)	80	5,312
30% AMoD (70% PT)	80	5,281

The environmental impact of these scenarios is also examined. It is assumed that existing (base case) private vehicle and public transport travel are undertaken using traditional vehicles with combustion engines, and that all futuristic AVs are electric (or hydrogen-fuel cells, i.e. non-polluting). Commuter includes a number of standard engine definitions, using data from the UK Transport Research Laboratory (TRL). An engine definition includes maximum speed, acceleration and braking rates, and emission levels for a range of exhaust gases (CO2, NOx, PM10). Each vehicle type has an associated engine definition (Duncan, 2013). For this study, the engine definitions for autonomous, traditional private vehicles and public transport buses are selected as electric, petrol car under 1300cc, and diesel bus, respectively. All coefficients are kept as the default values defined in Commuter.

In addition to the scenarios presented in Table 4-8, a new scenario using traditional single-occupant private vehicles is undertaken including 2,059 vehicles. Table 4-9 shows the total emitted exhaust gases from the vehicles in different scenarios. As shown in the table, the scenario which produces the largest amount of CO2 emissions is where the total demand is met using single-occupant private vehicles. However, there are zero emissions when all the vehicles in the scenario are autonomous and electric assuming that the electricity needed for vehicle operations is derived entirely from renewable energy. There is no improvement for the scenario with AMoD and diesel buses mainly because of the high level of emissions from diesel buses. These results indicate that although the integration of AMoD systems with traditional public transport systems has the potential to reduce fleet size and the number of rebalancing trips, it does not result in better environmental output unless the vehicles are fully electric. As expected, this suggests that a dramatic reduction in the environmental footprint requires the complete transition of all current traditional transport systems into fully electric vehicle fleets.

Table 4-9: Comparative evaluation of pollutant emissions under different scenarios

Scenario name	CO_2 (kg)	NO (g)	PM10 (g)
100% traditional single-occupant private vehicles	905	1,512	6.8
100% AMoD (0% PT)	0	0	0
70% AMoD (30% PT)	728	7,093	190

4.7. Chapter summary

The pilot study reported in this chapter demonstrated the feasibility of using the agent-based approach to evaluate the impact of AMoD systems. A base case scenario (current situation relying on traditional privately-owned vehicles) and five AMoD scenarios were simulated on a real transport network in Melbourne, Australia. The results showed that incorporating shared AVs can significantly reduce the total number of vehicles required to meet the transport needs of a community. It also significantly decreased the parking requirements which frees up this space for other purposes. The results, however, showed that there are likely to be some negative impacts such as increased total kilometres of travel due to repositioning.

The pilot study showed that rebalancing shared AVs poses a significant challenge for fleet operators. Therefore, in the main study, a more scientific rebalancing algorithm will be deployed to optimise the performance of the system. Note given the scope of this chapter, which was developing a proof of concept, we only deployed one rebalancing method as opposed to exploring various rebalancing algorithms. Investigating a vast range of AV redistribution approaches can be a potential future research direction.

The pilot study also raised many new questions which will be explored in the next chapters of this PhD dissertation. Some of these questions are as follows,

1. Would implementing an optimum rebalancing algorithm lead to an efficient shared AMoD system?
2. How do various rebalancing time-steps affect the performance of AMoD systems?
3. How sensitive is an AMoD system to fleet size?
4. How does the initial number of AVs at stations affect the efficacy of AMoD systems?
5. How can travel demand distribution affect the efficiency of AMoD systems?
6. Is there any specific relationship between fleet size and VKT?

Chapter 5 : Model Testing and Evaluations- Investigating the Network Impacts of AMoD Systems

A pilot study was conducted to obtain knowledge on the modelling framework chosen for this study and to identify potential modelling challenges. As the pilot study was carried out as a proof of concept, it had various limitations such as a small study area, non-calibrated travel demand, and a heuristic rebalancing model. Further, the variety of scenarios implemented in the pilot study was not sufficient to obtain comprehensive insight into the implications of AMoD systems. This was mainly due to the fact that many tasks in this stage of the study were performed manually, such as calculating the total increase in VKT, or dispatching idle driverless vehicles for rebalancing purposes.

After the completion of the pilot study, sufficient experience was gained to explore the behaviours of AMoD systems in a larger area using a larger data set. Moreover, the rebalancing process and related calculations will become automatic to produce a more feasible research platform to investigate the ramifications of AMoD systems thoroughly. In addition, travel demand in this stage of research will be calibrated and validated to generate a more realistic travel pattern within the network.

It is noteworthy that this study only investigates the performance of AMoD systems in terms of four measures: 1. fleet size 2. induced VKT 3. customer-waiting times 4. percentage of trip-requests serviced. AMoD systems are believed to have various impacts on urban areas (Milakis, van Arem and van Wee, 2017), such as decreasing the space need for parking and reducing greenhouse gas emissions. This study, however, does not explore these implications as they are beyond the scope of this research.

As discussed in chapter 2, section 2.9, models that have been developed in the literature to explore the implications of AMoD systems can be categorised into two groups: analytical models and simulation models.

Analytical models suffer from inherent limitations that prevent the modellers from producing more realistic transport models to study the problem at hand (see section 3.1.7). Their limitations mainly are rooted in the underlying assumptions proposed by the developers of these algorithms to circumvent the computational obstacles.

On the other hand, all the reported simulation models investigate the effects of AMoD systems disregarding the interactions between vehicles. The main agent-based simulation tool for the majority of these studies is MATSim, which has been used for large-scale scenarios. As per discussions in section 3.3.3.1, MATSim uses a queue-based approach to simulate traffic flow within the network to reduce computational burden (Horni, Nagel and Axhausen, 2016). It, therefore, fails to capture very complex car following and lane changing effects and leads to reduced model resolution.

Another limitation of MATSim is that the simulation of empty self-driving vehicles (e.g. those vehicles travelling within the road network searching for a customer or needing to travel to service a particular demand) is not possible. These studies, therefore, only estimate the empty VKTs through unrealistic assumptions in which vehicles are moved virtually between stations based on Euclidean distances from origins to destinations (Boesch, Ciari and Axhausen, 2016).

It should be noted that MATSim is open access software and experts from across the world can continually contribute to enhancing its capabilities (Horni, Nagel and Axhausen, 2016). In recent times, in particular, various modules have been added to MATSim, such as the dynamic dispatching of taxicabs or the scheduling of battery re-charging as well as models that capture the parking search behaviour of drivers (Bischoff and Maciejewski, 2014, 2016b; Fagnant and Kockelman, 2016; Bischoff and Nagel, 2017; Horl, 2017) which enables transport modellers to investigate a vast range of AMoD scenarios on a large scale.

To bridge this gap in the knowledge and address these limitations, this study takes a different approach and explores the quantitative contributions of AMoD systems at a microscopic level utilising Commuter (Duncan, 2010; Azalient, 2013). This tool is agent-based traffic simulation software, which features lane changing, gap acceptance, and car following algorithms to simulate the movements of vehicles in the network. It also includes microscopic features that enable the modelling of individual driver behaviour. Commuter is also capable of simulating the travel of empty vehicles on a real transport network (instead of assuming Euclidean distances between origins and destinations). Therefore, the travel times of both occupied and empty rebalancing AVs are calculated by Commuter.

Another contribution of this work is that for the first time, an optimum real-time rebalancing model is deployed in an agent-based AMoD simulation model to redistribute idle AVs across the network (unlike the existing agent-based simulation models in the literature that use a heuristic method). This real-time rebalancing model developed by (Pavone *et al.*, 2012) was only tested in MATLAB that lacks the key capabilities required for the realistic simulation of traffic. This study, therefore, shows how this rebalancing model contributes to the efficiency of AMoD systems on a real transport network. Note given the aforementioned paper proves this algorithm yields an optimum solution, we have refrained from repeating the same discussions in this dissertation.

In the literature, only one study (Boesch, Ciari and Axhausen, 2016) explores the effects of different fleet sizes on the level of service. However, none of the current studies investigate the elasticity of induced VKT with respect to different fleet sizes and rebalancing time-steps, which is an important criterion for the success of these systems. To address this gap, various scenarios are explored in this study to provide an insight into the sensitivity of levels of service and induced VKT to various fleet sizes and optimisation time-steps. The insights from this analysis will be useful for researchers interested in formulating the relationships between various system characteristics, and the policy makers who want to understand how different fleet sizes affect mobility in urban environments.

In addition, this research explores for the first time the impacts of travel demand heterogeneity on the efficiency of AMoD systems. The results reported later in this thesis suggest that the impact of this phenomenon is not trivial.

The remainder of this chapter is organised as follows. Section 5.1 deals with the data used to develop the present model. Section 5.2 describes the study area and its characteristics. Section 5.3 explains the calibration and validation process used in this study. Section 5.4 expresses the optimum real-time rebalancing model implemented in the simulation framework. Section 5.5 and 5.6 discuss the scenarios used in the simulation context and the associated results. Then, in section 5.7, a sensitivity analysis has been undertaken to explore the effects of initial AVs at stations on the overall performance of the AMoD system. In section 5.8, the effects of travel demand heterogeneity on the performance of AMoD systems are discussed and compared with the results of the preceding section. Section 5.9 outlines the limitations of the current study. Section 5.10 provides the overall conclusions that are derived to this point of the study.

5.1. Data collection and collation

This section discusses the data used to prepare the current model. Section 5.1.1 deals with the travel demand data used for conducting this research. It elaborates on the nature of this dataset and how it was derived. Section 5.1.2 explains how traffic signal information, vehicle count and road geometry data were obtained.

5.1.1. Travel demand data

The Victorian Integrated Survey of Travel and Activity (VISTA, 2016) is one of several datasets that provides an ongoing survey of travel and activity. This travel data repository, used for the current research is based on a sample of personal travel activities across the Victorian state that occur from home to access various activities. The currently available data covers the period from May 2007 to June 2010 and includes 11400 households for metropolitan Melbourne. Households are randomly selected from a listing of all residential addresses in the study areas and are asked to fill in a travel diary for one specified day of the year. All personal travel outside the home is reported, from a walk around the block through to a trip interstate.

Firstly, all the survey participants are asked to provide basic household information including number of family members, type of dwelling in which they live, type of ownership of dwelling (owned or rented), duration of stay at this dwelling, and number of vehicles and bicycles owned by the family. They are also asked to provide details of all household members (e.g. date of birth, gender, country of birth, having a driver's licence, employment details, etc.).

Secondly, all members of the family aged 5 and over are asked to complete a travel diary form which details their travel and activities on one particular travel day. For this survey, even short trips like walking to lunch or going for a jog are important.

Before advancing, it should be noted that based on VISTA, the terms stop, trip, and journey are defined as follows,

1. Stop:

Stop is the base record of individual travel stages. During travel, whenever there is a change of mode, vehicle or purpose, a new stop is defined. As an example, a drive to school to drop children off, followed by a drive to the train station, a train ride to the city, and a walk to work, would be recorded as four stops. The distances and times for these stops would be counted separately and attributed to the actual modes of travel.

2. Trip:

A trip refers to the overall travel between main activities. Trips are created by combining 'change mode' stops together. Trips therefore allow multi-modal definitions of travel to be described. Recalling the previous example (a drive to school to drop children off, followed by a drive to the train station, a train ride to the city, and a walk to work), the four stops would be combined to create two trips.

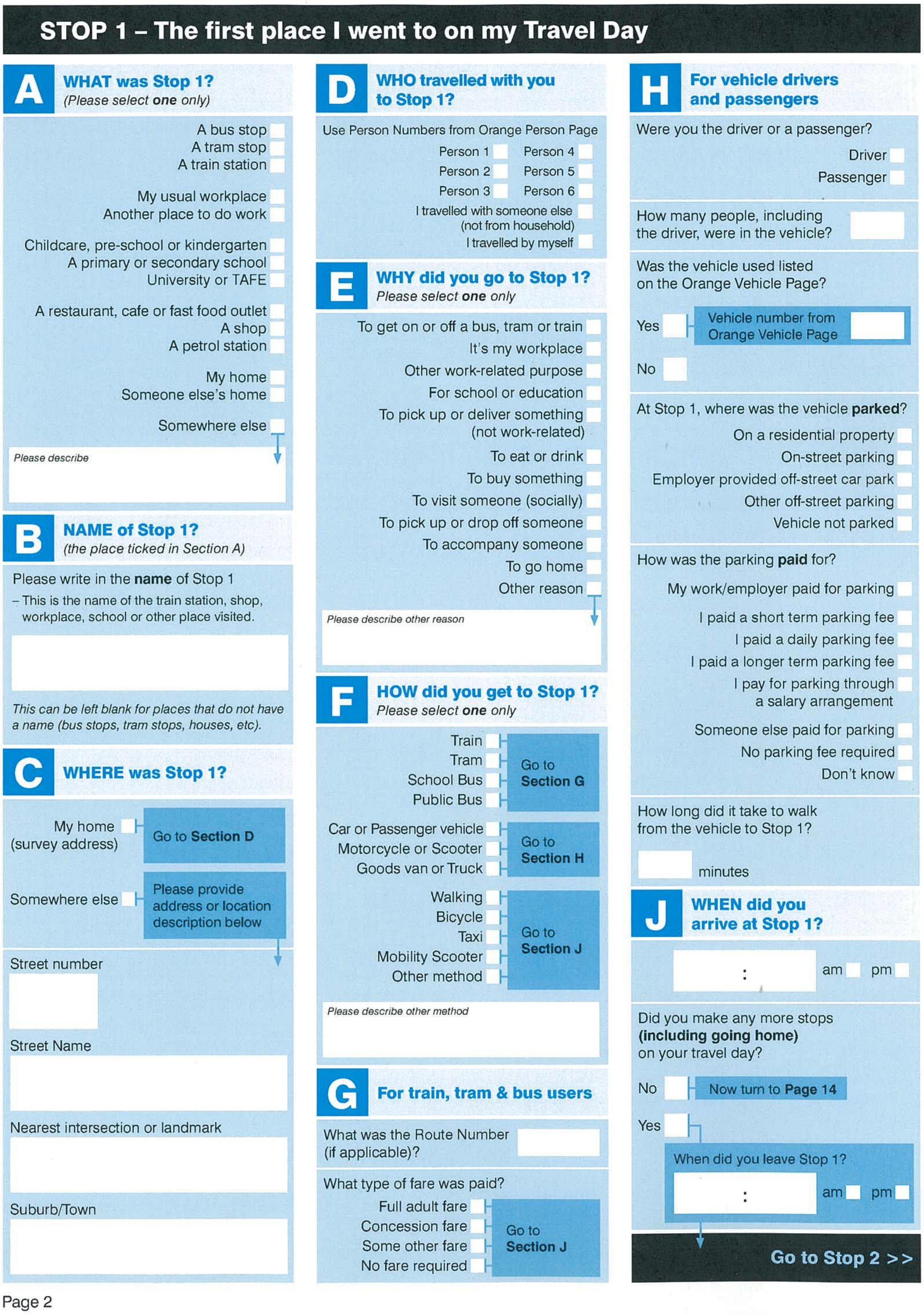
3. Journey:

There are two types of journeys predefined and available for analysis through the VISTA online tool: journeys between home and education, and journeys between home and work. Similar to the way stops are combined to create trips, journeys are created by linking individual trips together (VISTA, 2016).

The travel day for this survey starts at 4:00am and participants are asked to report where they were at this time, and when they first left this place from 4:00am on. Then, they are asked to provide information on their first stop (Stop1) after leaving the first place, which can be a bus stop, work place, university, restaurant, petrol station etc. After this, participants are required to answer the following questions: name of stop1, address of stop1, who they travelled with to stop1, the reason they travelled to Stop1, how they got to stop1 etc. These questions are repeated for the next stops as well. Figure 5-1 details all the questions regarding each stop in the survey.

This information provides a detailed picture of the travel including distribution of trips, trip rate, median trip distance, median trip time, mode share of travel, main method of travel etc., which helps the government make better transport and land-use planning decisions (VISTA, 2016).

Currently, VISTA online, a web-based tool, provides these data for the period 2007 to 2010. It is a stand-alone interface for accessing and interrogating data collected as part of VISTA. The analysis tool, built on a SuperWeb2 platform, is in a beta testing phase. This beta-version is focused on the creation of custom data tables and associated reporting of relative standard errors.


STOP 1 – The first place I went to on my Travel Day

A WHAT was Stop 1?
(Please select one only)

A bus stop
A tram stop
A train station

My usual workplace
Another place to do work

Childcare, pre-school or kindergarten
A primary or secondary school
University or TAFE

A restaurant, cafe or fast food outlet
A shop
A petrol station

My home
Someone else's home

Somewhere else

Please describe

B NAME of Stop 1?
(the place ticked in Section A)

Please write in the **name** of Stop 1
– This is the name of the train station, shop, workplace, school or other place visited.

This can be left blank for places that do not have a name (bus stops, tram stops, houses, etc).

C WHERE was Stop 1?

My home (survey address) – Go to Section D

Somewhere else – Please provide address or location description below

Street number

Street Name

Nearest intersection or landmark

Suburb/Town

D WHO travelled with you to Stop 1?

Use Person Numbers from Orange Person Page

Person 1 Person 4
Person 2 Person 5
Person 3 Person 6

I travelled with someone else (not from household)
I travelled by myself

E WHY did you go to Stop 1?
Please select one only

To get on or off a bus, tram or train
It's my workplace
Other work-related purpose
For school or education
To pick up or deliver something (not work-related)
To eat or drink
To buy something
To visit someone (socially)
To pick up or drop off someone
To accompany someone
To go home
Other reason

Please describe other reason

F HOW did you get to Stop 1?
Please select one only

Train
Tram
School Bus
Public Bus
– Go to Section G

Car or Passenger vehicle
Motorcycle or Scooter
Goods van or Truck
– Go to Section H

Walking
Bicycle
Taxi
Mobility Scooter
Other method
– Go to Section J

Please describe other method

G For train, tram & bus users

What was the Route Number (if applicable)?

What type of fare was paid?

Full adult fare
Concession fare
Some other fare
No fare required
– Go to Section J

H For vehicle drivers and passengers

Were you the driver or a passenger?

Driver
Passenger

How many people, including the driver, were in the vehicle?

Was the vehicle used listed on the Orange Vehicle Page?

Yes – Vehicle number from Orange Vehicle Page

No

At Stop 1, where was the vehicle **parked**?

On a residential property
On-street parking
Employer provided off-street car park
Other off-street parking
Vehicle not parked

How was the parking **paid** for?

My work/employer paid for parking
I paid a short term parking fee
I paid a daily parking fee
I paid a longer term parking fee
I pay for parking through a salary arrangement
Someone else paid for parking
No parking fee required
Don't know

How long did it take to walk from the vehicle to Stop 1?

minutes

J WHEN did you arrive at Stop 1?

: am pm

Did you make any more stops **(including going home)** on your travel day?

No – Now turn to **Page 14**

Yes – When did you leave Stop 1?

: am pm

Go to Stop 2 >>

Page 2

Figure 5-1: Stop properties in VISTA survey (VISTA, 2016)

VISTA data is packaged into a number of different databases, as shown in Table 5-1. Database selection depends on both the type of travel and the day of travel required. Once a database has been chosen, construction of a customised data table can begin. In this process, classification variables (e.g. gender, mode of travel, year of travel, home location etc.) can also be added to the rows and columns of the table.

Table 5-1: Description of the VISTA database (VISTA, 2016)

Database name	**Database description**
Stops- Average Weekday/ Weekend Day	**Stops** made on an average weekday or average weekend day.
Stops- Average day	**Stops** made on an average day of the year
Trips- Average Weekday/ Weekend Day	**Trips** made on an average weekday or average weekend day
Trips- Average Day	**Trips** made on an average day of the year
Journey to/ from Work- Average Weekday	**Journey** made between home and work on an average weekday
Journey to/ from Education- Average School day	**Journeys** made between home and education on an average school day

Transport for Victoria (TfV, 2016) also provides spreadsheets describing the detailed diary of each person from his origin to his destination using Census Collection Districts (CCDs). CCDs are areas designated by the Australian Standard Geographical Classification (ASGC) to define the areas a census collector can cover to deliver and collect census forms over about a ten-day period.

For the 2006 census, there are about 38200 CCDs throughout Australia, each including almost 225 dwellings in urban areas. This CCD is the second smallest geographic area defined in the ASGC, the smallest being the Mesh Block. Both significant changes in population within a given area and changes in boundaries of geographic areas are the principle impetus to create CCDs. In other words, if the population in a specific CCD reaches a point, which poses difficulty for the collectors or results in the expansion of the boundaries of the area, the CCD will be split into several CCDs. The Australian Bureau of Statistics (ABS) website provides shapefiles of every CCD in Australia online, which has been used to map these areas using a web-based program called CartoDB (ABS, 2011). This program assisted us in determining which CCDs fall within our study area.

The base travel demand according to VISTA data for the current model is shown in Table 5-2. It describes the travel demand within each Local Government Area (LGA) and between them by mode of transport. The study area covers four various LGAs in Melbourne namely: Yarra, Stonnington, Port Philip, and Glen Eira. Each LGA is made of several CCDs and the numbers shown in Table 5-2 are the sum of travel demands in each CCD.

Table 5-2: Base travel demand as per VISTA data used in the model

Private Transport				
LGA	Yarra	Stonnington	Port Philip	Glen Eira
Yarra	1396	150	96	92
Stonnington	1180	7453	1557	1162
Port Philip	348	314	3165	347
Glen Eira	407	1639	1351	8662
Public Transport				
	Yarra	Stonnington	Port Philip	Glen Eira
Yarra	183	43	88	69
Stonnington	121	65	124	110
Port Philip	89	143	508	111
Glen Eira	139	143	319	63
Others				
	Yarra	Stonnington	Port Philip	Glen Eira
Yarra	0	13	0	0
Stonnington	0	112	0	0
Port Philip	0	0	0	0
Glen Eira	0	0	0	113

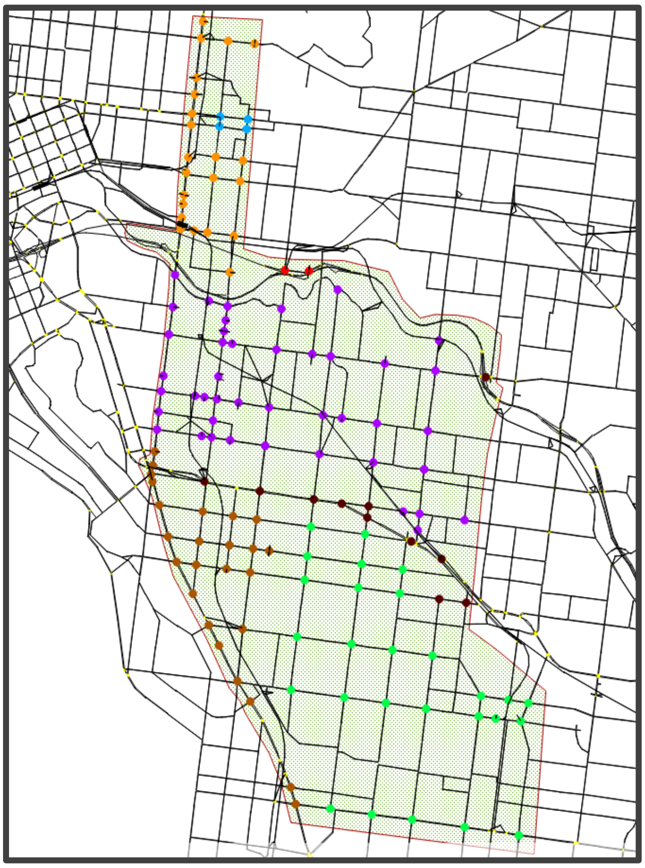
5.1.2. Traffic signal, vehicle counts and road geometry data

In this research, signal timing information was derived through SCATS (Sydney Coordinated Adaptive Traffic System). SCATS is an adaptive urban traffic management system that synchronises traffic signals to optimise traffic flow across a whole city, region or corridor (SCATS, 2018).

SCATS data is available to the University through a Virtual Private Network (VPN) connection to VicRoads. In total, the model contains 134 signalised intersections whose traffic signal data is based on SCATS. Figure 5-2 illustrate the location of signalised intersections along with their SCATS site information.

SCATS data available ranged from July 17 to August 17, 2015. Data for every Tuesday, Wednesday and Thursday has been used to generate an average of a typical day. The same process has been used for SCATS group and phasing configurations and it has been imported hourly into the model.

Once signalised intersections are imported into the model, other intersections and the roads between them are also imported. However, sometimes the geometry of roads are not entered properly and differ from the original one in the field. To fix this problem, all road segments' geometries were checked through Google Maps and amended if necessary. Note that vehicle counts derived through SCATS (based on loop detectors) were also used for calibrating and validating the model.



Regions	Count	Color
BRI	27	
CA1	4	
GLI	11	
KEW	2	
MC2	22	
SK1	43	
SK2	25	
Total	**134**	

Figure 5-2: Location of signalised intersections by region obtained via SCATS

5.2. Network specifications

The study area selected for this research features parts of four different local government areas (LGA) in Melbourne: Yarra, Stonnington, Port Phillip, Glen Eira with a total area of 88.75 km^2 (Figure 5-3).

This area includes 134 signalised intersections and various main arterials. The study area also comprises public transport facilities such as buses, trams, and trains. All public transport modes are simulated in Commuter according to their real operational time-tables available from Public Transprt Victoria (PTV, 2017).

The main reasons for choosing this part of Melbourne for the present study are as follows,

1. This area includes major bottleneck arterials such as Hoddle street and Punt road, which are the busiest corridors in Melbourne. If an area with low congestion levels had been selected, the real performance of the AMoD systems might have been overstated.

2. The selected area features all sorts of public transport modes such as train, tram, and bus. This, as a result, makes the area look more like a mid-sized city.

3. Data availability is another issue that limits the study to this part of Melbourne. The researcher only had access to vehicle count data, which is necessary for calibrating and validating the model, for this part of Melbourne.

As shown in Figure 5-3, the study area is grid-based and comprises various cells of different dimensions. The travel demand is aggregated into areas located at the centre of these blocks (centroids) with the sides of each block ranging from 200m up to 700m. These represent the main streets for which the observed vehicle counts are available for model calibration purposes. The study area consists of 53 centroids (ODs) located at the centre of these blocks, which are assumed to attract or generate the travel demand in that area (Figure 5-3). The study simulates a two-hour period for an average weekday during AM-Peak hours (07:00-09:00).

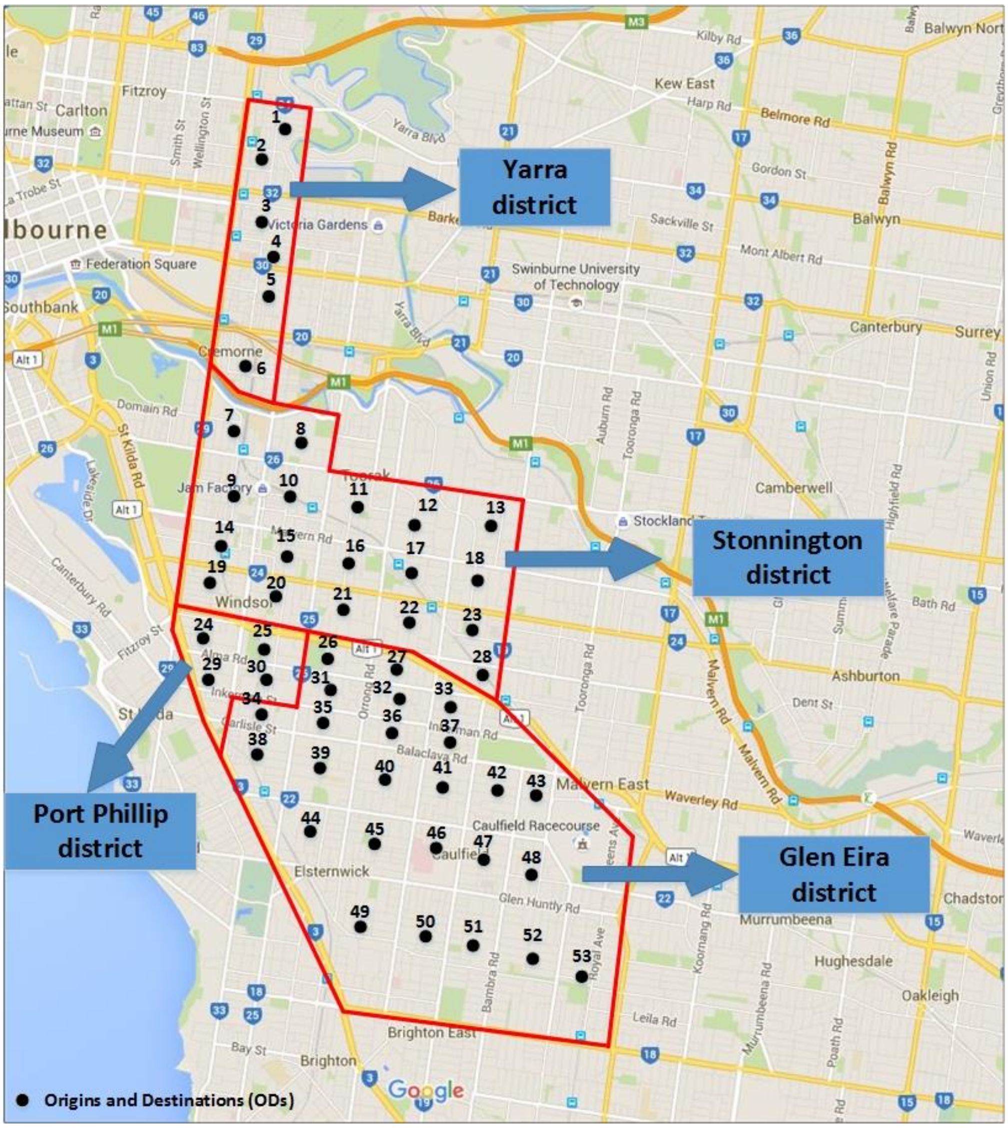


Figure 5-3: Study area and locations of the travel demand origins and destinations (ODs)

5.3. Model calibration and validation

To determine the spatial distribution of travel demand within the study area, vehicle count was chosen as the performance measure, and calibration and validation were undertaken based on this measure for the BC scenario. Note that the calibration and validation of AMoD scenarios is not possible as they are not operational yet.

The initial demand matrix used in this study is based on the available VISTA travel survey data (see Table 5-2). Two sets of count data are available for this study: 07:00-08:00am and 08:00-09:00am. The first data set is used for calibration purposes while the second is used to validate the model. The count data is based on the loop detectors, installed on each approach of any intersection in Melbourne.

Over the whole network, observed vehicle counts are collected for 225 points covering the entire area. Commuter uses an iterative proportional fitting (IPF) technique (also known as furnessing) to distribute the initial travel demand between different ODs across the network considering the observed traffic counts. This iterative process is followed until the travel demand converges to an acceptable confidence level. In the current model, this process takes around 25 hours.

To validate the accuracy of the model, two widely used measures are used: GEH value, and r-square test. The GEH statistic is a formula used in traffic engineering to compare two sets of traffic data (Lianyu Chu *et al.*, 2003). Its mathematical form is similar to an x-square test. Equation 5-1 is used to calculate the GEH statistic.

$$\boldsymbol{GEH} = \sqrt{\frac{\boldsymbol{2(M-C)^2}}{\boldsymbol{M+C}}} \qquad \textbf{Equation 5-1}$$

where

M: hourly traffic volume from the traffic model

C: real-world hourly traffic count

The GEH statistic is recognised as a useful validation measure as it considers both the absolute values of the observations being compared and their relative differences. Generally, a GEH value under 10 is considered a good replication of reality in traffic engineering applications. GEH values are valid only for hourly volumes. Table 5-3 shows that 80% of all selected points have GEH values under 10 for both periods.

As previously mentioned, Commuter uses the IPF technique to distribute demand between different areas. This method distributes the travel demand such that it captures the observed travel pattern in the field. Given the attractiveness of areas is the same during the whole simulation time, travel patterns within the study area remain similar over both periods. As a result, the obtained GEH values for these two periods are close to each other (Table 5-3).

Table 5-3: The GEH values for all the observations across the network

Time period	**GEH <= 10**	**10<GEH<20**	**20<= GEH**
07:00-08:00	80%	17%	3%
08:00-09:00	80%	15%	5%

R-squared is another performance measure which has been widely used in the literature, e.g. (Antoniou et al., 2016), to quantify the difference among observed and simulated vehicle counts. Its mathematical representation is as follows,

$$\boldsymbol{R^2} = \left(\frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{N s_x s_y}\right)^2 \qquad \textbf{Equation 5-2}$$

where

x_i : observed count
$\bar{x}$: mean of observed counts
y_i : modelled count
$\bar{y}$: mean of modelled counts
N : total number of observed counts
s_x : standard deviation of observed counts
s_y : standard deviation of modelled counts

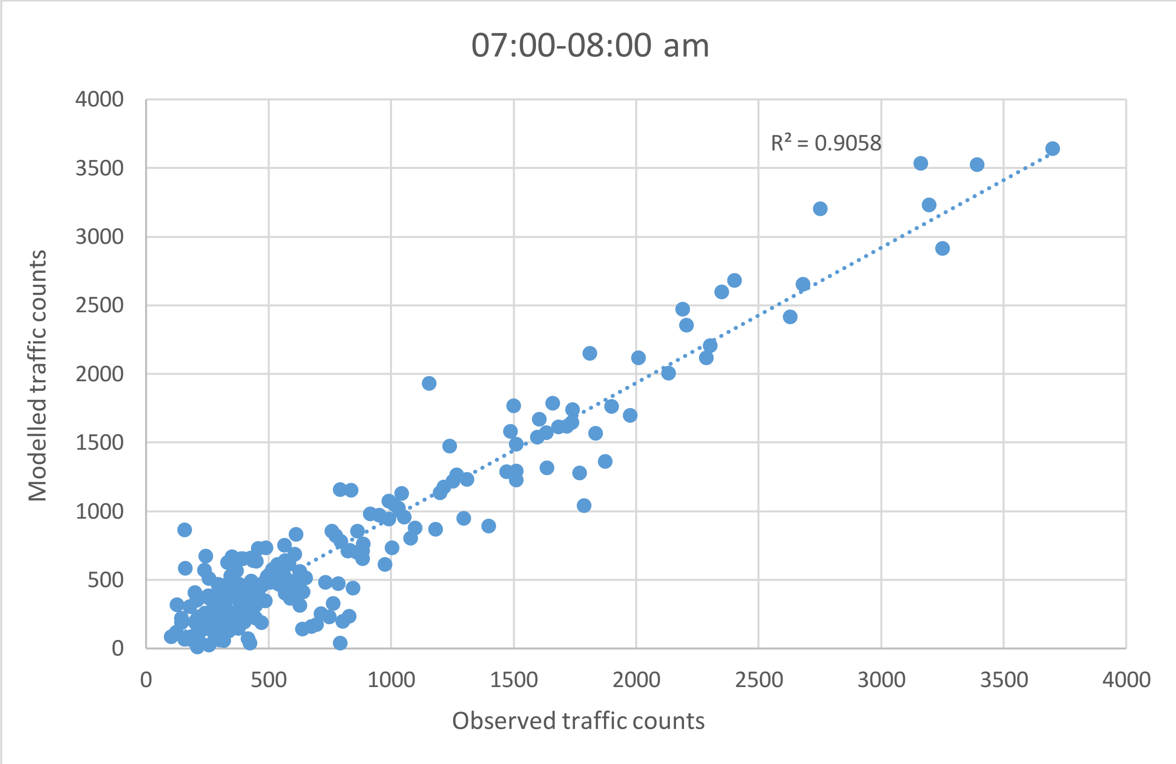
Figure 5-4 shows that the modelled traffic counts replicate the observed field data with almost 90% accuracy for the periods between 07:00 - 08:00am and 08:00 - 09:00am.

It is a common practice in statistics to examine the fit of the regression line through residuals (Moore, McCabe and Craig, 2012). In our study, a residual is identified as the difference between the observed and modelled counts as follows,

$$\boldsymbol{residual = observed\ count - modelled\ count} \qquad \textbf{Equation 5-3}$$

If the residuals of all counts are plotted in one graph, the resulting diagram is called the residual plot and it is used to assess the suitability of a linear regression model for the data. If the points in a residual plot are randomly dispersed around the horizontal axis, a linear regression model is appropriate for the data; otherwise, a non-linear model is more suitable (Stat Treck, 2017).

The residual plots for this study are shown in Figure 5-5. Given there is no special pattern in the residuals, it can be deduced that the regression line catches the overall pattern of data. In other words, the linear regression model is appropriate for this data set.



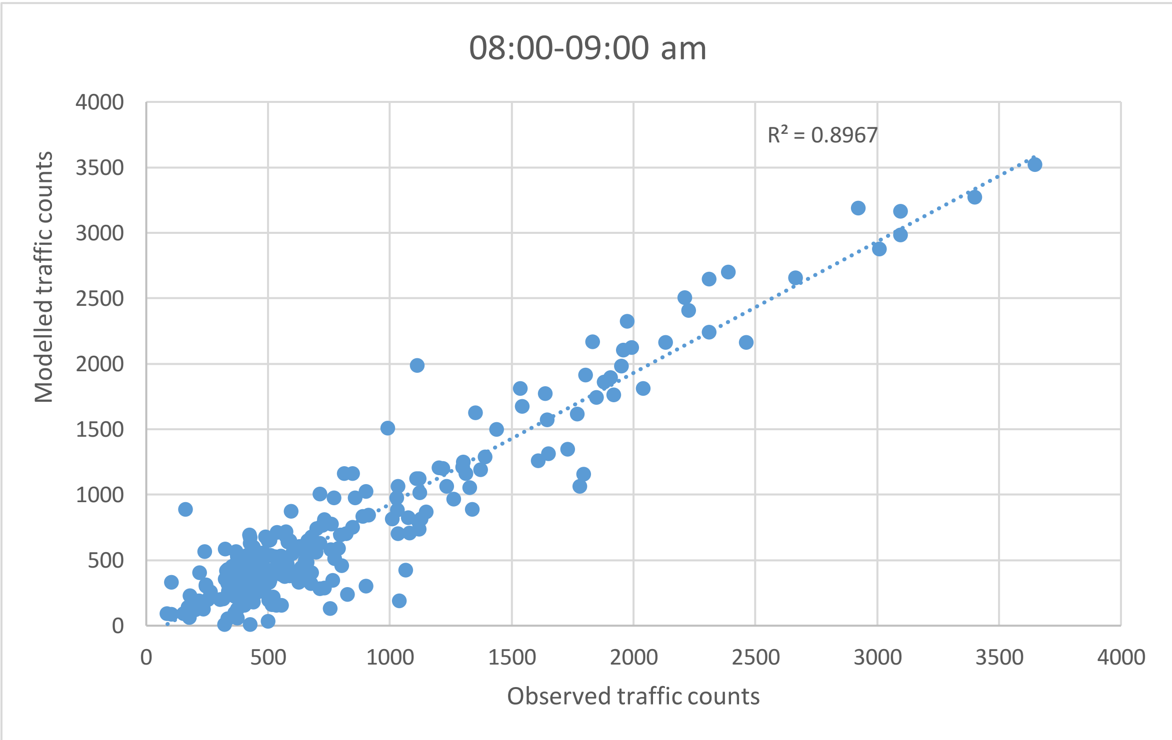


Figure 5-4: Modelled versus observed traffic counts for 07:00-08:00am, and 08:00-09:00am periods

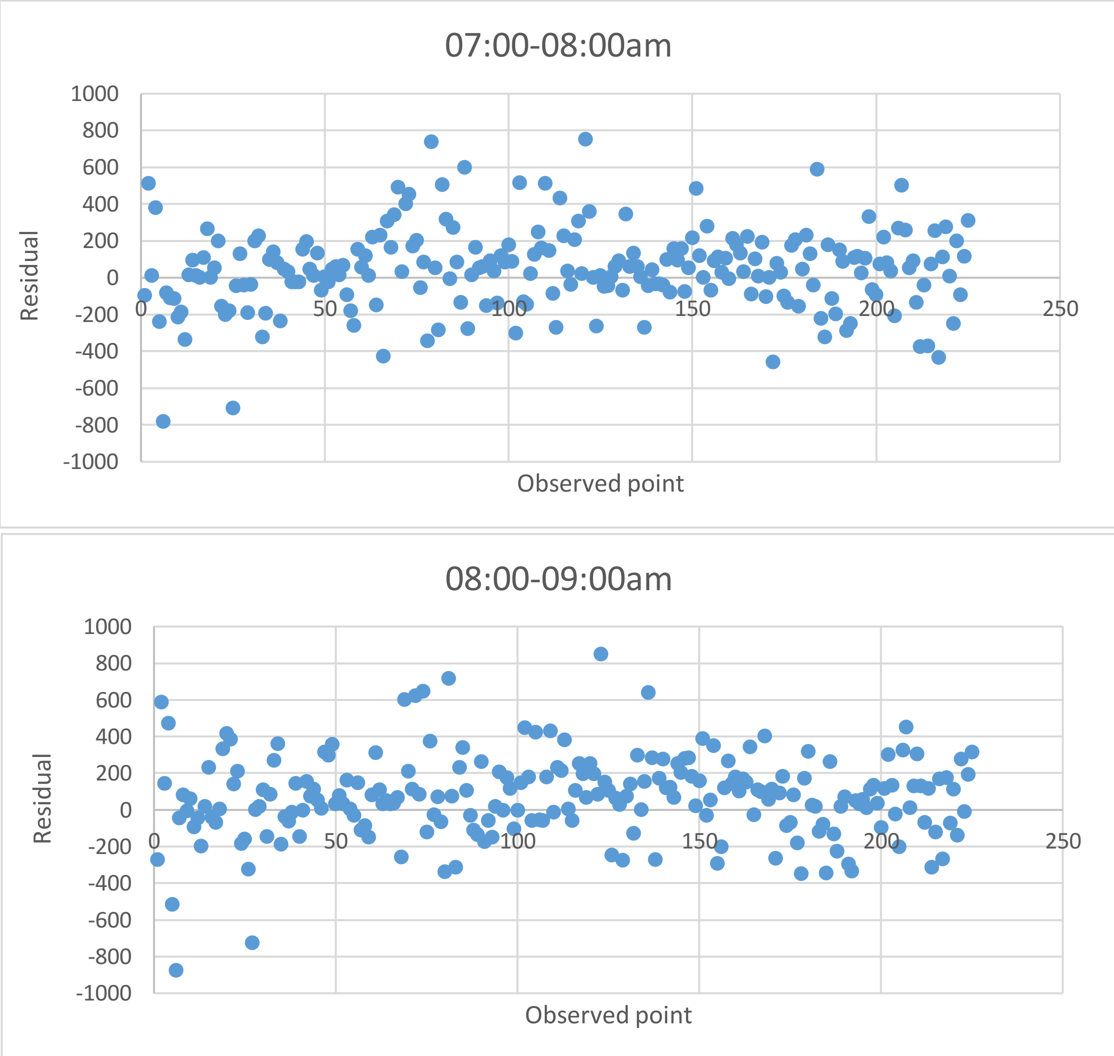


Figure 5-5: The residual plots for 07:00-08:00am, and 08:00-09:00am periods

The calibration and validation process ultimately revealed the distribution of the current travel demand within the study area. Note, a total of 150,095 private vehicle trips occur in the study area of which only 20,392 trips have both their origins and destinations within the area. To speed up the simulation, after calibration and validation, only the latter trips are kept in the model. The average, minimum, and maximum trip lengths are 3.90, 0.91, 13.97 km respectively.

Given Commuter utilises a dynamic route choice model, which is a function of the level of congestion in the network, the removal of through traffic might lead to less realism in the network. In the current model, once the network is not congested, vehicles choose the shortest route. As the congestion level grows, vehicles switch to longer routes with less traffic to decrease their travel times. Clearly, through traffic increases the congestion level on the network, which results in new routes being chosen by vehicles. However, these routes, in the presence of through traffic, will certainly be equal or longer (in terms of distance) than the condition in which through traffic has been eliminated. Therefore, the VKTs reported in this paper might increase if through traffic is included. Longer trips therefore lead to longer customer waiting times. As a result, the fleet operator might be obliged to scale up the fleet size such that customer waiting times remain unchanged.

5.4. Real-time optimum rebalancing model

The efficient supply and demand alignment procedures are vital for future AMoD systems (Maciejewski and Bischoff, 2015; Horl, 2016, 2017). The spatiotemporal nature of travel demand for these services poses a great challenge to fleet operators of AMoD systems. This phenomenon causes AVs to accumulate in attractive areas of the city and become depleted at others.

This study uses a real-time optimum rebalancing model to redistribute the idle AVs between AMoD stands. The model is based on the work reported in Pavone et al. (2012) who proposed an optimum real-time model to redistribute the shared AVs across the network in order to improve customers' access to vehicles and reduce the need to scale up the fleet size to a point where it becomes unprofitable.

For this purpose, a code was written in Java and the optimum rebalancing model developed by (Pavone et al., 2012) was embedded in Commuter as a new plugin. At the end of each specific time-step (e.g. each 5 minutes), an optimal linear program (LP) is solved by the simplex method based on the current information the model receives from the network and sends idle AVs from where they are accumulated to where they are needed. This time-step is referred to as optimisation time-steps (OTS) throughout the thesis. In other words, OTS is the amount of time the fleet operator has to wait before AVs are rebalanced. As discussed later, the optimisation process aims at minimising the total induced eVKT within the network.

Rebalancing AVs can be undertaken either with information on the upcoming demand (Spiecer *et al.*, 2015; Miller and How, 2017) or without (Pavone et al., 2012). The rebalancing algorithm, which is deployed in this model, assumes demand is unknown to the fleet operator and rebalancing is performed without any priori information. Note, although demand has already been introduced to the model, the rebalancing algorithm takes no account of this while redistributing the idle AVs across the network. That is, it performs the rebalancing task merely with the data it receives at the time.

Let $v_i(t)$ be the total number of AVs available at station i. Now, if station i has $c_i(t)$ customers, then the excess vehicles at station i is $v_i^{excess}(t) = v_i(t) - c_i(t)$. These are the vehicles that station i has currently available to send to other stations in need. Thus, the total number of excess vehicles in the system is $\sum_i v_i^{excess}(t) = V - \sum_i c_i(t)$. Note that by definition, $\sum_i v_i\,(t) = V$. At the end of an OTS, the excess vehicles are sent by solving the objective function described as Equation 5-4. This objective function represents the minimisation of the total induced eVKT in the system.

$$\textbf{min}\ \boldsymbol{eVKT} = \boldsymbol{min} \sum_{i,j} \boldsymbol{T_{ij} num_{ij}} \qquad \textbf{Equation 5-4}$$

Subject to,

$$\boldsymbol{v_i^{excess}(t) + \sum_{j \neq i}(num_{ji} - num_{ij}) \geq v_i^d(t) \qquad \forall i \in N} \qquad \textbf{Equation 5-5}$$

$$\boldsymbol{num_{ij} \in N \quad \forall i, j \in N, i \neq j}$$

where,

num_{ij} : number of rebalancing vehicles from station i to station j (num_{ij} is the reverse for num_{ji})

T_{ij} : travel time from station i to station j

$v_i^d(t)$: desired number of vehicles at station i at time t following rebalancing

$v_i^{excess}(t)$: excess vehicles at station i at time t

For this study, $v_i^d\,(t)$ is assumed to be zero, which means at the time of solving the LP, stations with an excess number of vehicles send all their idle AVs upon request and stations with a deficit number of AVs receive as many AVs as pick-up requests are logged at these taxi AMoD stands. In other words, if $v_i^d\,(t)$ is assumed one for a sender station, it sends all its idle AVs except one AV, which remains at the station. Similarly, if $v_i^d\,(t)$ is assumed one for a receiver station, it receives as many AVs as it needs plus one more AV.

It is obvious that the proper determination of $v_i^d\,(t)$ can only happen when demand is certain, which is difficult to predict. For example, if it is known that there is an upcoming demand at a station (say one person will come in 2 minutes' time), the system will keep one idle vehicle to service this forthcoming request. Similarly, this pre-emptive action can also apply to receiver taxi ranks. Note that investigating the optimum approaches of determining $v_i^d\,(t)$ is out of the scope of this paper.

If Equation 5-5 is rewritten considering that $v_i^d(t)$ is zero, and $v_i^{excess}(t) = v_i(t) - c_i(t)$, Equation 5-6 becomes:

$$\sum_{j \neq i}(num_{ji} - num_{ij}) \geq c_i(t) - v_i(t) \qquad \forall i \in N \qquad \textbf{Equation 5-6}$$

$$num_{ij} \in N \quad \forall i, j \in N, i \neq j$$

An illustrative example:

To grasp the formula given in the previous section, consider a simple network (Figure 5-6) consisting of five stations, S1, S2, S3, S4, S5, all of which are connected via two-way, two-lane roads and AVs can move between them and pick-up or drop-off customers at any station. Table 5-4 shows the number of available vehicles and customers at the end of one specific OTS. At this point in time, there are two and five customers at stations S1 and S2, respectively but no AV exists there. Table 5-4 describes the status of these stations as *Deficit*. On the other hand, there are 10, 2, and 3 idle AVs at station S3, S4, and S5 where no customer is present. The status of these stations are designated as *Excess* in Table 5-4.

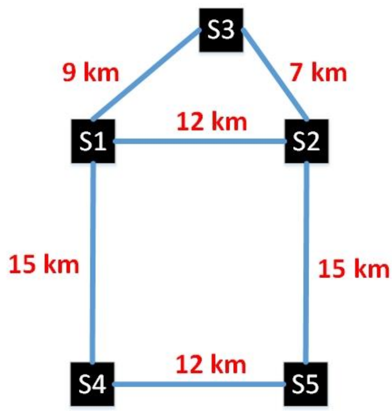


Figure 5-6: A transport network comprising five AMoD stations

Table 5-4: Status of the transport network at the end of one specific OTS

Station name	Available number of AVs (v)	Available number of passengers (c)	v-c	Status
S_1	0	2	-2	Deficit
S_2	0	5	-5	Deficit
S_3	10	0	10	Excess
S_4	2	0	2	Excess
S_5	3	0	3	Excess

If the speed limit within the network is 50 km/h, and considering the distances between different stations shown in Figure 5-6, to find the optimal number of rebalancing AVs, which must be sent from excess stations (S3, S4, S5) to deficit ones (S1 and S2) such that the induced eVKT becomes minimum, the LP for this network is written as follows,

$$min\left(\left(\frac{12\ km}{50} \times num_{12} + \frac{9\ km}{50} \times num_{13} + \frac{15\ km}{50} num_{14} + \frac{27\ km}{50} \times num_{15}\right) + \left(\frac{12\ km}{50} \times num_{21} + \frac{7\ km}{50} \times num_{23} + \frac{27\ km}{50} \times num_{24} + \frac{15\ km}{50} \times num_{25}\right) + \left(\frac{9\ km}{50} \times num_{31} + \frac{7\ km}{50} \times num_{32} + \frac{24\ km}{50} \times num_{34} + \frac{22\ km}{50} \times num_{35}\right) + \left(\frac{15\ km}{50} \times num_{41} + \frac{27\ km}{50} \times num_{42} + \frac{24\ km}{50} \times num_{43} + \frac{12\ km}{50} \times num_{45}\right) + \left(\frac{27\ km}{50} \times num_{51} + \frac{15\ km}{50} \times num_{52} + \frac{22\ km}{50} \times num_{53} + \frac{12\ km}{50} \times num_{54}\right)\right)$$

Subject to,

For station 1: $(num_{21} - num_{12}) + (num_{31} - num_{13}) + (num_{41} - num_{14}) + (num_{51} - num_{15}) \geq 2 - 0$

For station 2: $(num_{12} - num_{21}) + (num_{32} - num_{23}) + (num_{42} - num_{24}) + (num_{52} - num_{25}) \geq 5 - 0$

For station 3: $(num_{13} - num_{31}) + (num_{23} - num_{32}) + (num_{43} - num_{34}) + (num_{53} - num_{35}) \geq 0 - 10$

For station 4: $(num_{14} - num_{41}) + (num_{24} - num_{42}) + (num_{34} - num_{43}) + (num_{54} - num_{45}) \geq 0 - 2$

For station 5: $(num_{15} - num_{51}) + (num_{25} - num_{52}) + (num_{35} - num_{53}) + (num_{45} - num_{54}) \geq 0 - 3$

For solving this LP, Excel's LP solver is used and yielded the following results,

$$num_{12} = num_{13} = num_{14} = num_{15} = num_{21} = num_{23} = num_{24} = num_{25} = num_{34} = num_{35} = num_{41} = num_{42} = num_{43} = num_{45} = num_{51} = num_{52} = num_{53} = num_{54} = 0$$

$num_{31} = 2;\ num_{32}$=5

As can be seen from the LP outputs, the rebalancing algorithm sends the idle AVs to station S1 and S2 from the nearest station (i.e. S3) to minimise the total induced eVKT. The same rebalancing procedure is followed in this study and idle AVs are sent in accordance with the outputs of LP at the end of each OTS. The objective function, however, is much larger than the one discussed herein and features 2756 variables with 53 constraints.

Please note that although the example uses fixed speeds to compute travel times across the network, in practice and for our real-life application, travel times are calculated based on the real-time speeds within the network.

5.5. Simulation framework, assumptions and scenarios

As previously mentioned, a total of 20,392 complete trips are undertaken in the study area using privately-owned vehicles during AM-Peak hours (07:00-09:00am). The model developed in this study assumes that market penetration is 10% and the remaining trips continue to rely on privately-owned vehicles. Therefore, the travel demand for the AMoD system comprises 2,039 trips that use a shared AMoD to reach their destinations. In other words, in AMoD scenarios, there are 2039 less private vehicles compared to the base case scenario as their owners have moved to the new AMoD system. It is worth repeating here that the results reported in this paper do not include ride-sharing; rather it assumed that travellers continue to ride alone using a fleet of shared vehicles. In other words, the AMoD system modelled in this study represents a car-sharing rather than a ride-sharing scheme.

Furthermore, it is assumed that the service is a station-based AMoD system in which each centroid (OD) has a station where shared AVs are located to service the customers. That is, at the centre of each block (area), there is only one AMoD rank where AVs pick-up or drop-off their customers or wait if no trip request is received. The reason for choosing a station-based AMoD system as opposed to a door-to-door one is because an aggregate demand is used in this model. This means customers are imported into the model from only one point (i.e. from the ODs, shown in Figure 5-3), located at the centre of each area. The AMoD stations are placed at these points to service the imported demand into the model. In other words, if investigating a door-to-door AMoD system is of interest, a disaggregate demand should be used in which people enter the model from different points within each area rather than just one point. In this model, it is assumed that people need to walk a distance from their residences to the AMoD station. However, walk times are not taken into account in this study.

All travel is assumed to be one-way between the origin and the destination. Given the uncertainty in travel demand, the initial number of AVs (at the start of the simulation) is assumed equal at all stations. The passenger waiting time threshold is assumed to be 15 minutes: once a customer arrives at an AMoD stand (where AVs are available for pick-up and drop-off), the maximum amount of time they are willing to wait is 15 minutes – otherwise, they leave the AMoD stand and look for alternative transport. In this model, when a customer arrives at an AMoD stand, if no AV is available, there are only two ways the customer might receive an AV to travel:

There is an occupied AV on the way to the station in which the customer is waiting. In this case, the AV can pick up the waiting customer after having its on-board passenger dropped off.

Otherwise, the customer waits until the next rebalancing process is performed, which means, in the meantime, no AV is assigned from the neighbouring stations to service the waiting customer.

Although the second case might sound unrealistic, in practice, this can be resolved by taking very short OTS (say OTS=30 seconds). This means the LP can be solved every 30 seconds and idle AVs are dispatched accordingly. The shorter the OTS, the more responsive the AMoD system. In this study, an OTS shorter than 5 minutes is not chosen in order to avoid computing burden.

It is worth noting that the model takes into account the time passengers need to board or alight from an AV. The manoeuvre time each AV needs to get out of the rank or park inside this area is also considered. However, the manoeuvre times are based on conventional vehicles not AVs, as this data is not yet available.

A number of scenarios are investigated in this research. The key assumption in these scenarios is that market penetration does not exceed 10% (i.e. only 2,039 trips out of the 20,392 trips in the study area are undertaken using the AMoD system). In the base case (BC) scenario, all travellers (20,392 trips) were modelled using their own conventional vehicles. The BC scenario was followed by a total of 25 AMoD scenarios featuring five different fleet sizes (318, 424, 530, 636, and 848 vehicles) with different OTS (5, 15, 30, and 60 minutes). To determine the aforementioned fleet sizes, the following process was followed.

First, the minimum fleet size (318 AVs) was selected such that the total travel demand could be met when the OTS was set to minimum (i.e. 5 minutes in this study). Therefore, a number of fleet sizes were simulated, and finally it became clear that 318 AVs were enough to this end. Afterwards, the fleet size was gradually increased in order to capture the general trend of change in the performance of the AMoD system as the fleet size grows. Note, the fleet sizes must be chosen such that the equal distribution of AVs between 53 AMoD stations is possible. For instance, when fleet size is 848, each station has 16 vehicles (i.e. 848/53=16) at the start of the simulation. Similarly, if the fleet size is 318, 424, 530, 636, each station has 6, 8, 10, 12 AVs at the start of the simulation, respectively.

Given that 10% of the BC scenario (i.e. 10% market penetration) includes 2,039 traditional private vehicles (which are assumed to shift to the AMoD system), the fleet sizes selected comprised 16, 21, 26, 31, and 42 percent of the BC fleet size. A scenario without vehicle rebalancing was also conducted.

5.6. Simulation results

This section presents the results obtained from the simulation runs and reports on the elasticities of trips serviced (i.e. level of service) and VKT with respect to various fleet sizes and OTS. In total, in this section, 26 scenarios were run, each of which took almost 10 minutes to finish.

The results in Figure 5-7 and Figure 5-8 show that all the selected fleet sizes were successful in meeting the demand for travel when the OTS was 5 minutes. The results also show that, for each fleet size, the percentage of trips serviced decreases as the OTS increases. The decrease is steeper for smaller fleet sizes, which indicates that the system becomes less sensitive to OTS with larger fleet sizes.

The results in Figure 5-7 also show that as the fleet size increases, the percentage of trips serviced also increases. This increase, however, is more rapid for scenarios with longer OTS, which indicates that the system becomes more sensitive to fleet size with longer OTS. This can be observed, for example, through a comparison of the increase in percentage of trips serviced for a fleet size of 318 vehicles to a fleet size of 848 vehicles for different OTS, as shown in Figure 5-7. The scenarios in which no rebalancing strategy is implemented meet 65% of the total demand at best. (This happens for a fleet size of 848 vehicles).

Regarding customer waiting times, Figure 5-9 shows that the average passenger waiting time for the scenarios that meet the demand was around 4 minutes. For all scenarios, the average customer waiting time was between 3 to 7 minutes.

Figures 5-10 and 5-11 show that all AMoD scenarios contribute to more VKT compared to the BC scenario. Of the scenarios that meet the demand for travel, the scenario with 318 vehicles (16% of the base case fleet size) induced the largest increase in VKT (77%). As expected, the least increase in VKT (47%) was for the scenario with 848 vehicles (42% of the base case fleet size). This increase in VKT shows that shared AMoD systems lead to a significant amount of traffic congestion within the network.

Although these results are in line with the findings in (ITFa, 2015) and (Levin et al., 2017), there is a substantial discrepancy between these figures and the findings available in some other studies, as previously described. For instance, Fagnant and Kockelman (2014) reported that each shared AV can replace around eleven traditional vehicles while adding only 10% more VKT. In another study conducted in Austin by the same researchers, the results suggested that each shared AV could replace around nine conventional vehicles at the cost of only 8% more VKT (Fagnant, Kockelman and Bansal, 2015). Similarly, a Berlin study (Bischoff and Maciejewski, 2016a) showed that AMoD systems can reduce the fleet size up to 90% while generally only incurring 10% more in VKT in the city centre. A Stockholm study (Burghout, Rigole and Andreasson, 2015) suggested almost the same fleet reduction with 24% more VKT compared to the BC scenario. Another study (Boesch, Ciari and Axhausen, 2016) showed that an AV spent 4% of the day travelling empty to pick up the customers. Further, they suggested that the current fleet size could be cut by 90% by a fleet of shared AMoD systems without including any VKT provided that waiting times of 10 minutes were accepted.

Note that the study area used in this research is smaller than the ones mentioned herein. Given that the Berlin study (Bischoff and Maciejewski, 2016a) suggests the performance of AMoD systems deteriorates as the study area scales up, the results obtained in this study might deteriorate if the current study area is expanded.

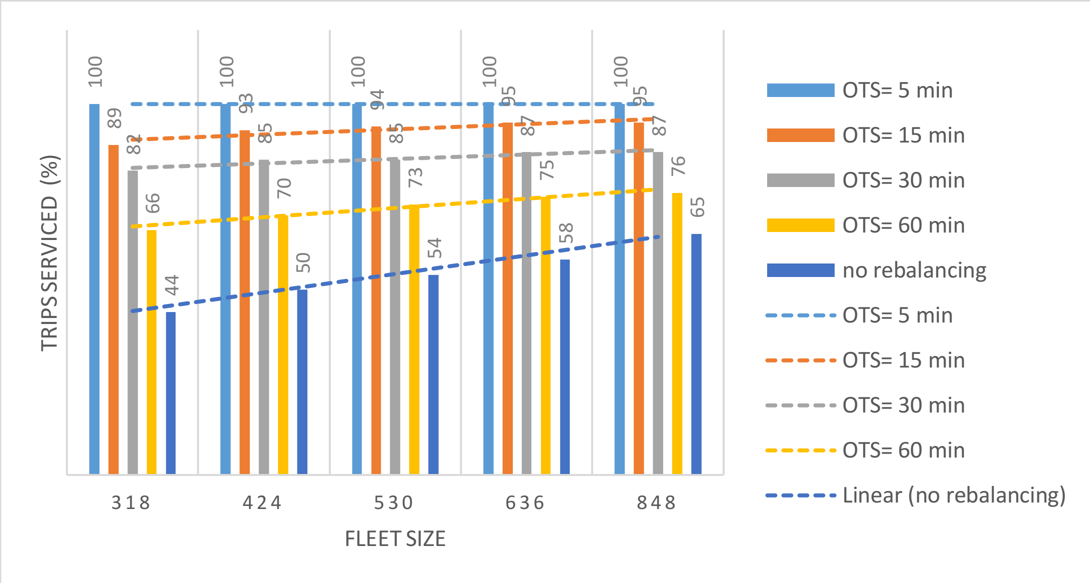


Figure 5-7: Relationship between fleet size and trips serviced for different OTSs

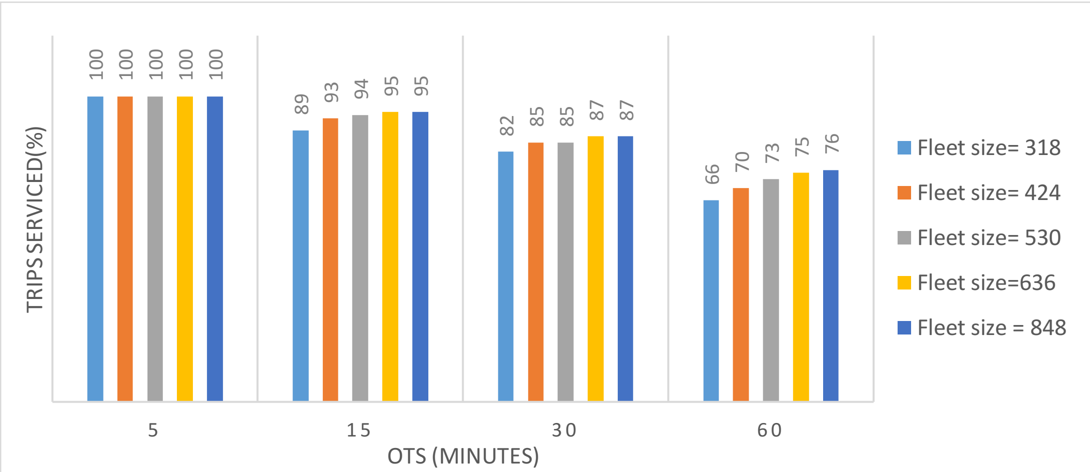


Figure 5-8: Relationship between OTSs and trips serviced for different fleet sizes

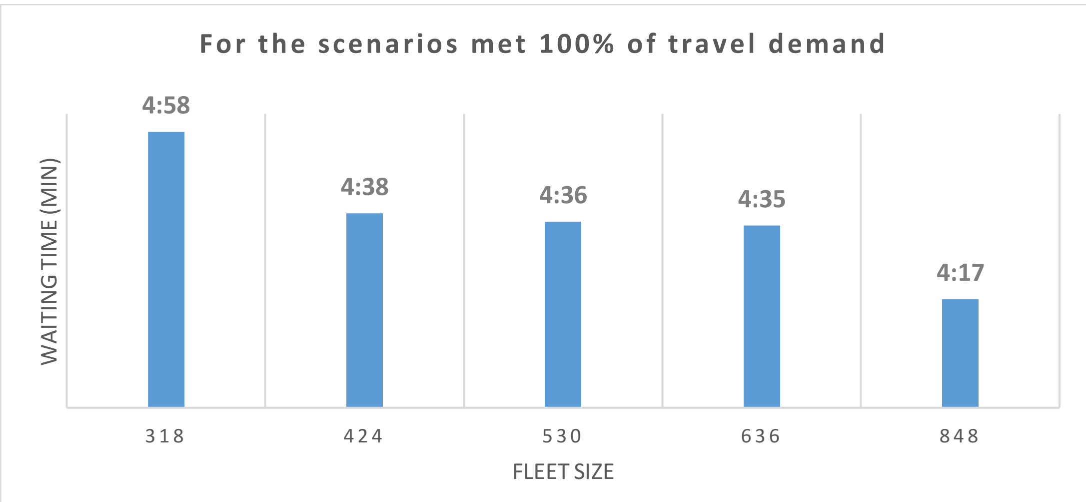


Figure 5-9: Average waiting times for the scenarios which were successful in meeting demand

This study identifiesd four potential causes of these discrepencies as follows:

1. One reason that could lead to these discrepencies is the fact that in these studies, the rebalancing AVs have only been moved on the shortest Euclidian distance rather than being simulated on the real transport network, which results in less VKT.

2. Another explanation for these discrepencies might be that these studies include a high percentage of ride-sharing cases in their scenarios, which decreases fleet size and total VKT considerably. For instance, there is a substantial difference between the fleet size and total generated VKT in cases where travellers only want to use car-sharing systems (i.e. the proportion of ride sharers is zero) compared to cases where all travellers use ride-sharing schemes in groups of four. The aforementioned studies do not clearly discuss whether they include ride-sharing cases in their simulation environments, and if so, what is the exact proportion of car and ride sharers in their scenarios.

3. Another source of difference could be that these studies assume demand certainty and provide the required number of AVs at the start of the simulation at the designated pick-up points, which makes it less realistic. In this research, however, demand is assumed uncertain and the initial number of AVs (i.e. at the start of the simulation) at AMoD stands are distributed equally between different areas, regardless of the number of requests that might be logged at each of these places.

4. Furthermore, the distribution of travel demand within the study area might be different in these studies which also contributes to these discrepencies. The effects of this phenomenon are discussed in the next section.

The results in Figure 5-10 show that as the fleet size increases, the system experiences less VKT for all OTS. The slope of change for VKT as a function of fleet size (Figure 5-10) is steeper than that for the percentage of trips serviced (Figure 5-7). This indicates that for a specific change in fleet size, VKT changes faster than the total percentage of trips serviced.

A comparison of Figure 5-8 and Figure 5-11 sheds some light on how the induced VKT is a key measure in assessing the efficacy of AMoD systems, rather than considering only the percentage of requests serviced and passenger waiting times as decision variables, which is the case in some studies in the literature e.g. (Spieser et al., 2014; Shen and Lopes, 2015; Zhang and Pavone, 2016; Alonso-Mora et al., 2017).

Figure 5-8 shows that for a specific OTS, the percentage of serviced trips for different fleet sizes is very close to each other, especially for shorter OTS. However, Figure 5-11 shows for the same OTS, there is a considerable difference between the induced VKT for different fleet sizes.

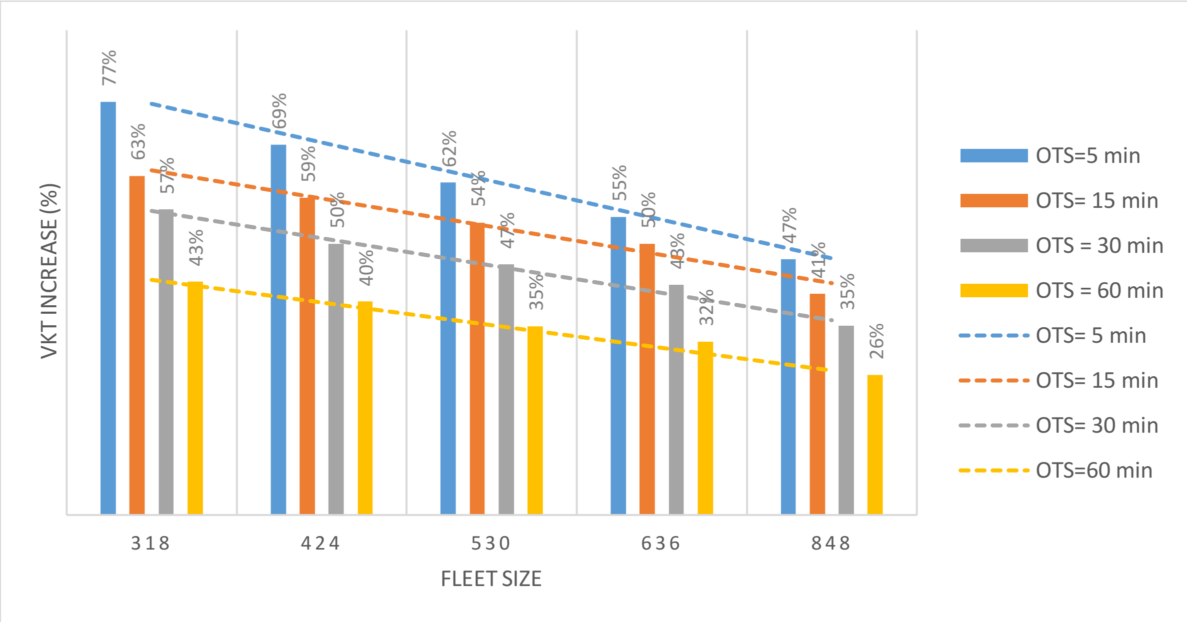


Figure 5-10: Relationship between fleet size and VKT increase for different OTSs

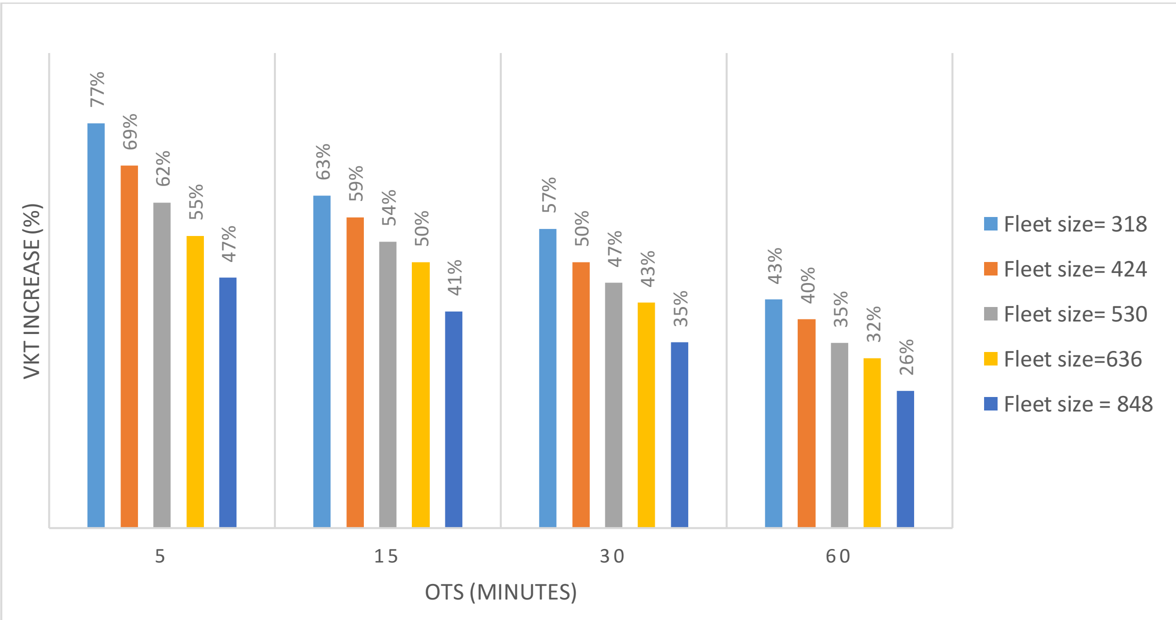


Figure 5-11: Relationship between different optimisation time-steps and VKT increase for different fleet sizes

Figure 5-12 illustrates how the VKT varies in proportion to the decrease in the current fleet size, for scenarios in which 100% of travel demand is met. For instance, consider the orange point on this graph (denoted by ◆), which represents a fleet size comprising 318 AVs. This point shows that if the current fleet size is decreased by 84% as a result of the introduction of an AMoD system, it induce 77% more VKT when proofread the total travel demand is met completely. This increase in VKT is 47% for cases where demand is completely met by a fleet size comprising 848 AVs (denoted by ✳ on the graph) which reduces the current fleet size by 58%.

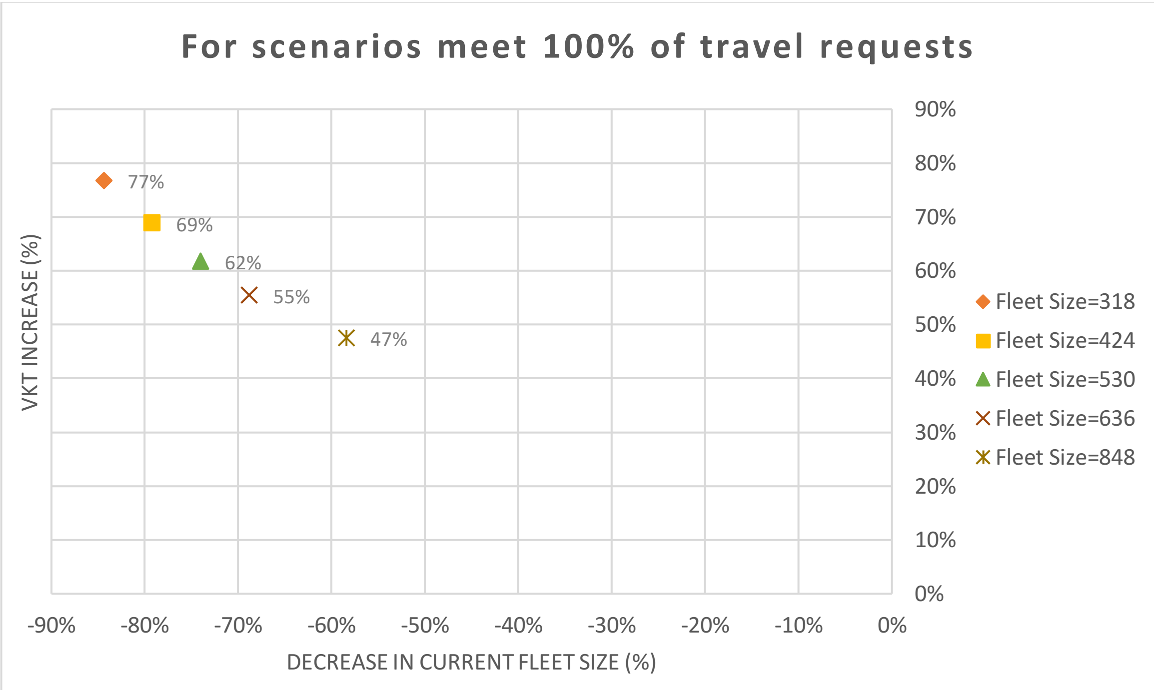


Figure 5-12: Percentage of increase in VKT as a function of the percentage of decrease in current fleet size when the aim is to meet demand completely

5.7. Sensitivity of AMoD Systems to Initial AVs at Stations

In this study, it is assumed that for each AMoD scenario, the same number of AVs are available at each station at the start of simulation. This section investigates how the performance of AMoD systems are impacted based on the initial travel demand assigned to each station. To this end, the number of available AVs at the beginning of the simulation at each station is determined in proportion to the number of trip requests logged in that station within the first 30 min of the simulation. In other words, the highest number of AVs is assigned to stations whose travel demand within the first 30 min is the highest. To do this, the following equation is used to estimate the number of AVs required at each station at the start of simulation,

$$\boldsymbol{N_i = \frac{a_i}{\sum_{i=1}^{53} a_i} \times FS} \qquad \textbf{Equation 5-7}$$

where

N_i : number of AVs assigned to station *i* at the start of the simulation

a_i : total number of trip requests at station i within the first 30 min of the simulation
FS : total number of AVs available in the system (i.e. fleet size)

Having assigned the initial AVs based on this approach, the simulations were run and the results were recorded for all the fleet sizes chosen as discussed in the previous section. Note that in this section, OTS was set to 5 min.

The results show that in this case, the percentage of trips serviced and average customer waiting times remain almost unchanged compared to the former approach in which AVs were distributed equally between the different stations.

As for the induced eVKT, Figure 5-13 shows that, on average, the new approach (i.e. unequal AV assignment technique) reduces eVKT by up to 4% in comparison to the previous method in which initial AVs were distributed equally. The AMoD scenarios, however, still lead to a significant increase in VKT ranging from 40% to 77%. While the performance of AMoD systems does not appear to be significantly sensitive to the initial number of AVs at stations, it can lead to a modest decrease (up to 4%) in the eVKT induced.

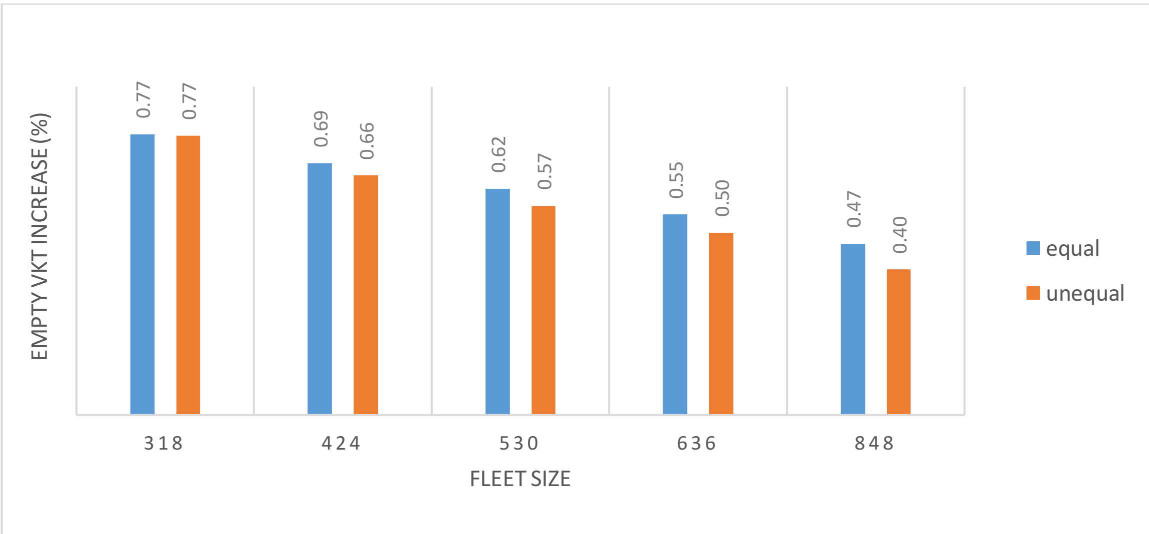


Figure 5-13: Comparison of induced empty VKT when initial AVs are distributed between different stations either equally or unequally

5.8. Effects of travel demand heterogeneity on VKT

One of the key motivations for fleet operators to implement optimal rebalancing strategies for their AMoD systems is the difficulty of predicting the heterogeneous travel demand across the road network. That is, varied land use characteristics of different parts of an urban context makes some areas more attractive than others (e.g. central business district areas compared to suburban areas). This phenomenon poses a challenge for AMoD fleet operators: in order to meet demand and maintain an acceptable quality of service in terms of customer waiting times, the fleet size needs to be increased to a level where it may become unprofitable. This section examines how the distribution of travel demand between different areas affects the efficiency of an AMoD system.

In this study, the distribution of travel demand is identified according to a measure called the Net Trip-Rate Ratio (NTRR). As shown in Equation 5-8, this is the proportion of the total number of incoming trips (I) to an area over the total number of outgoing trips (O) from that area over a specific period.

Equation 5-8

$$\boldsymbol{Net\ Trip - Rate\ Ratio\ (NTRR)} = \frac{\boldsymbol{Total\ number\ of\ incoming\ trips\ to\ an\ area\ (I)}}{\boldsymbol{Total\ number\ of\ outgoing\ trips\ from\ an\ area\ (O)}}$$

This definition means if the NTRR for an area is equal to 1, it attracts as many trips as it generates. On the other hand, if the NTRR is zero, this indicates that this area does not attract any trips. Similarly, an area will attract more trips than it generates if its NTRR is more than 1. For this research, the distribution of the NTRR within the study area is shown in Figure 5-14.

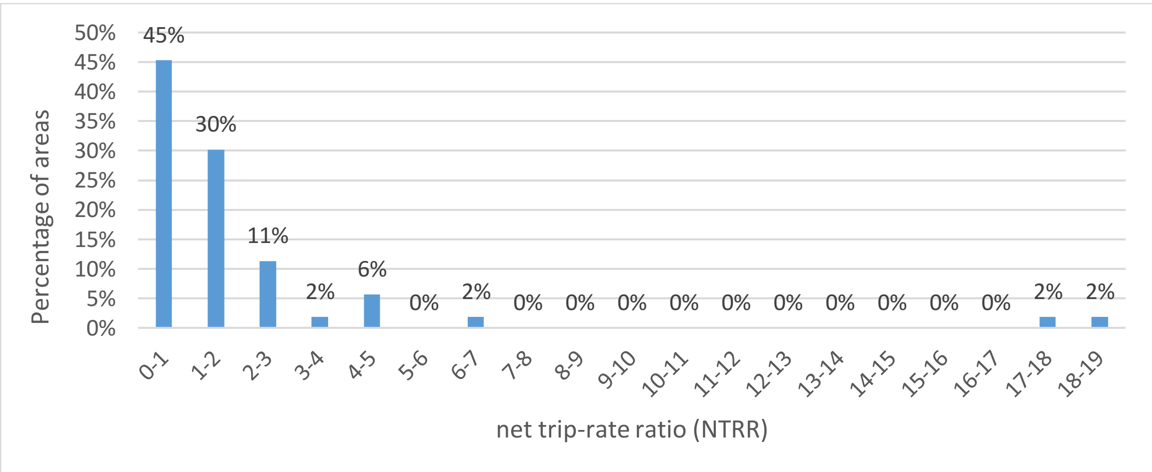


Figure 5-14: Distribution of NTRR within the study area for the current condition

To explore how the efficiency of AMoD systems is likely to be impacted by the NTRR, two hypothetical cases (Case 1 and Case 2) were tested and the results compared to the base case (BC) scenario. Case 1 represents the condition in which the NTRR of all areas is closely dispersed around 1 and demonstrates how the system behaves under such equal conditions. Case 2, however, examines the opposite situation in which certain parts of the study area are very attractive (e.g. the central parts of the study area which, on average, have an NTRR equal to 106, meaning each OD attracts 106 trips while generating only 1 trip), while the rest attracts very few trips. Case 2 is representative of travel patterns between suburbs and city centres during AM-peak hours when the majority of trips are undertaken from the suburbs (NTRR is almost zero) towards the city centre (NTRR is very high).

As shown in Figure 5-15, the currently designated fleet sizes do not meet the demand for travel in Case 2. At best, these fleets manage to meet around 92% of the travel demand (note that OTS is set to 5 minutes). However, for Case 1, the AMoD systems are always successful in meeting demand.

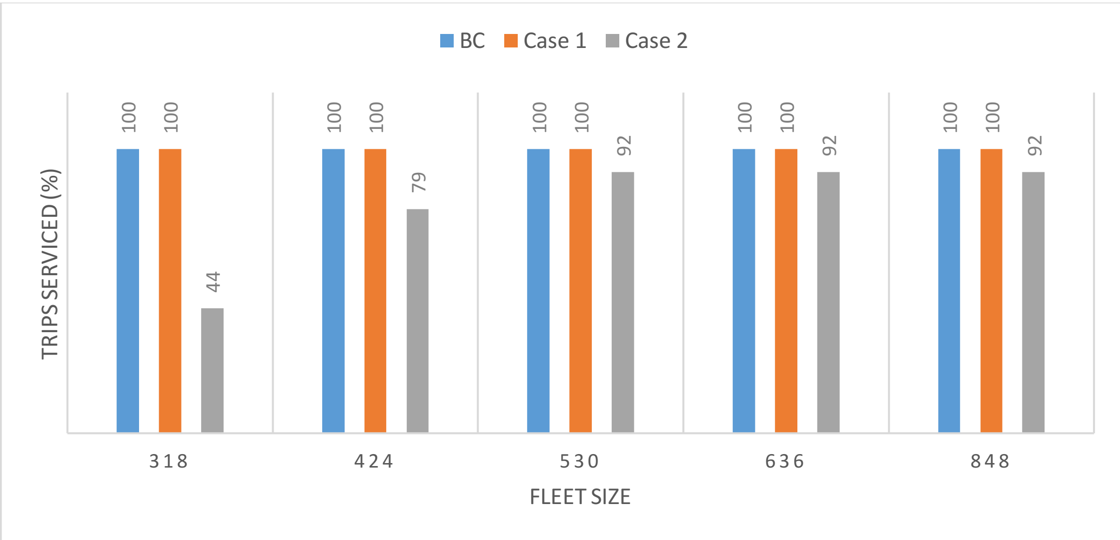


Figure 5-15: Percentage of trips serviced using different fleet sizes for BC, case 1, and case 2

Figure 5-16 and Figure 5-17 illustrate that VKT dramatically decreases (between 35-47%) in Case 1 compared to the BC for the same fleet sizes. In Figure 5-17, consider, for example, points denoted by blue (◆) for BC and orange (■) for case 1. Although both fleet sizes are 84% smaller than the current fleet size and meet the travel demand completely, the induced VKT under current demand patterns (BC) is 40% greater than that of case 1.

As depicted in Figure 5-15 and 5-16, travel demand is not met in Case 2 and the induced VKT is always larger than the BC (current travel pattern) and Case 1. From this information, it can be deduced that using an AMoD system during peak hours between city centres and suburbs is likely to fail in meeting travel demand and is likely to lead to more congestion in the network due to the increased empty travel.

The simulation runs reveal that the main reason for the deterioration in the performance of the AMoD system in Case 2 is the fact that customers in non-attractive areas always have to wait for the rebalancing process to occur before an AV arrives. In other words, AMoD's poor performance in Case 2 is not related to the level of congestion within the network, whereas in the BC, customers do not necessarily have to wait for rebalancing to find an AV because in this case, there may be customers who are travelling from other areas to this area, and the AV carrying them can pick up these waiting customers after dropping off their on-board passengers.

Note that in all these cases (BC, Case 1, and Case 2), travel demand is the same (2,039 requests are made to use the AMoD system). The only difference between these cases is the distribution of the NTRR within the study area. These findings suggest that the negative impact of demand heterogeneity on VKT is not trivial and should be considered more thoroughly before deploying these systems. It is also worth mentioning that using a homogenous travel demand for the pilot study is the key reason for the very small induced VKT in the pilot study as well.

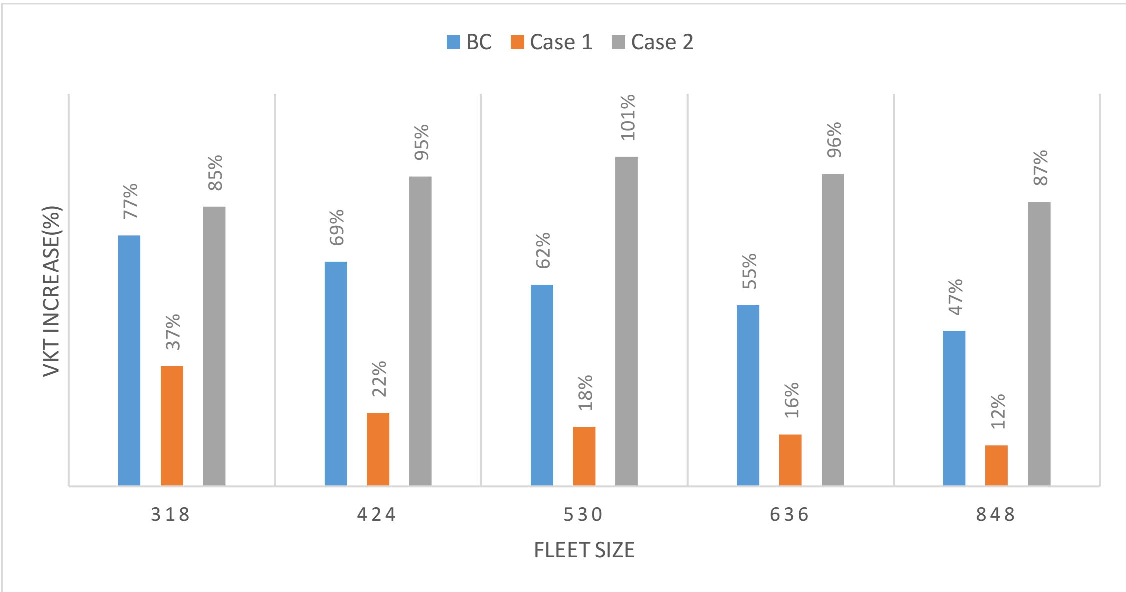


Figure 5-16: Percentage of VKT increase with different fleet sizes

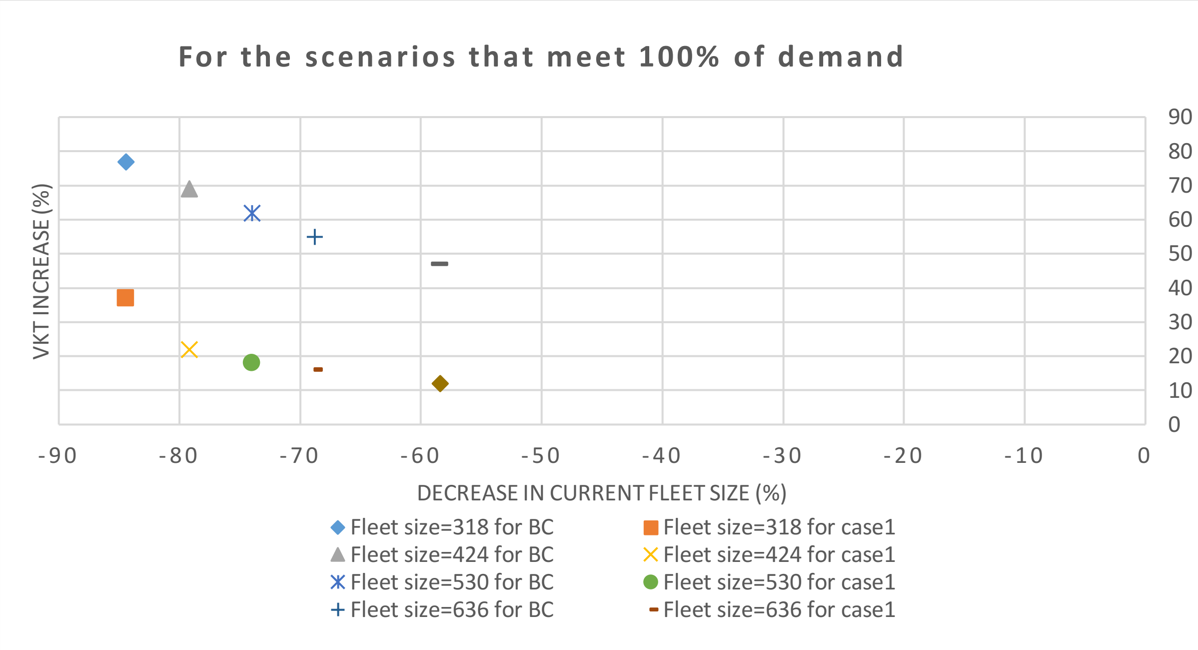


Figure 5-17: Percentage of increase in VKT as a function of percentage of decrease in fleet size for scenarios which meet 100% of demand

5.9. Limitations

As with any other research, this study also has some limitations, which mainly arise due to the limited computer power and availability of data. The computer used for this study had the following characteristics: CPU E5-1650 v3@ 3.50 GHz, RAM: 16 GB, 64 bit operating system.

The main limitations of this work are twofold:

1. This study compared to existing studies with a similar scope covers a smaller study area and shorter simulation period due to the model's quite high resolution in terms of network representation, traffic flow modelling, and rebalancing algorithm. In the transport modelling realm, there is always a trade-off between model resolution and the extent of the study area and simulation period. To date, the majority of articles on this topic resort to models that feature large areas with long simulation periods (usually 24 hours). As a result, these studies are forced to reduce the resolution of their models, which enables researchers to run their scenarios on the computer. This study, therefore, explores AMoD scenarios from a new perspective and observes to what extent the results of such a model differ from its previous counterparts.

   AMoD systems aim to mitigate congestion. Obviously, congestion mostly occurs during peak hours and if an AMoD system manages to alleviate congestion during this period, it can be concluded that it will also succeed in alleviating congestion at other times of the day. For these reasons, this study carries out a simulation for the morning peak hours (07:00-09:00am) as the most severe congestion occurs over this period in Melbourne (VISTA, 2016).

Further, it should be noted that modelling the whole Melbourne would certainly yield longer trips compared to this study in which just part of Melbourne was modelled. The longer trips become, the longer AVs are occupied, and as a result, the fleet operator will need to deploy more AVs to service the upcoming customers within a reasonable time. In other words, the more widespread the study area, the more AVs will be required by AMoD systems (Bischoff and Maciejewski, 2016a).

2. The current work only considers the empty AV relocations undertaken for servicing the customers. That is to say, the relocation of AVs to recharge the battery, or for maintenance or cleaning is not taken into account, similar to (Bischoff and Maciejewski, 2014; Chen, Kockelman and Hanna, 2016; Loeb, 2016).

5.10. Chapter summary

This chapter investigated the quantitative trade-offs between different AMoD fleet sizes and OTS using a microscopic agent-based simulation model, which included a real-time optimum rebalancing algorithm. The results suggest that the total travel demand in the study area can be serviced by an AMoD system using a fleet size which is 58% to 84% smaller than the current fleet size. The study also found that the reduction in the total number of vehicles comes at the expense of inducing 47% to 77% more vehicle kilometres travelled within the network, which contributes to more traffic congestion. These findings are not in line with what is suggested in some of the existing studies in the literature and indicates that the benefits of AMoD systems have generally been overstated in terms of their potential to mitigate congestion. The increase in VKT uncovered in this thesis shows that shared AMoD systems, without ride-sharing, might not be a sustainable transport solution for morning peak-hours.

Note that the eVKT reported in this chapter is only due to rebalancing the empty AVs. AVs also need to undertake other empty travels for recharging or refuelling purposes. Adding this type of empty driving to the ones, which occur due to rebalancing leads to even more VKT. In addition, the AMoD system used in this study is assumed to be a station-based type. Deploying door-to-door AMoD systems will definitely induce more VKT than the station-based system. This is because in door-to-door AMoD systems, people are picked up and dropped off at their residences rather than walking to an AMoD station, hence the walking trips in station-based systems are replaced with AV trips in door-to-door systems which results in more VKT.

In this chapter, the effects of travel demand heterogeneity on the efficiency of AMoD systems were also explored and the results show that this phenomenon has a significant impact on the efficacy of the system, suggesting that operating an AMoD system during peak hours between city centres and suburbs can result in additional congestion while also failing to completely service the travel demand.

Other findings of this study are as follows:

- The system becomes less sensitive to OTS with larger fleet sizes.
- The system becomes more sensitive to fleet size with longer OTS.
- For a specific change in fleet size, VKT changes more rapidly than the percentage of trips serviced

Chapter 6 : Model Testing and Evaluations- Formulating the Relationship between Fleet Size and VKT

In Chapter 5, the performance of shared AMoD systems was analysed and the results uncovered some negative implications of such systems caused by the empty repositioning of AVs. This occurs when no ride-sharing is allowed in the modelling context and AMoD systems operate as car-sharing systems. This chapter quantifies the transport implications of AMoD systems under both car- and ride-sharing scenarios. Further, in this chapter, an attempt is made to formulate the relationship between AMoD fleet size and the corresponding induced VKT by examining various scenarios that reveal the behaviour of these systems on a real transport network.

This chapter is structured as follows. Section 6.1 describes the simulation scenarios and assumptions used for the study. The simulation results and associated discussions are provided in section 6.2. Section 6.3 illustrates the process undertaken to formulate the relationship between fleet size and VKT. In section 6.4, the effects of travel demand heterogeneity on this general relationship are explored. Finally, section 6.5 summarises the overall findings of the investigations reported in Chapter 6.

6.1. Simulation scenarios and assumptions

The current model is the same as the one deployed in Chapter 5 (e.g. transport network, travel demand, traffic flow model, rebalancing algorithm, public transport schedules, initial AVs at AMoD stands, and simulation period) with the difference in this chapter being that more fleets of varying sizes are utilised and also ride-sharing systems are introduced.

This chapter investigates the performance of AMoD systems when used as either car-sharing or ride-sharing systems at 10% market penetration. The base case (BC) scenario represents the current condition where people use their privately-owned vehicles to reach their destinations. This scenario is followed by 72 AMoD scenarios to obtain a comprehensive insight into how these systems work in an urban environment. Scenarios vary in terms of fleet size and rebalancing time-step. Half of the AMoD scenarios explore the effects of AMoD systems when AVs are deployed as car-sharing systems and the other half investigate the implications when AVs provide ride-sharing services to customers.

Please note that each AMoD scenario features either car-sharing or ride-sharing. That is to say, car-sharing and ride-sharing systems cannot co-exist in this model. As a result, the impacts of each system on the network are observed separately and compared with each other.

Further, in this study, no mode choice model is implemented such as the one discussed in (Liu *et al.*, 2017). In other words, travel demand for each transport mode is unchanged during the simulation, irrespective of the level of service in the network. Given the major aim of this study is to explore the supply side of AMoD scenarios, deploying a constant travel demand with fixed mode shares is more helpful. By doing so, researchers can focus more intently on formulating the impacts of supply change on current traffic conditions.

It is also worth mentioning that the majority of AMoD studies appraised in this paper deploy the same approach and the assumed travel demand and mode shares are unchanged throughout their simulations. Therefore, this thesis implements the same framework, which enables a comparison to be made between the thesis results and the results in the existing literature so that disparities can be identified.

It is also assumed that people use ride-sharing systems in groups of two (i.e. ride-sharing is not allowed for groups larger than two passengers). Ride-sharing clusters larger than two people seems unrealistic for Melbourne as the current average car occupancy rate in Victoria is 1.55 people per car, and this trend is estimated to decline in the future (Truong *et al.*, 2017).

In the ride-sharing scenarios, it is assumed that people who travel as a group have the same origins and destinations. This means that no detour occurs to pick up or drop off customers at different places. In other words, no DRS strategy is implemented in the current model such as the ones discussed in (Agatz et al., 2010, 2011; Shuo Ma, Yu Zheng and Wolfson, 2013; Fagnant and Kockelman, 2015).

Further, it is assumed that any person who intends to share ride with someone else has come to an agreement in advance with his or her fellow riders regarding the start time of their journey. As a result, in this model, ride-sharers are imported into the model at the same time. That is to say, ride-sharers do not spend time waiting for their fellow riders at a station before departure.

At the start of the simulation, the initial number of available AVs is equal at each of the AMoD stands, as demand is assumed to be uncertain for the fleet operator. As shown in Figure 6-1, nine fleet sizes are considered for this study such that the equal distribution of AVs at the start of simulation is possible. For instance, when fleet size is 318 AVs, 6 vehicles (i.e. 318/53=6) can be equally distributed among 53 stations across the network. The process of choosing these fleet sizes was explained in Chapter 5, section 5.5.

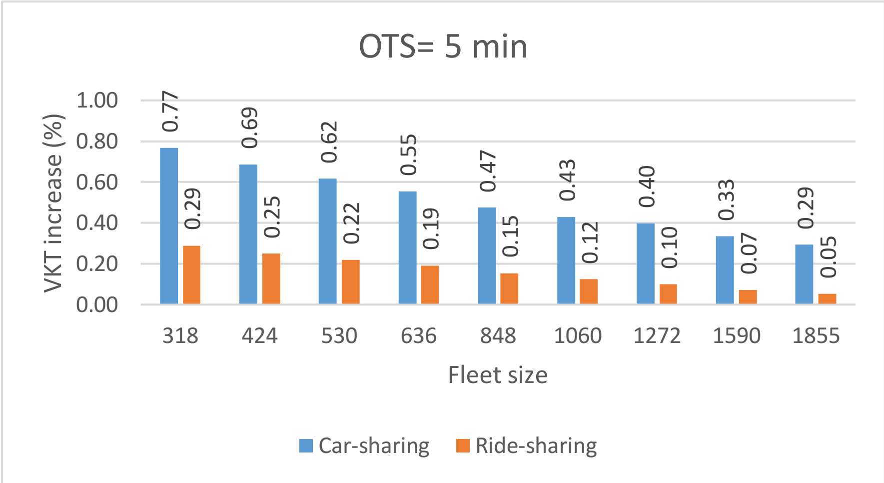
6.2. Simulation results

The simulation was run for four OTSs (5, 15, 30, and 60 min) using a scenario where no rebalancing was implemented. As previously mentioned, the simulation was conducted for the 07:00-09:00am peak period for the same calibrated and validated travel demand as discussed in Chapter 5. Overall, in this part of study, 133 scenarios were explored to gain a clear insight into the behaviour of AMoD systems.

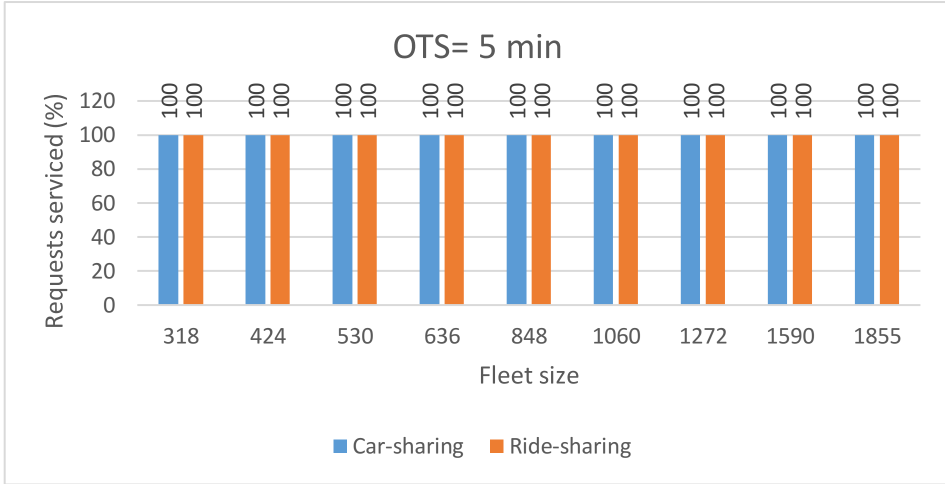
Figure 6-1-b shows that when OTS is set to 5 minutes, all fleet sizes in both ride-sharing and car-sharing systems are able to service travel demand completely. As OTS grows (Figure 6-1-d, Figure 6-2-b & Figure 6-2-d), the percentage of serviced requests drops. This decrease in the level of service is more rapid for car-sharing fleets than ride-sharing systems. These numbers indicate that the percentage of serviced requests in the ride-sharing system is always higher than that for the car-sharing system; however, this difference is not substantial especially for shorter OTSs. Note that passenger waiting time for all scenarios is always less than 7 minutes.

On the other hand, Figure 6-1-a, Figure 6-1-c, Figure 6-2-a, and Figure 6-2-c show that AMoD systems induce more VKT due to the rebalancing of empty AVs. The highest and the least increase in VKT for all fleet sizes occur when OTS is set to 5 and 60 minutes, respectively. However, there is a considerable difference between the induced VKT in the car-sharing systems compared to the ride-sharing systems. For instance, when the AMoD system comprises 318 vehicles and the OTS is 5 minutes, the increase in VKT for the car-sharing system is 48 percent more than that for the ride-sharing system when both systems completely meet the travel demand. This phenomenon, first, shows the crucial role of implementing ride-sharing schemes in boosting the efficiency of AMoD systems and preventing the generation of new VKT due to rebalancing. Moreover, it highlights the importance of considering induced VKT as a key performance measure in assessing the efficacy of AMoD systems, rather than considering only the percentage of trips serviced and passenger waiting times as decision variables, which is the case in several studies in the literature e.g. (Spieser *et al.*, 2014; Shen and Lopes, 2015; Zhang and Pavone, 2016; Alonso-Mora *et al.*, 2017).

Figure 6-3 illustrates the percentage of requests serviced for different fleet sizes in both car- and ride-sharing systems when no rebalancing strategy is deployed. These figures show if no rebalancing strategy is deployed, the AMoD systems of small fleet size are not be successful enough in meeting the travel demand and deploying larger fleets is necessary to maintain an acceptable level of service.



(a)



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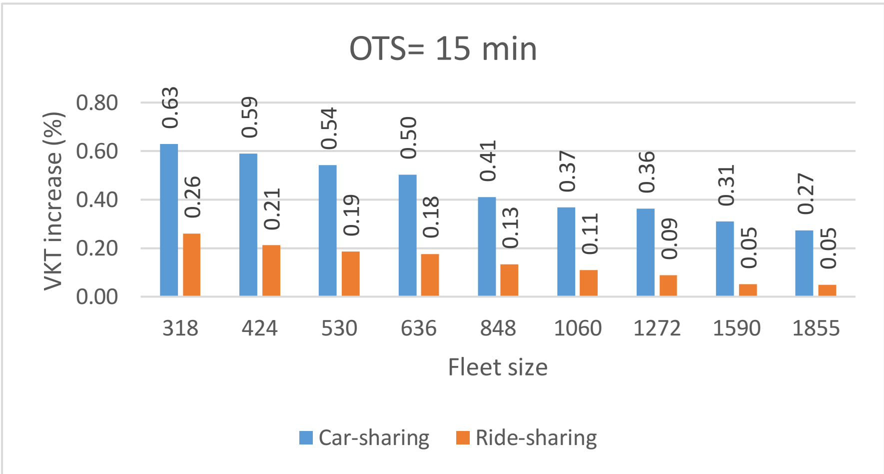

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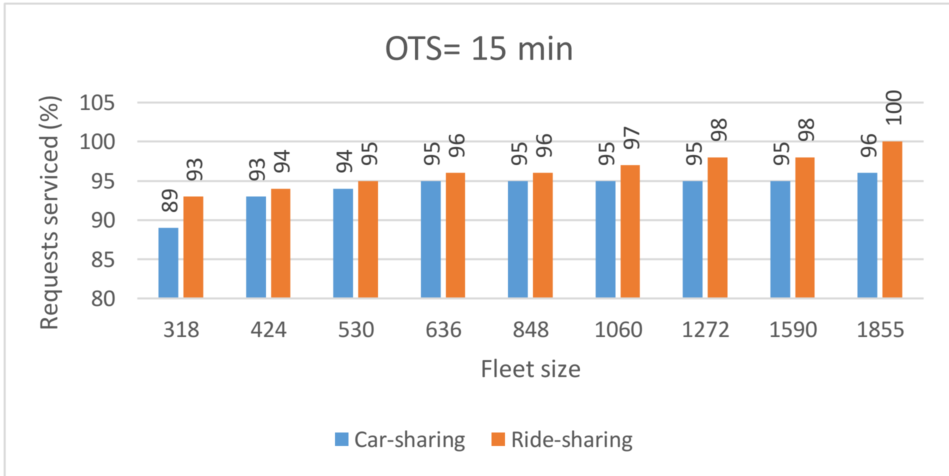
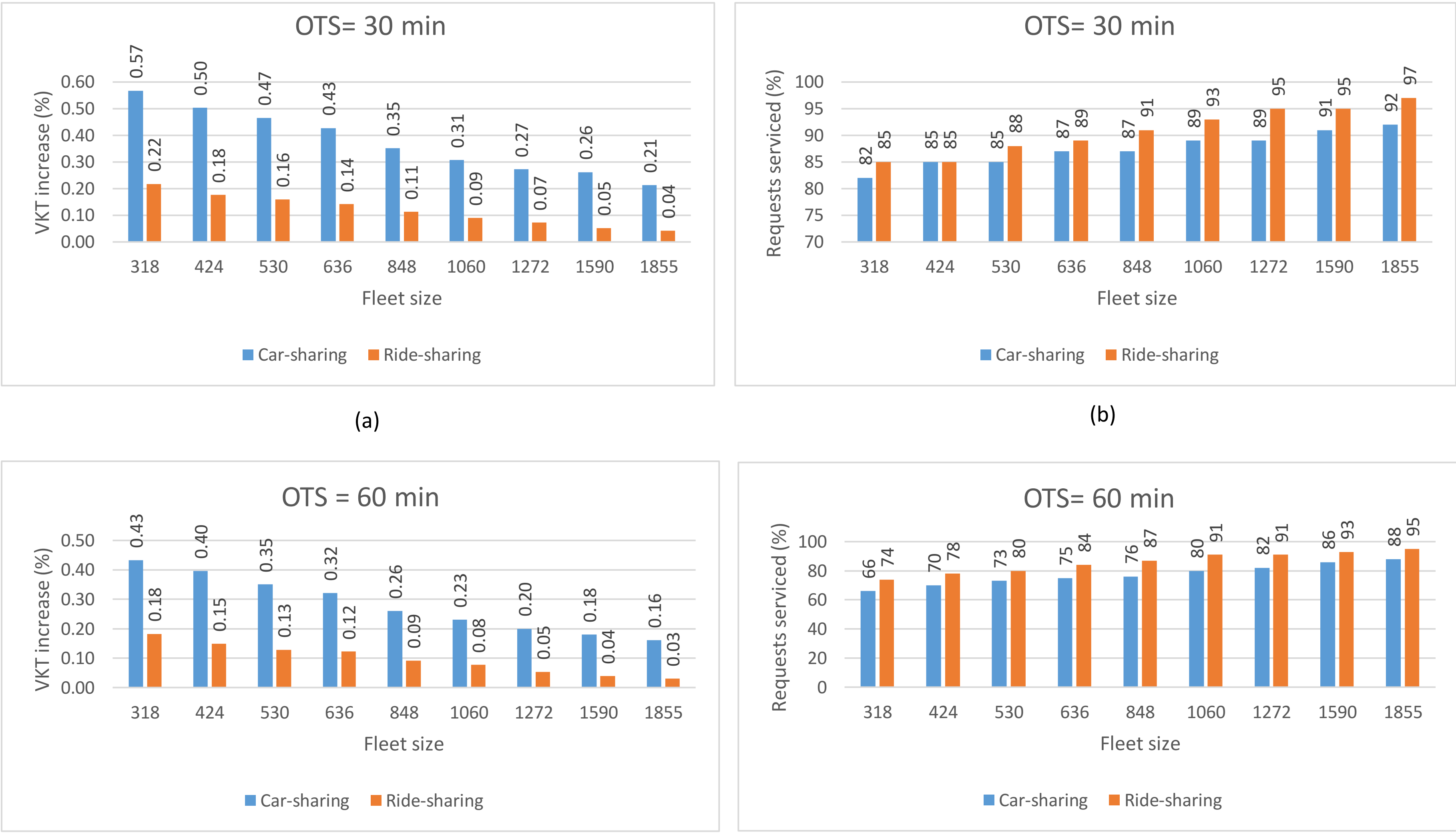


(d)

Figure 6-1: Relationships between fleet size, VKT increase and percentage of requests serviced for 5 and 15 min OTSs



(c) (d)

Figure 6-2: Relationships between fleet size, VKT increase and percentage of requests serviced for 30 and 60 min OTSs

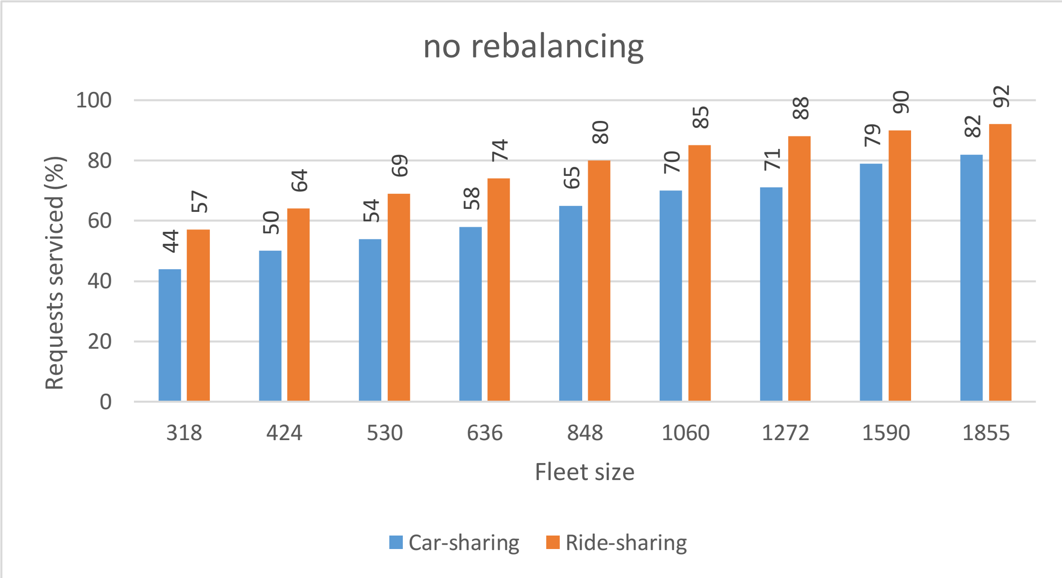


Figure 6-3: Relationship between fleet size and percentage of trips serviced when no rebalancing is undertaken

6.3. Formulating the relationships between AMoD fleet sizes and induced VKT

This section investigates whether there is a specific relationship between AMoD fleet size and induced VKT. To answer this question, this study defines each AMoD fleet in terms of the amount of decrease in fleet size compared to the base case fleet size (current condition comprising conventional vehicles).

Consider, for instance, an AMoD fleet comprising 318 AVs which is 16% of the base case fleet comprising 2039 vehicles, hence, the deployment of this AMoD fleet cuts the base case fleet size by 84%. Similarly, AMoD fleets comprising 424, 530, 636, 848, 1060, 1272, 1590, and 1855 AVs cut the base case fleet size by 79%, 74%, 69%, 58%, 48%, 38%, 22%, and 9% respectively.

Figures 6-4 to 6-7 illustrate the amount of induced VKT due to deploying the aforementioned AMoD fleets for various OTS. Note that each point on these graphs represents an AMoD fleet. These figures show there is always a quadratic relationship between the amount of decrease in the base case fleet size and induced VKT. In other words, as the AMoD fleet size decreases, the induced VKT increases on a parabola.

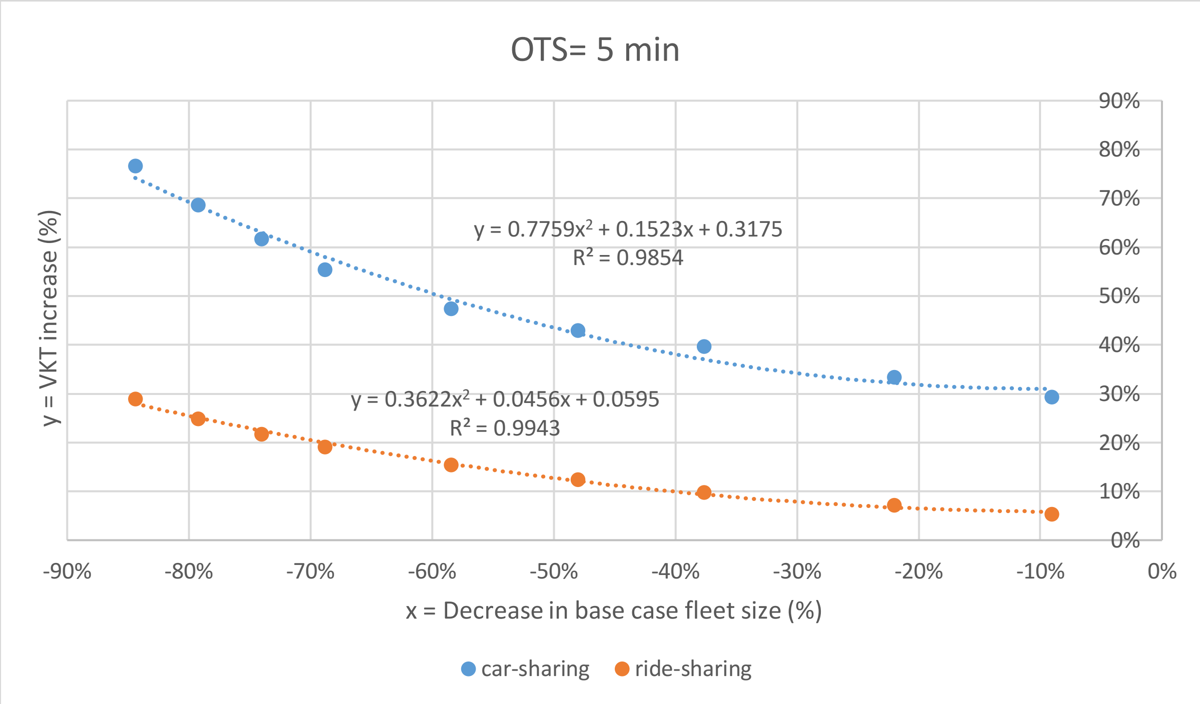


Figure 6-4: Percentage of increase in VKT as a function of the decrease in current fleet size when OTS is 5 min

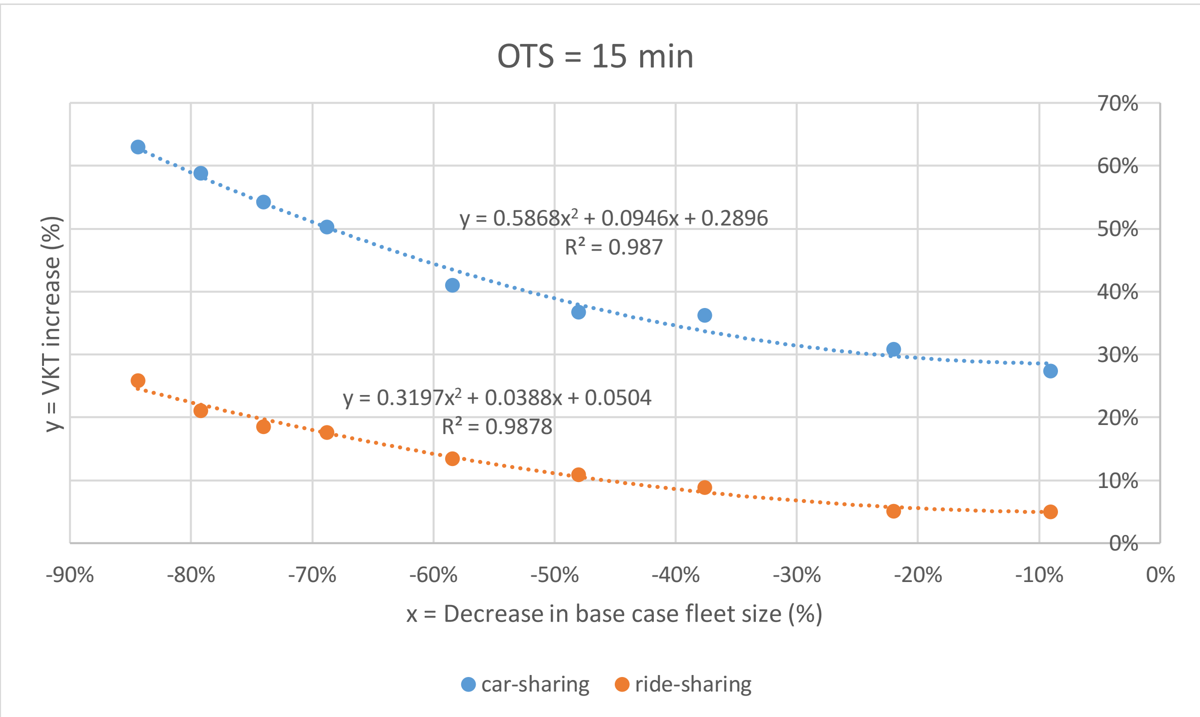


Figure 6-5: Percentage of increase in VKT as a function of the decrease in current fleet size when OTS is 15 min

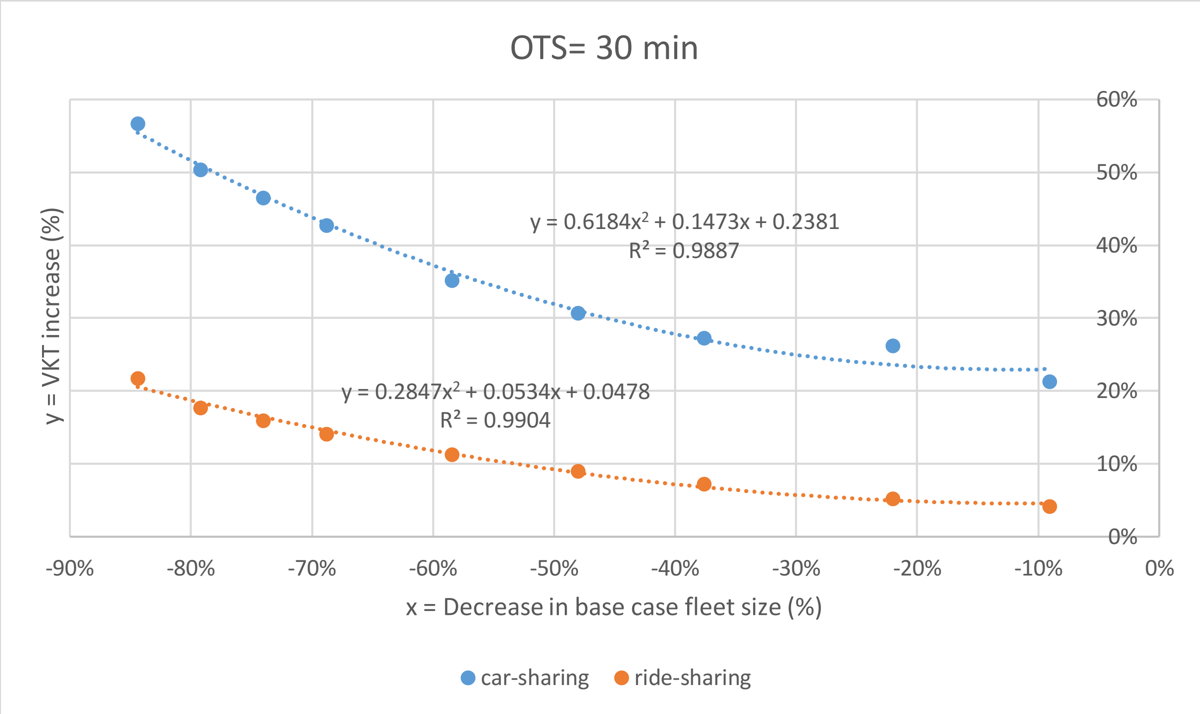


Figure 6-6: Percentage of increase in VKT as a function of the decrease in current fleet size when OTS is 30 min

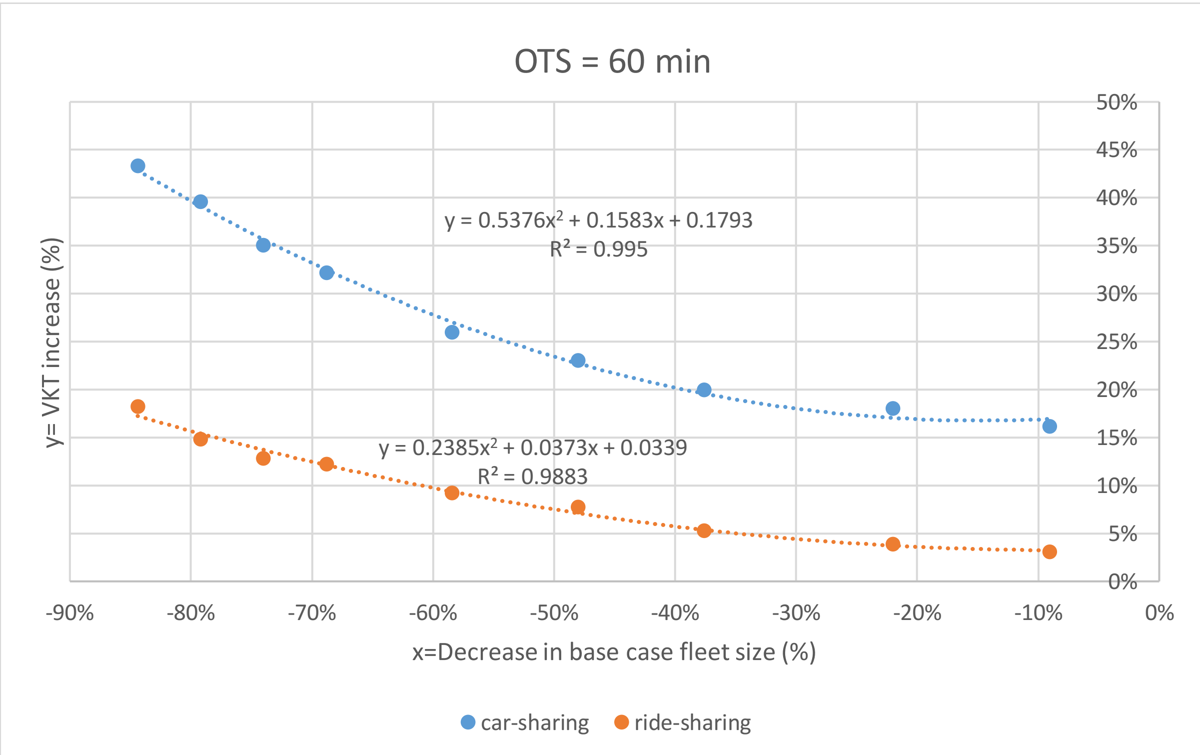


Figure 6-7: Percentage of increase in VKT as a function of the decrease in current fleet size when OTS is 60 min

Another question that arises is will any change in the amount of travel demand affect this relationship while the demand pattern is the same (i.e. will the attraction rates of different areas remain the same?)

To answer this question, five travel demands were designated which represent the conditions when market penetration is 2%, 4%, 6%, 12% or 20%. For each of these travel demands, three AMoD fleet sizes were designated and the induced VKT for various OTS were calculated through both simulation and using the quadratic equations displayed in Figures 6-4 to 6-7 for 10% market penetration. Tables 6-1 and 6-2 show the results of 60 scenarios with the last column displaying the difference between the simulated and estimated results (error). These results show that the calculated increase in VKT for both the simulation and the quadratic equation derived for 10% market penetration returns almost the same amount with an average 2.7% error.

These results indicate that the percentage of increase in VKT for a specific decrease in fleet size is independent of the amount of travel demand and the VKT increase can be estimated using the equations derived for 10% market penetration irrespective of the travel demand as long as the demand pattern (i.e. the attraction rates of areas) remains unchanged.

The significance of the findings discussed in this section is in providing fleet operators and policy makers with quick estimates of the future VKT for different scenarios when once-shared AMoD systems are operational. Furthermore, given the discussions in the Analytical Models section, there is a need to enhance the accuracy of the current analytical models in the literature. The relationship between AMoD fleet size and VKT identified in this paper can potentially be utilised in developing future analytical methods to evaluate similar technology-enabled transport systems.

Table 6-1: Estimating the increase in VKT using both a simulation and empirical equation

Demand for AMoD	AMoD Fleet Size (FS)	BC Fleet Size	AMoD FS/BC (%)	FS decrease compared to BC (%) = x	OTS (min)	VKT increase (%) – Simulation	VKT increase (%) – Estimated = y	Error (%)
2% Market Penetration	106	411	26	-74	5	71	74	3
					15	57	54	3
					30	45	47	2
					60	36	36	0
	212	411	52	-48	5	45	50	5
					15	39	38	1
					30	30	31	1
					60	23	23	0
	318	411	77	-23	5	34	36	2
					15	28	30	2
					30	22	24	2
					60	15	17	2
4% Market Penetration	212	816	26	-74	5	68	74	6
					15	54	54	0
					30	45	47	2
					60	29	29	6
	424	816	52	-48	5	45	50	5
					15	37	38	1
					30	29	31	2
					60	21	23	2
	636	816	78	-22	5	33	36	3
					15	27	30	3
					30	20	24	4
					60	14	17	3
6% Market Penetration	265	1224	22	-78	5	76	79	3
					15	60	57	3
					30	52	50	2
					60	39	38	1
	530	1224	43	-57	5	48	57	9
					15	43	43	0
					30	35	36	1
					60	26	26	0
	954	1224	78	-22	5	34	36	2
					15	29	30	1
					30	23	24	1
					60	17	17	0

Table 6-2: Estimating the increase in VKT using both a simulation and empirical equation

Demand for AMoD	AMoD Fleet Size (FS)	BC Fleet Size	AMoD FS/BC (%)	FS decrease compared to BC (%)	OTS (min)	VKT increase (%) - Simulation	VKT increase (%) - Estimated	Error (%)
12% Market Penetration	530	2447	22	-78	5	69	79	10
					15	60	57	3
					30	51	50	1
					60	41	38	3
	1007	2447	41	-59	5	51	59	8
					15	44	44	0
					30	37	37	0
					60	28	28	0
	1855	2447	76	-24	5	37	36	1
					15	31	30	1
					30	24	24	0
					60	19	17	2
20% Market Penetration	1060	4079	26	-74	5	63	74	11
					15	57	54	3
					30	50	47	3
					60	37	36	1
	1855	4079	45	-55	5	51	55	4
					15	42	42	0
					30	40	34	6
					60	27	25	2
	2968	4079	73	-27	5	40	37	3
					15	37	31	6
					30	30	24	6
					60	21	18	3

6.4. Investigating the effects of travel demand heterogeneity on the general relationship between fleet size and induced VKT

In the previous section, it was shown that in general, there is a quadratic relationship between fleet size and induced VKT. This section explores whether this relationship holds if the travel demand pattern (TDP) varies when demand is unchanged. To achieve this, a hypothetical travel demand, comprising 2000 trips with four TDPs (D1, D2, D3, and D4) is introduced to the model. For each TDP, eight scenarios of varying fleet sizes (424, 530, 636, 848, 1060, 1272, 1590, 1855) and a constant rebalancing time-step (5 minutes) is undertaken. Note that in all the scenarios, only car-sharing is allowed and all the trips happen in the study area.

In this chapter, travel demand heterogeneity is represented by the distribution of NTRR within the study area along with their associated standard deviation (SDV) values. By definition, for each TDP (Dj), the value of NTRR for each area (i) is computed as follows,

$$\boldsymbol{NTRR_{ij}} = \frac{\textbf{Total number of incoming trips to area } \boldsymbol{i}}{\textbf{Total number of outgoing trips from area } \boldsymbol{i}}$$ **Equation 6-1**

Where,

$NTRR_{ij}$: net trip-rate ratio of area *i* when TDP is *Dj*

The value of SDV for the whole study area when TDP is *Dj* is calculated as follows,

$$\boldsymbol{SDVj = SDV\left(NTRR_{1j}, NTRR_{2j}, \dots, NTRR_{ij}\right)}$$ **Equation 6-2**

where

$SDVj$: Standard deviation of NTRR values for the whole study area when TDP is Dj

For this study, $i \in (1, 2, 3, \dots, 53)$ and $j \in (1, 2, 3, 4)$.

The distribution of NTRR in the study area for each TDP and their related SDV is shown in Figure 6-8. As shown in the graph, in the first and second TDPs (D1, and D2), the central parts of the study area (i.e. area 9 to 34) have the highest NTRR values (5.50 for D1, 3.33 for D2), meaning these regions are popular in comparison to the other areas[2] whereas, for the third TDP (D3), the central parts of the study area are less attractive than the other regions with a NTRR value of 0.67. Finally, for the fourth TDP (D4), the NTRR of all the areas within the study area is equal to 1, meaning the attractiveness of all regions are on a par.

As shown in Figure 6-8, as TDP moves from D1 to D4, the value of SDV gradually declines from 2.51 to 0. In fact, D1 represents the case in which the study area comprises regions with very different attractiveness levels, and as TDP approaches D4, all areas display an equal attractiveness.

It is most likely to observe a TDP, similar to D1 or D2 between suburbs and city centres over peak hours when most people travel from their residences to CBD for work. During off-peak

[2] Note that the NTRR values in D1 and D2 are the same (0.56) for the area 34 to 53 (Figure 6-8).

hours, the travel demand distribution within the city can be approached by D3 or D4. However, observing a TDP similar to D4 in reality is quite difficult.

Figure 6-9 illustrates the simulation results for all 32 AMoD scenarios, showing there is still a quadratic relationship between fleet size and induced VKT irrespective of demand pattern. In other words, given the simulation results obtained throughout this study, it can be deduced that there is always a quadratic relationship between fleet size and induced VKT irrespective of the level of demand or the pattern. All the scenarios were successful in completely meeting the travel demand with customer waiting times always less than 5 minutes.

Figure 6-10, however, shows that the demand pattern has a substantial effect on the induced VKT. Note that the number of trips (demand) is the same (2000 trips) for all the scenarios investigated. As seen in this graph, for a specific fleet size, there is a considerable difference between the VKT generated in each demand pattern. For instance, when the fleet size is 424, the induced VKT for D1 is 39% more than that of D4. This happens because in D1, customers in the non-attractive areas whose NTRR is low can only be serviced by sending idle vehicles from the attractive areas (central parts in this study) whose NTRR is high, whereas in D4, customers do not have to rely only on rebalanced AVs as they can also be picked up by AVs which have taken passengers from other parts of the city to this area and have dropped them off. Hence, the reason why D4 has less VKTs is due to the number of trips coming from other areas, however non-attractive areas such as D1 receive few trips from other areas. As a result, in D1, the AMoD system is heavily dependent on the rebalancing process to meet the travel demand, which ultimately leads to high VKTs

As a result, in D1, the AMoD system is heavily dependent on the rebalancing process to meet the travel demand, which ultimately leads to high VKTs.

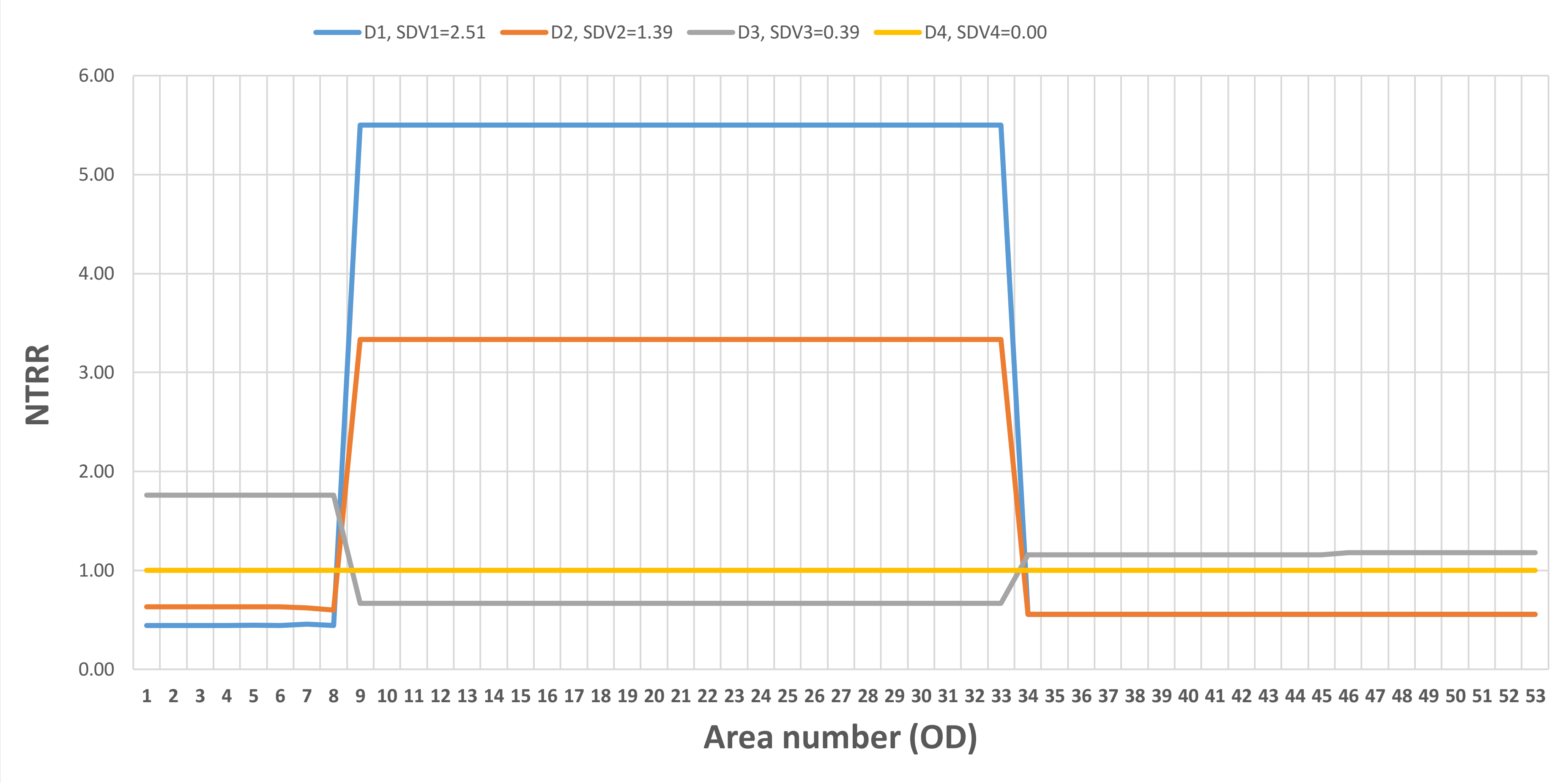


Figure 6-8: The distribution of NTRR within the study area for various travel demand patterns

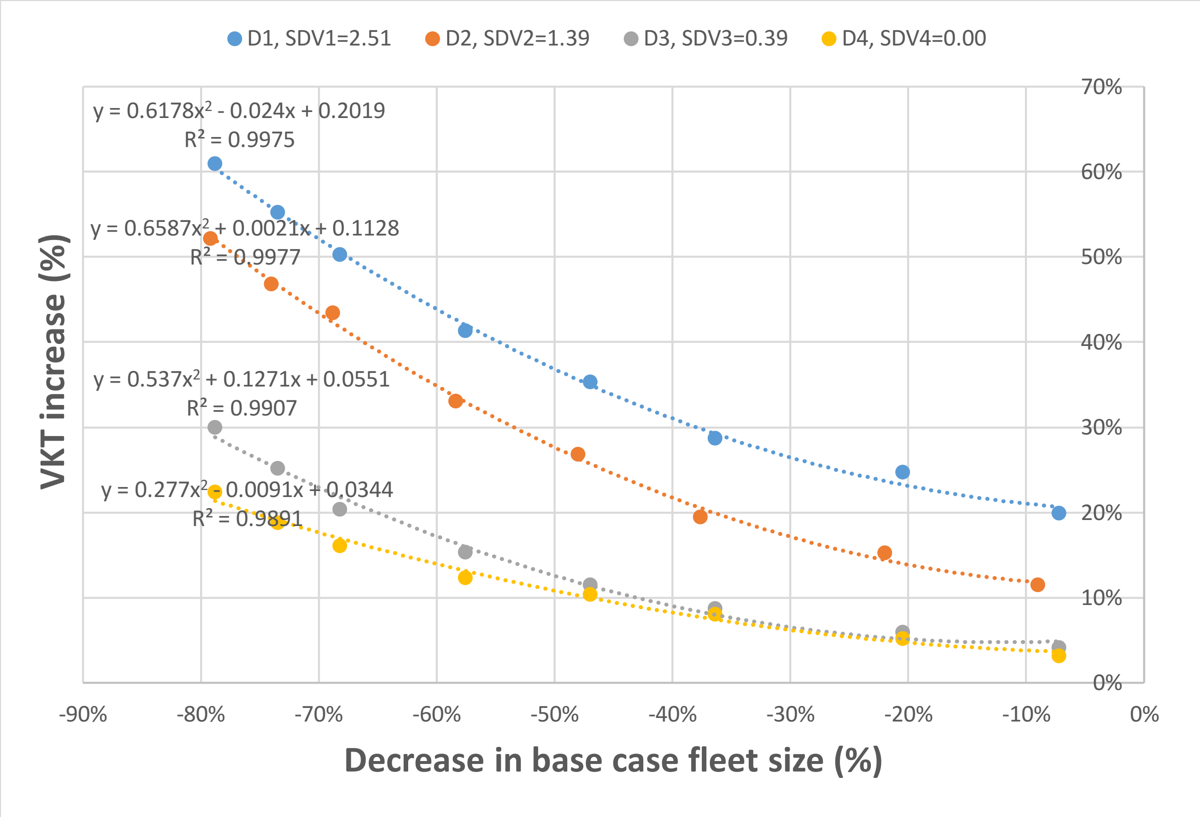


Figure 6-9: The relationship between fleet size and VKT for a constant demand with various patterns

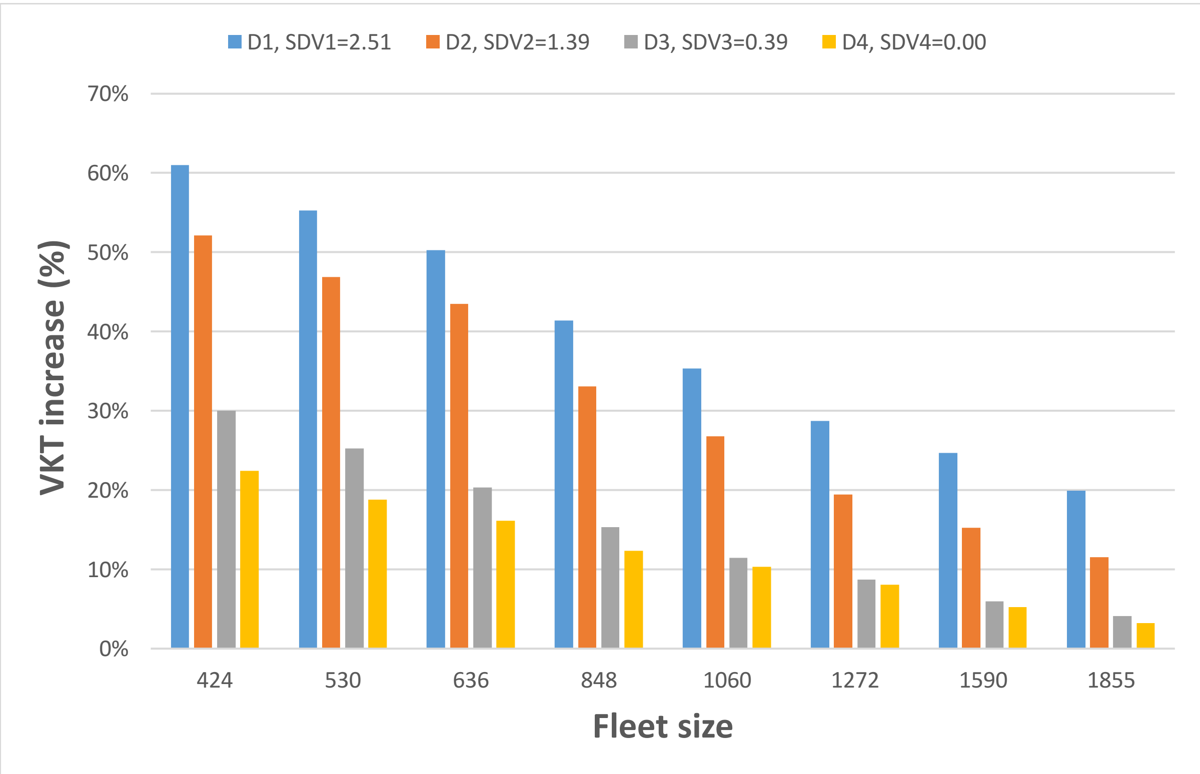


Figure 6-10: Induced VKT for different fleet sizes with a constant demand but various patterns

6.5. Chapter summary

The investigations discussed in this chapter show that an AMoD system, which provides either a car-sharing or ride-sharing service, is able to cut the current fleet size by 84%. This system, however, can increase the current VKT by up to 77% when used as a car-sharing system. On the other hand, there is a 29% increase in VKT for the ride-sharing system, which is 55% less than the former system. This suggests that shared AMoD systems might not be a sustainable solution to the current urban mobility challenges by themselves and deploying ride-sharing schemes with high car-occupancy is crucial.

The model also shows that there is a quadratic relationship between AMoD fleet size and the induced VKT in the system, which is independent of the total number of trips and demand pattern. The significance of the current finding could lie in providing fleet operators and policy makers with a more computationally efficient technique to assess the performance of AMoD systems. Further, this relationship could potentially be used as one of the key underlying assumptions of the future analytical approaches.

This chapter also explored the effects of travel demand heterogeneity on the performance of AMoD systems and showed that the more heterogeneous the travel demand is, the higher the VKT becomes.

In general, the findings of this work show that many studies in the existing literature are overoptimistic about the potential benefits of AMoD systems. This is due to unrealistic models and the assumptions used in these studies. The results also advocate the idea that extensive public transport systems will play a key role in providing more efficient mobility services. In this regard, AMoD systems could be utilised as a complementary component to the current public transport systems through increasing the accessibility of mass transit systems to members of the public.

Chapter 7 : Synthesis of Results, Summary of Impacts and Policy Implications

This chapter presents the findings of this PhD research in a concise manner. Further, it demonstrates how these findings could assist policy makers in preparing a sustainable transport agenda for the years ahead. These discussions could help governments and other stakeholders develop a realistic insight into the potential of emerging technologies in resolving urban transport issues.

7.1. Synthesis of results

This section summarises the main findings of this dissertation. The key discoveries of this work are outlined as follows,

1. The current literature is overoptimistic about the role of shared AMoD systems in reducing traffic congestion and producing a sustainable mobility system. This is mainly due to the simplistic models used and unrealistic assumptions made.

2. AMoD systems always lead to more VKT in the system. However, the extent of this increase is determined by fleet size, vehicle occupancy and TDP. Shared AMoD systems with no ride-sharing translate into 29% to 77% more VKT.

   Adding ride-sharing services with only two people on board cuts down the induced VKT up to 48%. Further, TDP has a considerable effect on the induced VKT. The more heterogeneous the travel demand becomes, the higher the induced VKT becomes. In this study, changes in TDP increased the induced VKT up to 39%, which shows the significance of this phenomenon in exploring the performance of AMoD systems.

3. AMoD systems are always successful in meeting the travel demand when OTS is set to 5 minutes. The average customer waiting times are always around 4 minutes.

4. The system becomes less sensitive to OTS with larger fleet sizes.

5. The system becomes more sensitive to fleet size with longer OTS.

6. For a specific change in fleet size, VKT changes more rapidly than the percentage of trips serviced.

7. AMoD systems are not as sensitive to the initial number of AVs at stations.

8. There is always a quadratic relationship between fleet size and VKT irrespective of travel demand or TDP. This finding could be used in estimating future VKT. It can also help researchers improve the accuracy of the current analytical methods.

7.2. Policy insights

The findings of this research can also benefit governments and help policy makers come up with more thoughtful and realistic decisions. Some of these policy insights can be outlined as follows,

1. Deploying AMoD to service customers within the whole urban area would certainly lead to a sizable increase in VKT. Therefore, implementing ride-sharing schemes in these systems seems to be imperative to avoid the potential growth in congestion.

   Governments should also invest more in researching ways to convince travellers to share rides with other people. Having a realistic insight into people's travel behaviour and expectations will assist governments in introducing new schemes that encourage more ride-sharing.

2. Given the significant potential of AMoD systems to increase VKT in urban areas, deploying these systems to improve the accessibility of current mass public transit systems seems more sustainable.

   Implementing shared AVs between residential areas and public transport stations will promote more mass transit use, which is already in place. In other words, introducing AMoD systems as last mile solutions in the current urban environment could persuade more people to use them and reduce the number of vehicles on roads.

   Further, the increased interest in mass transit will result in attracting more funds to enhance the existing public transport systems, and thereby the number of travellers using these systems will grow. This strategy will not only cut VKT in the network, but it will also establish a sustainable mobility system.

3. This study, for the first time in the literature, proposed a method to explore the impacts of travel demand heterogeneity (or TDP) on the efficiency of AMoD systems. The results

show that this phenomenon can substantially affect the efficacy of these systems and render them unsustainable.

This study shows that deploying an AMoD system between suburbs and city centres during peak hours might not be a wise solution to address the congestion problem in urban areas. Governments should take this issue into account along with other decision-making factors while establishing new urban transport agendas in the age of emerging technologies.

4. Public transport investments, particularly high capacity rail, will remain critical even in future mobility scenarios. Together with walking and cycling, public transport should continue to be promoted as an important mode of transport, particularly in urban areas.

5. Transport policies and deployment strategies should consider the shape, type and size of AMoD fleets and ensure that the right mix between public transport and shared vehicles is reached to minimise empty running and avoid increased congestion and emissions in cities.

6. Environmental benefits will depend on vehicle technology, car occupancy, and total VKT in the system. An AMoD fleet comprising efficient and advanced AVs that deploys wise ride-sharing schemes will most likely succeed in delivering an environmentally friendly transport system.

7. To ensure the public transport industry remains viable and relevant, it needs to be more entrepreneurial and step forward as an actor in shaping the regulatory frameworks and the future use of AVs. Otherwise, it will be mainly shaped by the automobile and technology companies. The transport industry can do this by supporting public transport SAV trials to raise its profile and increase public awareness. The regulatory frameworks will need to be adapted to allow public transport operators to innovate and launch such pilot studies.

8. Public authorities should promote and adapt policies to prepare citizens for the shared use of vehicles. This can be achieved by demonstrating support, removing barriers and providing tax incentives for shared mobility schemes to support the trend in declining car ownership and the increasing acceptance of shared ownership of vehicles. More shared mobility and more digital services today will lay the foundation for AV fleets and AMoD services tomorrow.

9. The commercial sector and the provider of an AMoD should design fare systems and pricing structures for mobility services that ensure the sustainability of the service. To the traveller, it will not matter in the future who provides the service however, the type and cost of the service is important. These services will need to be run in line with public policy goals to provide safe, clean, equitable, accessible and affordable mobility solutions.

10. If well planned and implemented, AMoD will mean better cost per passenger kilometre resulting in reduction of individual car usage leading to reduced congestion and emissions.

Chapter 8 : Conclusions and Future Directions

This research investigated transport network impacts of AMoD systems in an urban area. The study commenced by reviewing the current AMoD studies and exploring the methods which have been utilised in the literature. The literature review provided sufficient evidence that an agent-based simulation model would be the best option to achieve the goals of the project.

For this study, Commuter, an agent-based traffic simulation tool, was selected as the modelling environment. To develop a proof of concept, a pilot study was conducted using a small case study located in Melbourne. The pilot study was successful in providing the researchers with the sufficient level of knowledge necessary to develop an AMoD model over a larger area (the main study).

The main study was undertaken in the context of a case study located in Melbourne with an area (88.75 km^2), much larger than the pilot one (6 km^2). The main model featured new characteristics compared to its counterparts in the literature in terms of traffic flow, network representation, and rebalancing algorithm. These new modelling features led to some new insights into the performance of AMoD systems, which have not been previously discussed in the literature.

Further, this research, for the first time, introduced a new measure, called travel demand heterogeneity to explore the performance of AMoD systems and showed that the impacts of this phenomenon is not trivial. Sections 8.1 and 8.2 discuss the findings of this research and future research directions, respectively.

8.1. Findings

The current study provides the quantitative trade-offs between AMoDs of different fleet size and OTS. The results suggest that an AMoD system with no ride-sharing can reduce the current fleet size by 84%. This reduction in fleet size, however, comes at the cost of 77% more VKT in the system due to the need for AV rebalancing. The induced VKT reported in the current study is not in line with what is suggested in the majority of the existing literature, which is an indication of over-optimism regarding the potential of AMoD systems to mitigate congestion[3].

[3] Readers are referred to chapter 5, section 5.6, for a comprehensive discussion on the possible causes of these discrepancies.

The results also showed that implementing a ride-sharing scheme led to 55% less VKT compared to a scenario in which no ride-sharing was permitted. This finding indicates the key role of ride-sharing in the ultimate success of AMoD systems and providing a sustainable mobility service to the public.

In this study, ride-sharing scenarios comprised AVs with a capacity of two people. This assumption was made based on studies that suggest ride-sharing in groups larger than two people might be unrealistic. Undoubtedly, encouraging a larger number of people to ride-share ride with other people would translate into more efficient AMoD systems as a result of less induced VKT. This objective, however, will never materialise unless wise ride-sharing schemes that convince more travellers to use ride-sharing systems are implemented.

This research also quantified the elasticities of trip success rate and VKT with respect to different fleet sizes and rebalancing time-steps, which could be helpful for formulating the relationships between different system characteristics.

In addition, the current research discovered a quadratic relationship between AMoD fleet size and VKT, which is independent of travel demand. Although travel demand patterns (TDP) may affect the amount of induced VKT in the system, the quadratic relationship between fleet size and VKT always holds, irrespective of TDP.

This research used a new criterion, called travel demand heterogeneity, to consider the performance of AMoD systems. A method was proposed which takes into account the effects of this phenomenon on the efficiency of these systems. The results revealed that the more heterogeneous the demand is, the less efficient the AMoD systems become. This investigation also showed that AMoD systems might not be a sustainable transport solution during peak hours between suburbs and city centres.

The obtained results have significant policy implications, particularly in relation to the need for continued investment in public transport, especially heavy rail mass transit between the suburbs and city centres in large cities. The results also suggest that the real value of AMoD systems is likely to be in meeting the demand for intra-suburban and inter-suburban travel, particularly first and last kilometre solutions for transporting travellers from their homes to the nearest public transport hubs.

8.2. Future directions

1. Similar to other studies, this thesis investigated the increase in capacity, which might be realised thanks to the need for fewer parking lots in AMoD scenarios. Future work could investigate the performance of AMoD systems while taking into account this potential increase in capacity along with the measures discussed in this thesis to gain a more realistic insight into the contributions of AMoD systems.

2. Given this study only quantified the network benefits of AMoD systems for AM-peak hours, future studies will investigate the performance of AMoD systems during off-peak and evening peak hours as well, before making a general conclusion about the overall efficiency of AMoD systems.

3. The eVKT reported in this research was only based on rebalancing the empty AVs. Future work could extend this by considering how AVs will also need to undertake other empty travels for recharging or refuelling purposes. Depending on where the charging stations are located, this type of empty driving may well lead to even more eVKT.

4. The AMoD system used in this study was assumed to be station-based. We expect that deploying door-to-door AMoD systems will induce more eVKT than the station-based system. In the door-to-door AMoD system, people are picked up and dropped off at their residences rather than walking (or cycling or taking a bus etc.) to an AMoD station. This means that these types of trips in the station-based system will be replaced with AV trips in the door-to-door system and will result in more eVKT. This suggests, and should be explored in future research, that their deployment as ride-sharing schemes (especially in the outer suburbs for first and last kilometre services) supplemented with extensive public transport systems between the suburbs and city centres, is going to be critical for their success as an urban mobility solution in future cities.

5. The results reported in this study suggest that the real value of AMoD systems is likely to be in meeting the demand for intra-suburban and inter-suburban travel particularly first and last kilometres solutions for transporting travellers from their homes to the nearest public transport hubs. Future research should aim to verify and quantify these assertions through extended simulations.

6. Due to computer power and computational constraints, the current research only modelled part of Melbourne during morning peak hours to conduct this study. In the future, much larger areas should be investigated over the course of the whole day or so, using super computers and cloud computing techniques. Note that the simulation models developed in this study are scalable and can be easily extended to cover the wider Melbourne network. For new cities, the same modelling techniques used in this study can be applied in the context of new transport networks with different characteristics. These developments would be exciting for researchers and would help them gain a vaster insight into the behaviour of AMoD systems. These expanded models could also be used to verify the findings of the current study and build on its findings.

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Appendices

Appendix A: Instructions to Create a Plugin in Commuter

To create and install a plugin in Commuter the following steps must be taken,

1. Ensure you have a license for creating user-defined plugins. The Help / About window should display “User Plugins”

2. Write your plugin java source code: the plugin class must extend com.azalient.api.BasePlugin, and implement any event interfaces for which you want to register

3. Your classes should be in an appropriate package to avoid name clashes. By convention, reverse your internet domain: for example, if your domain is thu.edu.cn, the package should be cn.edu.thu

4. In the constructor of the plugin class, add a call to register the plugin for each event

5. The event interfaces are in packages com.azalient.api.event.model.* and com.azalient.api.event.agent.*

6. For example if you implement ModelEventTimeStep, and you register the plugin using addModelEventTimeStepListener(this); your plugin will be called on every simulation time step. Similarly if you implement AgentEventLoop, and add the relevant registration call, your plugin will be called whenever a vehicle activates a loop.

7. Once you have written the Java code for your plugin, compile it into a class file. Follow standard Java conventions: the class file should be in a folder that agrees with the package name. For example, if your plugin is MyPlugin..java in package cn.edu.thu, the class file should be in a file cn/edu/thu/MyPlugin.class

8. Package up the class file(s) into a JAR file, and put that jar file into the bin directory of your Commuter installation, beside the other jar files. This is normally C:/Azalient/Commuter/bin. It will be automatically added to the class path from here by the Commuter.exe launcher.

9. Add a 3-letter acronym, the name of the plugin and the "main" class (this class) to commuter.plugins.csv
For example: "XYZ,Test Plugin,cn/edu/thu/MyPlugin"
(The 3-letter acronym is historical, it is required but the value is not important)

10. When you next start Commuter, your plugin will be visible in the Plugins Tab

The following simple template can be used in order to produce a desired plugin in Commuter,

```
package com.azalient.test;

import java.awt.Color;
import java.awt.Window;
import java.io.File;
import java.io.IOException;
import java.io.PrintWriter;
import javax.swing.JFrame;
import javax.swing.JLabel;
import com.azalient.api.BasePlugin;
import com.azalient.api.b.control.IController;
import com.azalient.api.b.control.IGroup;
import com.azalient.api.b.control.IPhase;
import com.azalient.api.draw.IDrawing;
import com.azalient.api.event.model.ModelEventViewLegend;
import com.azalient.api.quick.Api;
import com.azalient.apo.SC;
import com.azalient.apo.enums.Signal;

/** This is a template for a Commuter plugin.
*
* <p>
* The steps you need to take to install a plugin are as follows:
* <ul>
* <li> The new plugin must extend BasePlugin, and implement any event interfaces
* for which you want to register
* <li> Add a 3-letter code, the name of the plugin and the "main" class (this class)
* to commuter.plugins.csv <br>
* For example: "TTT,Test Plugin,com/mydomain/test/TestPlugin".
* The 3-letter code is historical, it is not important.
* <li> Package up the class files into a JAR file, and put that jar file into the bin directory
* of your Commuter installation, beside the other jar files. This is normally
* C:/Azalient/Commuter/bin. It will be automatically added to the class path from here
* by the Commuter.exe launcher.
*
* </ul> */

public class TestPlugin extends BasePlugin
implements ModelEventViewLegend

/* implement the event handlers corresponding to the events you want
to be sent to this plugin */
{
/**
```

```
* In the constructor, register for the events you want to be sent to this
* plugin. See the packages com.azalient.api.event.agent and .model for all
* the events. There are both model events, corresponding to significant
* transitions in the model loading and handling cycle, and agent avents,
* which correspond to significant events in the life cycle of an agent
* (vehicle, pedestrian etc) in any simulation
**/

public TestPlugin()

{
addModelEventViewLegendListener(this);
frame.getContentPane().add(new JLabel("Add your own controls here, to allow user
interaction with your plugin."));
frame.pack();
}

/** This is the implementation of the event handler registered above */
public void viewLegend(IDrawing drw)
{
drw.colour(Color.WHITE.getRGB());
drw.string("Test Plugin", 0.5, 0.7, 0, 0.5);
}

/** This is called for all plugins, after the network "document" has been loaded */
public void pluginOpen()

{
File file = new File("c:/temp/phases.csv");
Try

{
PrintWriter pw = new PrintWriter(file);
pw.println("Phase,Group*,Group*,Group*,Group*,Group*,Group*,Group*,Group*,Group*,
Grou
p*,Group*,Group*,Min,Gap,Loop*,");
for (IPhase phase: Api.model().control().phases())

{
Signal[] signals = phase.signalArray();
IController c = phase.controller();
IGroup[] ga = c.groups();
int ns = signals.length;
int ng = ga.length;
pw.print(phase.name()+SC.CM);
for (int i = 0; i < ng && i < ns; i++)
```

```
{
if (signals[i] == Signal.Green)
{
pw.print(SC.N+ga[i].index()+SC.CM);
}
}
pw.println();
}
pw.close();
}
catch (IOException iox) {}
}

/** This is called for all plugins, when a network "document" is closed */
public void pluginClose()
{
frame.setVisible(false);
frame.dispose();
}
/** This is called for all plugins, when "File/Save" is selected, to save any data in the
plugin */
public void pluginSave() {}
private JFrame frame = new JFrame("Test Plugin User Interface");
/** called when the "Configure" button is pressed on the Plugins tab */
public Window pluginWindow()
{
return frame;
}
}
```

Appendix B: Plugin codes used in this research for rebalancing purposes

The plugin used in this study in order to rebalance the idle vehicles according to the algorithm described in the thesis is composed of various java codes. The following sections express those codes in detail.

1. Empty taxi measure

```
package com.gmx.xgd;

import com.azalient.api.sim.agents.IVehicle;

public class EmptyTaxiMeasure

{

  private final IVehicle taxi;

  private double distanceTravelledEmptyM;

  private double timeEmptyS;

  private RedirectRequest redirectRequest;


  public EmptyTaxiMeasure(IVehicle v)

  {

    this.taxi = v;

  }

  public void reset()

  {

    this.distanceTravelledEmptyM = 0.0D;

    this.timeEmptyS = 0.0D;

  }

  public double distanceTravelledEmptyM()

  {

    return this.distanceTravelledEmptyM;

  }


  public void incDistanceTravelledEmptyM(double d)

  {
```

```
    this.distanceTravelledEmptyM += d;
  }
  public double timeEmptyS()
  {
    return this.timeEmptyS;
  }
  public void incTimeEmptyS(double t)
  {
    this.timeEmptyS += t;
  }
  public RedirectRequest redirect()
  {
    return this.redirectRequest;
  }
  public void redirect(RedirectRequest rr)
  {
    this.redirectRequest = rr;
  }
}
```

2. Taxi redirector

```
package com.gmx.xgd;

import com.azalient.api.API;
import com.azalient.api.APU;
import com.azalient.api.BasePlugin;
import com.azalient.api.a.IModel;
import com.azalient.api.a.IRouting;
```

```
import com.azalient.api.a.ISimulator;
import com.azalient.api.a.model.INetwork;
import com.azalient.api.a.model.IParameters;
import com.azalient.api.a.position.IBezier;
import com.azalient.api.a.position.IPosition;
import com.azalient.api.a.position.IXyz;
import com.azalient.api.b.network.ILane;
import com.azalient.api.b.network.ILink;
import com.azalient.api.b.network.IZone;
import com.azalient.api.b.parameters.IBehaviour;
import com.azalient.api.b.parameters.ITerm;
import com.azalient.api.b.parameters.IVehicleType;
import com.azalient.api.b.parking.IParkingLane;
import com.azalient.api.b.parking.IParkingVehicle;
import com.azalient.api.b.trips.IVehicleTrip;
import com.azalient.api.event.agent.AgentEventMove;
import com.azalient.api.event.agent.AgentEventOccupantIn;
import com.azalient.api.event.agent.AgentEventOccupantOut;
import com.azalient.api.event.agent.AgentEventTimeStep;
import com.azalient.api.event.model.ModelEventTimeRewind;
import com.azalient.api.event.model.ModelEventTimeSec;
import com.azalient.api.sim.agents.IAgent;
import com.azalient.api.sim.agents.IMotor;
import com.azalient.api.sim.agents.IOccupant;
import com.azalient.api.sim.agents.IUnit;
import com.azalient.api.sim.agents.IVehicle;
import com.azalient.api.sim.routes.IZoneRouter;
```

```
import com.azalient.apo.basics.Distance;

import com.azalient.apo.basics.DistanceLong;

import com.azalient.apo.basics.Price;

import com.azalient.apo.basics.UTime;

import java.awt.Window;

import java.util.ArrayList;

import java.util.Hashtable;


public class PluginTaxiRedirect

  extends BasePlugin

  implements AgentEventTimeStep, ModelEventTimeRewind, AgentEventMove,
ModelEventTimeSec, AgentEventOccupantIn, AgentEventOccupantOut

{

  private TaxiRedirectOptimizer optimizer = new TaxiRedirectOptimizer();

  private TaxiRankWindow ui = new TaxiRankWindow("Taxi Ranks");

  private TaxiRank[] taxiRankArray;

  private Hashtable<IZone, TaxiRank> zoneToRank = new Hashtable();

  private Hashtable<IZone, ArrayList<RedirectRequest>> redirectRequestTable = new
Hashtable();

  private double[][] interTaxiRankFreeFlowTravelCost;


  public PluginTaxiRedirect()

  {

    addModelEventTimeRewindListener(this);

    addModelEventTimeSecListener(this);


    addAgentEventMoveListener(this);

    addAgentEventTimeStepListener(this);
```

```
  addAgentEventOccupantInListener(this);
  addAgentEventOccupantOutListener(this);
}

public void pluginOpen()
{
  ArrayList<TaxiRank> taxiRankList = new ArrayList();
  for (IZone zone : API.model().network().zones()) {
    if (zone.parkingTaxiRank())
    {
      TaxiRank taxiRank = new TaxiRank(zone);
      if (taxiRank.valid())
      {
        taxiRankList.add(taxiRank);
        this.zoneToRank.put(zone, taxiRank);
      }
    }
  }
  this.taxiRankArray = ((TaxiRank[])taxiRankList.toArray(new TaxiRank[taxiRankList.size()]));

  this.ui.initialise(this.taxiRankArray)

  status(this, 2);
}
public void pluginClose() {}
public void pluginSave() {}
```

```
  public Window pluginWindow()
  {
    return this.ui;
  }
  public void timeSec()
  {
    for (TaxiRank taxiRank : this.taxiRankArray) {
      taxiRank.timeStep();
    }
    this.ui.fireTableUpdate();

    int interval = this.ui.optInterval();
    UTime now = new UTime(API.simulator().simulationTime());
    if (now.timeInt() % interval == 0)
    {
      APU.reportF("%s Calling Optimizer", new Object[] { now.toString(Boolean.valueOf(true))
});

      fetchRouteCosts();

      RedirectRequest[] rra = this.optimizer.optimize(this.taxiRankArray,
this.interTaxiRankFreeFlowTravelCost);
      addRequestsToQueue(rra);
    }
  }

  private void addRequestsToQueue(RedirectRequest[] rra)
```

```
{
  if (rra.length == 0) {
    return;
  }
  for (RedirectRequest rr : rra)
  {
    pushRequest(rr)
    this.ui.countRequest(rr.redirectFrom(), rr.redirectTo());
  }
}
private synchronized void pushRequest(RedirectRequest rr)
{
  if ((rr.redirectFrom() == null) || (rr.redirectTo() == null)) {
    return;
  }
  ArrayList<RedirectRequest> fromRequestList =
(ArrayList)this.redirectRequestTable.get(rr.redirectFrom());
  if (fromRequestList == null)
  {
    fromRequestList = new ArrayList();
    this.redirectRequestTable.put(rr.redirectFrom(), fromRequestList);
  }
  fromRequestList.add(rr);
}
private synchronized RedirectRequest popRequest(IZone zone)
{
  ArrayList<RedirectRequest> fromRequestList =
(ArrayList)this.redirectRequestTable.get(zone);
```

```
  if (fromRequestList == null) {
    return null;
  }
  if (fromRequestList.size() == 0) {
    return null;
  }
  RedirectRequest firstRR = (RedirectRequest)fromRequestList.remove(0);
  return firstRR;
}
private void fetchRouteCosts()
{
  IZoneRouter zr = API.routing().zoneRouter();
  int taxiBehaviourIndex = -1;
  for (IVehicleType vt : API.model().parameters().vehicleTypes()) {
    if (vt.isTaxi())
    {
      taxiBehaviourIndex = vt.behaviour().index();
      break;
    }
  }
  int nRank = this.taxiRankArray.length;
  this.interTaxiRankFreeFlowTravelCost = new double[nRank][nRank];
  for (int i = 0; i < nRank; i++)
  {
    IZone zi = this.taxiRankArray[i].zone();
    ILink ziLink0 = zi.links()[0];
    for (int j = 0; j < nRank; j++) {
```

```
      if (i != j)
      {
        IZone zj = this.taxiRankArray[j].zone();
        Price costIJ = zr.routeCost(ziLink0, zj.index(), taxiBehaviourIndex);
        this.interTaxiRankFreeFlowTravelCost[i][j] = costIJ.dollars();
      }
    }
  }
}

private boolean keepToThroughLane(IVehicle taxi)
{
  ILink link = taxi.link();
  if (link == null) {
    return false;
  }
  IZone zone = link.zone();
  if (zone == null) {
    return false;
  }
  if (zone != taxi.trip().destination())
  {
    int lo = -1;
    int hi = -1;
    for (ILane lane : link.lanes()) {
      if (!lane.isParking())
      {
```

```
        int index = lane.index();
        if ((lo == -1) || (index < lo)) {
          lo = index;
        }
        if (index > hi) {
          hi = index;
        }
      }
    }
    if ((lo > 0) && (hi >= lo)) {
      taxi.laneLowHigh(lo, hi);
    }
    return true;
  }
  return false;
}

public void move(IAgent agent)
{
  if (!(agent instanceof IVehicle)) {
    return;
  }
  IVehicle taxi = (IVehicle)agent;
  if (!taxi.isTaxi()) {
    return;
  }
  if (keepToThroughLane(taxi)) {
```

```
    return;
  }
  if (taxi.occupant() != null) {
    return;
  }
  IParkingVehicle pv = taxi.parkingVehicle();
  if ((!taxi.isParking()) || (pv == null)) {
    return;
  }
  IParkingLane pl = pv.parkingLane();
  if (pl == null) {
    return;
  }
  if (!pv.parked())
  {
    if (API.simulator().simulationTime() -
API.model().parameters().simulationTerm().start().time() < 2.5D *
API.model().parameters().timeStep()) {
      if (taxi.leader() != null)
      {
        IBezier cl = pl.lane().centreline();
        double centrePositionFromEnd = taxi.laneOrderIndex() * pl.bayLength() +
taxi.halfLength();
        IPosition c = cl.position(cl.length() - centrePositionFromEnd);
        taxi.centre().set(c);
      }
    }
    return;
```

```
  }
  RedirectRequest rr = popRequest(pl.zone());
  if (rr == null) {
    return;
  }
  EmptyTaxiMeasure etm = emptyTaxi(taxi);
  etm.redirect(rr);
  IZone redirectFrom = rr.redirectFrom();
  IZone redirectTo = rr.redirectTo();
  assert (pl.zone() == redirectFrom);
  taxi.trip().destination(redirectTo);
  pv.leavingZoneBay(0);

  APU.reportF("%s Dispatch Taxi %d: %s to %s", new Object[] {
    new UTime(API.simulator().simulationTime()).toString(Boolean.valueOf(true)),
    Integer.valueOf(taxi.uniqueID()), redirectFrom, redirectTo });

  this.ui.countDispatch(rr.redirectFrom(), rr.redirectTo());
}

private Hashtable<IVehicle, EmptyTaxiMeasure> emptyTaxis = new Hashtable();
private double completedEmptyTaxiTimeS;
private double completedEmptyTaxiDistanceM;
private double incompleteEmptyTaxiTimeS;
private double incompleteEmptyTaxiDistanceM;

private EmptyTaxiMeasure emptyTaxi(IVehicle taxi)
```

```
{
 EmptyTaxiMeasure etm = (EmptyTaxiMeasure)this.emptyTaxis.get(taxi);
 if (etm == null)
 {
  etm = new EmptyTaxiMeasure(taxi);
  this.emptyTaxis.put(taxi, etm);
 }
 return etm;
}
public void timeStep(IAgent agent)
{
 if (((agent instanceof IVehicle)) && (((IVehicle)agent).isTaxi()))
 {
  IVehicle taxi = (IVehicle)agent;
  EmptyTaxiMeasure etm = emptyTaxi(taxi);
  if (taxi.occupant() == null)
  {
   double dt = API.simulator().timeStep();
   double dd = taxi.speedMPS() * dt;

   etm.incTimeEmptyS(dt);
   etm.incDistanceTravelledEmptyM(dd);

   this.incompleteEmptyTaxiTimeS += dt;
   this.incompleteEmptyTaxiDistanceM += dd;
   if ((etm.redirect() != null) && (taxi.link().zone() == etm.redirect().redirectTo()))
   {
```

```
        APU.reportF("%s Arrive Taxi %d: %s to %s", new Object[] {
          new UTime(API.simulator().simulationTime()).toString(Boolean.valueOf(true)),
          Integer.valueOf(taxi.uniqueID()), etm.redirect().redirectFrom(),
etm.redirect().redirectTo() });
        this.ui.countArrival(etm.redirect().redirectFrom(), etm.redirect().redirectTo());
        etm.redirect(null);
      }
    }
    keepToThroughLane(taxi);
  }
}

public void timeRewind()
{
  this.redirectRequestTable.clear();

  this.completedEmptyTaxiTimeS = 0.0D;
  this.completedEmptyTaxiDistanceM = 0.0D;
  this.incompleteEmptyTaxiTimeS = 0.0D;
  this.incompleteEmptyTaxiDistanceM = 0.0D;

  updateEmptyTaxiPanel();
  for (TaxiRank taxiRank : this.taxiRankArray) {
    taxiRank.rewind();
  }
  this.ui.rewind();
}
```

```
  private void updateEmptyTaxiPanel()
  {
    this.ui.updateEmptyTaxiPanel(new UTime(this.completedEmptyTaxiTimeS,
UTime.HHMMSS), new DistanceLong(this.completedEmptyTaxiDistanceM, Distance.M),
      new UTime(this.incompleteEmptyTaxiTimeS, UTime.HHMMSS), new
DistanceLong(this.incompleteEmptyTaxiDistanceM, Distance.M));
  }
  public void occupantIn(IUnit unit, IOccupant occupant)
  {
    if (unit.pathway() != null)
    {
      IZone origin = occupant.vehicle().trip().origin();
      TaxiRank rank = (TaxiRank)this.zoneToRank.get(origin);
      if (rank != null) {
        rank.enRouteInc(1);
      }
    }
    IMotor m = unit.aboardMotor();
    if (((m instanceof IVehicle)) && (((IVehicle)m).isTaxi()))
    {
      IVehicle taxi = (IVehicle)m;
      EmptyTaxiMeasure etm = (EmptyTaxiMeasure)this.emptyTaxis.get(taxi);
      if (etm != null)
      {
        if (etm.redirect() != null)
        {
          pushRequest(etm.redirect());
          this.ui.uncountDispatch(etm.redirect().redirectFrom(), etm.redirect().redirectTo());
```

```
        etm.redirect(null);
      }
      this.incompleteEmptyTaxiTimeS -= etm.timeEmptyS();
      this.completedEmptyTaxiTimeS += etm.timeEmptyS();
      this.incompleteEmptyTaxiDistanceM -= etm.distanceTravelledEmptyM();
      this.completedEmptyTaxiDistanceM += etm.distanceTravelledEmptyM();
      etm.reset();

      updateEmptyTaxiPanel();
    }
  }
}

public void occupantOut(IUnit unit, IOccupant occupant)
{
  if (unit.pathway() != null)
  {
    IZone origin = occupant.vehicle().trip().origin();
    TaxiRank rank = (TaxiRank)this.zoneToRank.get(origin);
    if (rank != null) {
      rank.enRouteInc(-1);
    }
  }
}
}
```

3. Redirect OD

```
package com.gmx.xgd;

import com.azalient.api.b.network.IZone;

public class RedirectOD
{
  private final IZone origin;
  private final IZone destination;
  private int requested;
  private int dispatched;
  private int arrived;

  public RedirectOD(IZone a, IZone b)
  {
    this.origin = a;
    this.destination = b;
  }

  public String toString()
  {
    return this.origin.name() + "-" + this.destination.name();
  }

  public int requested()
```

```
{
  return this.requested;
}

public void incRequested()
{
  this.requested += 1;
}
public int dispatched()
{
  return this.dispatched;
}
public void incDispatched()
{
  this.dispatched += 1;
}
public void decDispatched()
{
  this.dispatched -= 1;
}
public int arrived()
{
  return this.arrived;
}

public void incArrived()
{
```

```
    this.arrived += 1;
  }

  public void clear()
  {
    this.requested = 0;
    this.dispatched = 0;
    this.arrived = 0;
  }
}
```

4. Redirect request

```
package com.gmx.xgd;

import com.azalient.api.b.network.IZone;

public class RedirectRequest
{
  private final IZone redirectFrom;
  private final IZone redirectTo;

  public RedirectRequest(TaxiRank from, TaxiRank to)
  {
    this.redirectFrom = from.zone();
    this.redirectTo = to.zone();
  }
```

```
  public IZone redirectFrom()
  {
    return this.redirectFrom;
  }

  public IZone redirectTo()
  {
    return this.redirectTo;
  }
}
```

5. Redirect Table model

```
package com.gmx.xgd;

import com.azalient.api.API;
import com.azalient.api.a.IModel;
import com.azalient.api.a.model.INetwork;
import com.azalient.api.a.store.IStore;
import com.azalient.api.b.network.IZone;
import java.util.Hashtable;
import javax.swing.table.AbstractTableModel;

public class RedirectTableModel
  extends AbstractTableModel
{
```

```
public static final String[] COLS = { "O-D", "Requested", "Dispatched", "Arrived" };
private RedirectOD[] redirectsOD = new RedirectOD[0];
private int nRanks = 0;
private Hashtable<String, RedirectOD> lookupByODName = new Hashtable();

public void init()
{
  IStore<IZone> zones = API.model().network().zones();

  this.nRanks = 0;
  for (IZone zone : zones) {
    if (zone.parkingTaxiRank()) {
      this.nRanks += 1;
    }
  }
  this.redirectsOD = new RedirectOD[this.nRanks * this.nRanks - this.nRanks];
  this.lookupByODName.clear();

  int zi = 0;
  for (IZone origin : zones) {
    if (origin.parkingTaxiRank()) {
      for (IZone dest : zones) {
        if (dest.parkingTaxiRank()) {
          if (origin != dest)
          {
            RedirectOD rod = new RedirectOD(origin, dest);
```

```
            }

            this.redirectsOD[(zi++)] = rod;

            String key = origin.name() + "-" + dest.name();
            this.lookupByODName.put(key, rod);
          }
        }
      }
    }
  }
}

public RedirectOD redirectOD(IZone a, IZone b)
{
  String key = a.name() + "-" + b.name();
  return (RedirectOD)this.lookupByODName.get(key);
}

public int getRowCount()
{
  return this.redirectsOD.length;
}

public int getColumnCount()
{
  return COLS.length;
}
```

```
public String getColumnName(int col)
{
  return COLS[col];
}


public Object getValueAt(int row, int col)
{
  if ((row < 0) || (row >= this.redirectsOD.length)) {
    return null;
  }
  RedirectOD rod = this.redirectsOD[row];
  if (rod == null) {
    return null;
  }
  if (col == 0) {
    return rod.toString();
  }
  if (col == 1) {
    return rod.requested() == 0 ? null : Integer.valueOf(rod.requested());
  }
  if (col == 2) {
    return rod.dispatched() == 0 ? null : Integer.valueOf(rod.dispatched());
  }
  if (col == 3) {
    return rod.arrived() == 0 ? null : Integer.valueOf(rod.arrived());
  }
  return null;
```

```
  }

  public void rewind()
  {
    for (RedirectOD rod : this.redirectsOD) {
      rod.clear();
    }
    fireTableDataChanged();
  }
}
```

6. Taxi rank

```
package com.gmx.xgd;

import com.azalient.api.b.network.IChannel;
import com.azalient.api.b.network.ILane;
import com.azalient.api.b.network.ILink;
import com.azalient.api.b.network.IZone;
import com.azalient.api.b.parking.IParkingLane;

public class TaxiRank
{
  private final IZone zone;
  private final IParkingLane parkingLane;
  private int peopleWaiting;
  private int enRoute;
```

```
private int taxisWaiting;


public TaxiRank(IZone z)
{
  this.zone = z;
  this.parkingLane = findParkingLane();
}


public String toString()
{
  return this.zone.toString();
}


private IParkingLane findParkingLane()
{
  for (ILink link : this.zone.links()) {
    for (ILane lane : link.lanes())
    {
      IParkingLane parkLane = lane.parkingLane();
      if ((parkLane != null) && (parkLane.isTaxiRank())) {
        return parkLane;
      }
    }
  }
  return null;
}
```

}

```
  public boolean valid()
  {
    return (this.zone != null) && (this.parkingLane != null) && (this.parkingLane.zone() ==
this.zone) && (this.parkingLane.channel() != null);
  }

  public IZone zone()
  {
    return this.zone;
  }

  public IParkingLane parkingLane()
  {
    return this.parkingLane;
  }

  public int peopleWaiting()
  {
    return this.peopleWaiting;
  }

  public int taxisWaiting()
  {
    return this.taxisWaiting;
  }

  public void timeStep()
  {
```

```
    this.peopleWaiting = (this.parkingLane.channel().population() - this.enRoute);

    this.taxisWaiting = this.parkingLane.lane().motors().length;
  }

  public void rewind()
  {
    this.peopleWaiting = 0;
    this.taxisWaiting = 0;
    this.enRoute = 0;
  }

  public void enRouteInc(int n)
  {
    this.enRoute += n;
  }
}
```

7. Taxi rank table model

```
package com.gmx.xgd;

import com.azalient.api.b.network.IZone;
import javax.swing.table.AbstractTableModel;

public class TaxiRankTableModel
  extends AbstractTableModel
```

```
{
  public static final String[] COLS = { "Taxi Rank", "People Waiting", "Taxis Waiting", "Deficit"
};
  private TaxiRank[] taxiRanks = new TaxiRank[0];

  public void init(TaxiRank[] tra)
  {
    this.taxiRanks = tra;
  }

  public int getColumnCount()
  {
    return COLS.length;
  }

  public String getColumnName(int col)
  {
    return COLS[col];
  }

  public int getRowCount()
  {
    return this.taxiRanks.length;
  }

  public Object getValueAt(int row, int col)
  {
    if ((row < 0) || (row >= this.taxiRanks.length)) {
```

```
      return null;
    }
    TaxiRank rank = this.taxiRanks[row];
    if (rank == null) {
      return null;
    }
    if (col == 0) {
      return rank.zone().name();
    }
    if (col == 1) {
      return Integer.valueOf(rank.peopleWaiting());
    }
    if (col == 2) {
      return Integer.valueOf(rank.taxisWaiting());
    }
    if (col == 3) {
      return rank.peopleWaiting() > rank.taxisWaiting() ? "Yes" : "No";
    }
    return null;
  }
}
```

8. Taxi rank window 1

```
package com.gmx.xgd;

import com.azalient.apo.basics.UTime;
```

```
import java.awt.event.ActionEvent;
import java.awt.event.ActionListener;
import javax.swing.JTextField;

class TaxiRankWindow$1
  implements ActionListener
{
  TaxiRankWindow$1(TaxiRankWindow paramTaxiRankWindow) {}

  public void actionPerformed(ActionEvent e)
  {
    int newOptInterval = UTime.parseInt(UTime.HHMMSS,
TaxiRankWindow.access$0(this.this$0).getText());
    if (newOptInterval > 0)
    {
      TaxiRankWindow.access$1(this.this$0).set(newOptInterval);

TaxiRankWindow.access$0(this.this$0).setText(TaxiRankWindow.access$1(this.this$0).toString(
Boolean.valueOf(false)));
    }
  }
}
```

9. Taxi rank window 2

```
package com.gmx.xgd;

import com.azalient.api.b.network.IZone;
import com.azalient.apo.basics.Distance;
```

```
import com.azalient.apo.basics.ImageLoader;
import com.azalient.apo.basics.UTime;
import java.awt.FlowLayout;
import java.awt.GridLayout;
import java.awt.event.ActionEvent;
import java.awt.event.ActionListener;
import javax.swing.BorderFactory;
import javax.swing.JFrame;
import javax.swing.JLabel;
import javax.swing.JPanel;
import javax.swing.JScrollPane;
import javax.swing.JTabbedPane;
import javax.swing.JTable;
import javax.swing.JTextField;

public class TaxiRankWindow
  extends JFrame
{
  private TaxiRankTableModel taxiRankTableModel = new TaxiRankTableModel();
  private JTextField optIntervalTextField = new JTextField(8);
  private UTime optInterval = new UTime(300.0D, UTime.HHMMSS);
  private RedirectTableModel redirectModel = new RedirectTableModel();
  private JTextField completeTaxiTimeField = new JTextField(8);
  private JTextField completeTaxiDistanceField = new JTextField(8);
  private JTextField incompleteTaxiTimeField = new JTextField(8);
  private JTextField incompleteTaxiDistanceField = new JTextField(8);
```

```
public TaxiRankWindow(String title)
{
  super(title);

  JTable rankTable = new JTable(this.taxiRankTableModel);
  JScrollPane rankScrollPane = new JScrollPane(rankTable);
  rankTable.setFillsViewportHeight(true);

  JTable odTable = new JTable(this.redirectModel);
  JScrollPane odScrollPane = new JScrollPane(odTable);
  odTable.setFillsViewportHeight(true);

  JTabbedPane tabbedPane = new JTabbedPane();
  tabbedPane.addTab("Taxi Ranks", rankScrollPane);
  tabbedPane.addTab("Redirects", odScrollPane);

  add(tabbedPane, "Center");

  JPanel intervalPanel = new JPanel(new FlowLayout(2, 5, 5));
  intervalPanel.add(new JLabel("Optimization Interval"));
  intervalPanel.add(this.optIntervalTextField);
  add(intervalPanel, "North");

  JPanel emptyTaxiPanel = new JPanel(new GridLayout(4, 2));
  emptyTaxiPanel.setBorder(BorderFactory.createEmptyBorder(4, 4, 4, 4));
  emptyTaxiPanel.add(new JLabel("Empty Taxi Complete Drive Time"));
  emptyTaxiPanel.add(this.completeTaxiTimeField);
```

```
    emptyTaxiPanel.add(new JLabel("Empty Taxi Complete Drive Distance"));
    emptyTaxiPanel.add(this.completeTaxiDistanceField);
    emptyTaxiPanel.add(new JLabel("Empty Taxi Incomplete Drive Time"));
    emptyTaxiPanel.add(this.incompleteTaxiTimeField);
    emptyTaxiPanel.add(new JLabel("Empty Taxi Incomplete Drive Distance"));
    emptyTaxiPanel.add(this.incompleteTaxiDistanceField);
    add(emptyTaxiPanel, "South");



    this.optIntervalTextField.setText(this.optInterval.toString(Boolean.valueOf(false)));
    this.optIntervalTextField.addActionListener(new ActionListener()
    {
      public void actionPerformed(ActionEvent e)
      {
        int newOptInterval = UTime.parseInt(UTime.HHMMSS,
TaxiRankWindow.this.optIntervalTextField.getText());
        if (newOptInterval > 0)
        {
          TaxiRankWindow.this.optInterval.set(newOptInterval);

TaxiRankWindow.this.optIntervalTextField.setText(TaxiRankWindow.this.optInterval.toString(
Boolean.valueOf(false)));
        }
      }
    });
    pack();


    ImageLoader.setIcon(this);
```

```
    setSize(400, 300);
  }

  public void initialise(TaxiRank[] tra)
  {
    this.taxiRankTableModel.init(tra);

    this.redirectModel.init();
  }

  public void fireTableUpdate()
  {
    this.taxiRankTableModel.fireTableDataChanged();
  }

  public int optInterval()
  {
    return this.optInterval.timeInt();
  }

  public void updateEmptyTaxiPanel(UTime timeC, Distance distanceC, UTime timeI, Distance
distanceI)
  {
    this.completeTaxiTimeField.setText(timeC.toString(Boolean.valueOf(false)));
    this.completeTaxiDistanceField.setText(distanceC.toString());
    this.incompleteTaxiTimeField.setText(timeI.toString(Boolean.valueOf(false)));
    this.incompleteTaxiDistanceField.setText(distanceI.toString());
```

```
}

public void countRequest(IZone a, IZone b)
{
  this.redirectModel.redirectOD(a, b).incRequested();
  this.redirectModel.fireTableDataChanged();
}

public void countDispatch(IZone a, IZone b)
{
  this.redirectModel.redirectOD(a, b).incDispatched();
  this.redirectModel.fireTableDataChanged();
}

public void uncountDispatch(IZone a, IZone b)
{
  this.redirectModel.redirectOD(a, b).decDispatched();
  this.redirectModel.fireTableDataChanged();
}

public void countArrival(IZone a, IZone b)
{
  this.redirectModel.redirectOD(a, b).incArrived();
  this.redirectModel.fireTableDataChanged();
}

public void rewind()
```

```
  {
    this.redirectModel.rewind();

    fireTableUpdate();
  }
}
```

10. Taxi redirect optimiser

```
package com.gmx.xgd;

import com.azalient.api.API;
import com.azalient.api.APU;
import com.azalient.api.a.ISimulator;
import com.azalient.apo.basics.UTime;
import java.util.ArrayList;
import org.apache.commons.math3.optim.MaxIter;
import org.apache.commons.math3.optim.OptimizationData;
import org.apache.commons.math3.optim.PointValuePair;
import org.apache.commons.math3.optim.linear.LinearConstraint;
import org.apache.commons.math3.optim.linear.LinearConstraintSet;
import org.apache.commons.math3.optim.linear.LinearObjectiveFunction;
import org.apache.commons.math3.optim.linear.NonNegativeConstraint;
import org.apache.commons.math3.optim.linear.Relationship;
import org.apache.commons.math3.optim.linear.SimplexSolver;

public class TaxiRedirectOptimizer
{
```

```
  private ArrayList<RedirectRequest> rrList = new ArrayList();

  public RedirectRequest[] optimize(TaxiRank[] taxiRanks, double[][]
interTaxiRankFreeFlowTravelCost)
  {
    this.rrList.clear();

    optimizeRanks(taxiRanks, interTaxiRankFreeFlowTravelCost);

    return (RedirectRequest[])this.rrList.toArray(new RedirectRequest[this.rrList.size()]);
  }

  private void requestRedirect(TaxiRank from, TaxiRank to)
  {
    this.rrList.add(new RedirectRequest(from, to));

    APU.reportF("%s Optimizer Request: %s to %s", new Object[] {
      new UTime(API.simulator().simulationTime()).toString(Boolean.valueOf(true)),
      from, to });
  }

  private void optimizeRanks(TaxiRank[] ranks, double[][] interTaxiRankFreeFlowTravelCost)
  {
    int n = ranks.length;

    boolean anyRanksWithDeficit = false;
```

```
for (int ri = 0; ri < n; ri++)
{
  int V = ranks[ri].taxisWaiting();
  int C = ranks[ri].peopleWaiting();
  if (C > V)
  {
    anyRanksWithDeficit = true; break;
  }
}
if (!anyRanksWithDeficit) {
  return;
}
int nX = n * (n - 1);
double[] T = new double[nX];

int x = 0;
for (int i = 0; i < n; i++) {
  for (int j = 0; j < n; j++) {
    if (j != i) {
      T[(x++)] = interTaxiRankFreeFlowTravelCost[i][j];
    }
  }
}
LinearObjectiveFunction lof = new LinearObjectiveFunction(T, 0.0D);
ArrayList<LinearConstraint> lca = new ArrayList();
for (int ri = 0; ri < n; ri++)
{
```

```
    int V = ranks[ri].taxisWaiting();
    int C = ranks[ri].peopleWaiting();

    double[] coefficients = new double[nX];
    double value = C - V;
    Relationship relationship = Relationship.GEQ;
    int x = 0;
    for (int i = 0; i < n; i++) {
      for (int j = 0; j < n; j++) {
        if (j != i) {
          coefficients[(x++)] = (j == ri ? 1 : i == ri ? -1 : 0);
        }
      }
    }
    lca.add(new LinearConstraint(coefficients, relationship, value));
  }
  LinearConstraintSet lcs = new LinearConstraintSet(lca);
  try
  {
    SimplexSolver simplexSolver = new SimplexSolver();

    pvp = simplexSolver.optimize(new OptimizationData[] { new MaxIter(10000), lof, lcs, new
NonNegativeConstraint(true) });

    double[] point = pvp.getPoint();
    double value = ((Double)pvp.getValue()).doubleValue();

    int x = 0;
```

```
    for (int i = 0; i < n; i++) {
      for (int j = 0; j < n; j++) {
        if (j != i)
        {
          int redirectsIJ = (int)Math.round(point[(x++)]);
          if (redirectsIJ > 0)
          {
            TaxiRank rankI = ranks[i];
            TaxiRank rankJ = ranks[j];
            for (int r = 0; r < redirectsIJ; r++) {
              requestRedirect(rankI, rankJ);
            }
          }
        }
      }
    }
  }
  catch (Exception x)
  {
    PointValuePair pvp = 1;
  }
}

private void optimizeRanks_Simple(TaxiRank[] taxiRanks, double[][]
interTaxiRankFreeFlowTravelCost)
{
  for (TaxiRank rankA : taxiRanks) {
    if ((rankA.peopleWaiting() == 0) && (rankA.taxisWaiting() > 1)) {
```

```
        for (TaxiRank rankB : taxiRanks) {
         if (rankB != rankA) {
          if (rankB.peopleWaiting() > rankB.taxisWaiting())
          {
           requestRedirect(rankA, rankB);
           break;
          }
         }
        }
       }
      }
     }
    }
```