Network Impacts of Autonomous Shared Mobility

Hussein DIA
Associate Professor
Department of Civil Engineering
Swinburne University of Technology
Melbourne AUSTRALIA
HDia@swin.edu.au

Farid JAVANSHOUR
PhD Candidate
Department of Civil Engineering
Swinburne University of Technology
Melbourne AUSTRALIA
FJavanshour@swin.edu.au

Jack HILL
PhD Candidate
Department of Civil Engineering
Swinburne University of Technology
Melbourne AUSTRALIA
JackHill@swin.edu.au

ABSTRACT
Disruptive transport technologies are introducing new opportunities for providing travelers 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. Shared networks of autonomous vehicles, in particular, are already perceived as holding great promise for addressing the urban mobility challenges in our cities. This paper presents results from a simulation-based study which aimed to demonstrate the feasibility of using agent-based simulation tools to model the impacts of shared autonomous vehicles. A base case scenario representing the current situation (i.e. using traditional privately owned vehicles) and future scenarios of autonomous mobility on-demand (AMoD) were simulated on a real transport network in Melbourne, Australia. In addition to assessing the mobility impacts of AMoD, the paper also presents an assessment of how mode choice preferences impact the operation of fleets of autonomous vehicles. The results showed that using an AMoD system resulted in a significant reduction in both the number of vehicles required to meet the transport needs of the community (reductions between 43% and 88%), and the required on-street parking space (reductions between 57% and 83%. Investigations of shared mode choice preferences (car-share versus ride-share) also showed that shifting 40% of travelers to autonomous on-demand ride-sharing has the potential to deliver a 70% reduction in the total vehicle fleet size and 14% reduction in the total vehicle-kilometers-travelled compared to the Base Case Scenario.

CCS Concepts
• **Emerging Technologies → Emerging Simulation** • **Network Performance Evaluation →Network Simulations. Modeling and Simulation → Model Development and Analysis**

Keywords
autonomous vehicles; autonomous shared mobility-on-demand; smart cities; smart mobility.

1. INTRODUCTION
Over the past few years, innovations in the transport sector have been driven by a growing recognition that cars, once anonymous with freedom and mobility, have become victims of their own success. [1] The narrative is also changing - "transport" has become "mobility" and sustainability in the built environment is more often cited in research papers and policy documents. [2] Digital disruptions and new business models, inspired by the sharing or collaborative economy, are also starting to shape an exciting new era in mobility. Research is showing that car ownership is increasingly making less sense to many people, especially in urban areas. [3] Consumers are finding it difficult to justify tying up capital in an under-utilized asset that stays idle for 20-22 hours every day. The arrival of on-demand ride services, car-sharing, ride-sharing, bike-sharing and other innovative solutions are all poised to change car ownership models and how people move around cities. The coming together of these powerful trends has the potential to create much broader economic and disruptive impacts and transform how people live and work. They are also likely to create new business opportunities and have a broad reach – touching companies and industries beyond the automotive industry, and giving rise to a wide range of products and services. Driverless on-demand shared vehicles, for example, would provide a sensible option as a second car for many people and as the trend becomes more widespread, it may also begin to challenge the 'first' car.

Vehicles which drive themselves may very well be on our roads within 5 years. Vehicles with varying levels of self-driving capability are already available to consumers today, and the transition to full autonomous operation is expected to be gradual taking up to 15-20 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.

Although autonomous vehicles are still a few years away, they have already started to shape some visions for a mobility transformation driven by four key converging forces: Vehicle electrification, automated self-driving, mobile computing and on-demand car-sharing. The coming together of these powerful trends is shaping an urban mobility future inspired by a vision of zero road injuries and low carbon living.

The fast pace of developments in this space has prompted a number of researchers to explore how "driverless shared vehicles" could play a prominent role in the future mix of urban transportation options. This paper aims to provide an analysis of the potential impacts of a fleet of Shared Autonomous Vehicles aimed at replacing private car commuter trips in urban areas through shared autonomous vehicle services.

2. THE 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 [4], just 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. 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 [5], 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 [6] 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 imposes a hefty amount of damages in terms of human and economic. [7] A number of studies reported in the literature have also documented evidence showing that the environmental footprint of traditional transport systems, and in particular private vehicles with combustion engines, is not sustainable. [8] Globally, 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 OECD (Organization for Economic Co-operation and Development) average while transport contributes 14 percent of GHG emissions. [9] Moreover, road traffic continues to account for around 80 percent of transport CO_2 emissions and is estimated to reach 9,000 Megaton per year by 2030 if the current mobility trends are not curbed. [8]

Pursuing conventional approaches and relying on building new infrastructure to respond to increased travel demands has so far met with limited success and proven to be ineffective in meeting these challenges. New approaches are needed.

3. THE OPPORTUNITIES

Decision makers and leaders who run these complex cities are increasingly recognizing the role of smart technologies in improving the efficiency of existing infrastructure and sweating of assets through better utilization of available infrastructure. [10] 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 communicating with each other to enhance infrastructure capability and resilience, and capturing volumes of data. Through data mining, artificial intelligence and predictive analytics tools, smart infrastructure systems can help city managers to 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 livable. [10]

4. NEW PARADIGM: TECHNOLOGY-DRIVEN URBAN INFRASTRUCTURE

Smart cities of the future will include advanced network operations management and control systems that utilize field sensors to detect and respond quickly to equipment and infrastructure faults. Vital infrastructure downtimes will be cut using sensors that monitor the health of critical infrastructure, collect data on system functioning, alert operators inside an integrated urban control center to the need for predictive maintenance, and identify potential breakdowns before they occur. In transport, smarter vehicles, trains and public transport systems will sense their surrounding environments, and slow down or stop without human intervention in emergency situations. On-board public transport, a range of GPS, position fixing, video surveillance, and communications equipment will provide accurate and reliable multi-modal real-time passenger information, resulting in better informed travelers and ensuring a smoother, safer and more reliable experience for customers. A combination of sensors and position fixing equipment will maximize the efficiency of existing roads by providing route and network-wide levels of priority for emergency vehicles, light rail, and other modes of transport so as to maximize the movement of goods and passengers safely and efficiently. Back-office systems that leverage sensors, web, mobile, and GPS technologies will utilize smart algorithms, data mining and predictive modeling tools to reduce delays to passengers by optimizing schedules and capacities in real time. Near railroad level crossings, a range of train-to-infrastructure and train-to-vehicle technologies will improve passenger safety by detecting fast approaching vehicles and providing warnings to avoid collisions. Electric vehicle charging infrastructure will also be integrated into a smart grid network, providing consumers with access to sustainable and equitable forms of connected mobility. A combination of technologies and sensors will also improve safety and security by permitting operators to remotely disable or enable a public transport service in the event of a security threat (e.g. an unauthorized driver).

Adoption of technology-based customer-centric approaches have the potential to introduce substantial improvements in customer satisfaction, and create a shift in attitude to cost and value. A smarter city will mean better access to sustainable forms of transport; electricity and drinking water that can be counted on; and energy-efficient buildings resulting in enhanced standards and quality of life for today's increasingly empowered citizens and consumers. Given the maturity levels and affordability of smart technologies, these benefits can be achieved at a fraction of the cost of investment in new infrastructure. In a study published in 2009, Access Economics [11] reviewed the potential economic benefits from the adoption of smart technologies in transport, electricity, irrigation, health, and broadband communications. The report examined how smart systems will allow the use of vast amounts of data collected in all areas of city activity far more effectively, providing the potential to radically alter our economy and society for the better. Their research demonstrated that smart technologies would have significant benefits including a 1.5 percent increase in GDP, and increase in the net present value (NPV) of GDP by $35-80 billion over the first ten years. In another report prepared by The Climate Group [12] on behalf of the Global e-Sustainability Initiative, it is estimated that a 15 percent reduction in emissions can be realized in 2020 through smart technologies that achieve energy and resource efficiency using adaptive and proactive technologies. In Australia, the challenges are further amplified by the fact that around 96 percent of Australian total energy consumption is made up of non-renewable resources, while its fuel stocks hold no more than three weeks' worth of oil and refined fuels onshore. Given that Australia's transport system accounts for 26 percent of whole Australia's energy consumption [9], the reform of urban mobility becomes more crucial.

5. OPPORTUNITIES FOR LOW CARBON MOBILITY

The convergence of physical and digital worlds is creating unprecedented opportunities to enhance the travel experience for millions of people every day through new mobility solutions driven by disruptive forces and providing consumers with more choices to meet their transport needs. Although some of these disruptive forces are still a few years away (e.g. driverless vehicles), they have already started to shape a vision for a mobility transformation driven by six key converging forces: Vehicle electrification, automated self-driving, mobile computing, on-demand shared mobility services, Big Data and predictive analytics. The coming together of these powerful trends is shaping an urban mobility future inspired by a vision of low carbon living and zero road injuries. In particular, there has been some enthusiasm recently surrounding autonomous and semi-autonomous driving and the shared economy. Shareable networks of autonomous electric vehicles, in particular, are reported to hold great promise for addressing the urban mobility challenges and promoting sustainable transport. Autonomous mobility-on-demand (AMoD) systems are novel and transformative mode of transportation aimed at reducing carbon emissions as well as vehicle accidents. However, principal challenge for researchers is to ensure the same benefits of privately-owned cars in parallel with cutting down reliance on non-renewable resources, minimizing pollution, and decreasing the need for constructing new roads and parking spaces. [13] Furthermore, key to the success of these systems is a good understanding of the role of enabling technologies and new business models in improving the efficiency urban mobility and meeting people's demand for travel through low carbon mobility solutions. These systems can significantly improve operations, reliability, safety, and meet consumer demand for better services with relatively small levels of investment. This work is part of a research project which is fundamentally an investigation into the development and evaluation of new methods to provide urban transport and active travel options. These new mobility solutions would offer travelers with more choices and provide efficient, affordable and flexible trips while reducing reliance on private vehicle use and promoting low carbon mobility. This paper will focus mainly on one aspect of the research which is the development of models for evaluating the impacts.

6. MOTIVATION AND SCOPE OF WORK

The work reported in this paper is part of a research agenda aimed at developing innovative low carbon mobility solutions driven by disruptive technologies which are changing the mobility landscape and generating new opportunities for consumers to meet their transport needs. These include six key converging forces: Vehicle electrification, automated self-driving, mobile computing, on-demand shared mobility services, Big Data and Deep Learning/Artificial Intelligence. Amalgamation of these powerful technologies is revolutionizing the future of urban mobility inspired by a vision of low carbon living and zero road injuries. This research also aims to investigate the main driving factors affecting the demand for mobility under these emerging forces and understanding the resulting benefits in terms of enhanced mobility, reduced emissions and improved road safety conditions.

This paper is focused on one of the main objectives of this research which is the development of simulation models that can be used to model AMoD systems and assess their impacts on mobility, congestion, parking supply and how they can be used to supplement existing transport systems. This includes developing methodologies to estimate how future carbon emissions can be best mitigated using the proposed intervention measures. This work comprises a number of research challenges which will need to be overcome, including enhancements of existing tools to allow for modeling autonomous vehicles and also optimization of vehicle fleet sizes using innovative rebalancing strategies which aim to reduce the total kilometers of empty travel.

7. REVIEW OF RELEVANT LITERATURE AND CASE STUDIES

Providing access to high-quality urban transport services requires a variety of planning and operational innovations, as well as better understanding of travel behavior, operational processes, and the factors which affect these issues. A growing body of literature over the past few years have addressed the issues of disruptive technologies and their future potential. In this section of the paper, we provide a high level review of some of these technologies and discuss a number of overseas studies which have attempted to evaluate their impacts.

7.1 Demystifying Disruptive Technologies

New technologies are poised to revolutionize the way in which communities interact with their daily issues including mobility needs. Autonomous Vehicles (AVs), Mobile Internet, Internet of Things (IoT), Cloud Technology, and Energy Storage are seen as the key drivers of smart urban transport systems.

- Autonomous vehicles. An autonomous vehicle is one that can maneuver with reduced or no human intervention. [14] The main contributions of these vehicles are reductions in greenhouse emissions as well as reducing road car crashes. Vehicle automation has a great potential for decreasing these numbers by removing the weakest link, the human driver, from the driving equation.

- Mobile computing. 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 for obtaining real-time traffic information. Network-based solutions, which rely on 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. [15]

- Big Data. Big Data refers to the large amounts of real-time data that is being generated from millions of connected devices and interactions including data from cell phones, social media, card readers, navigation systems and so forth. Every day almost 2.5 quintillion bytes of data are created [16] including tweets on various topics and vehicles travelling from one point to another. Harnessing such a flow of data will benefit a multitude of sectors including transport systems. Urban areas are equipped with many sensors and actuators collecting information from different aspects of city dwellers' activities. Smart phones with built-in GPS systems can record and transmit their own trails which can be used for multiple purposes such as forecasting travel demand through machine learning without recourse to highly expensive traditional manual surveys. [17] Transponders can be used to monitor throughput through a road network, measuring vehicle flow along a road or the number of empty spaces in a car park, and track the progress of buses and trains along a route. These devices and sensors provide urban managers with dynamic, well-defined and relatively cheap data on city activities enabling them to establish real-time analytics and adaptive management and governance systems. [18]

- The Internet of Things (IoT). The IoT refers to the use of sensors, actuators, and data communications technology, built into physical objects from roadways to pacemakers, to enable these objects to be tracked, coordinated, or controlled across a data network or the Internet. [14] 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.

- Cloud computing. 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. [18] With the support of cloud computing technologies, it will 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. [20]

- Energy storage systems. These convert electricity into a form that can be stored and converted back into electrical energy for later use, providing energy on demand. [14] Lithium batteries are widely used in small applications, such as mobile phones and portable electronic devices. This type of batteries 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. [21]

7.2 Autonomous Mobility On-Demand (AMoD)

Several recent studies which relied on millennial surveys report that younger people are less keen to own private cars. In a study by car sharing company Zipcar, it is reported that half of millennials interviewed say they would prefer public transport and car sharing systems to privately owned cars. [3] With this in mind, shareable autonomous electric vehicles (particularly those in which electricity is produced through clean resources e.g. wind turbines or solar systems) appear like a promising proposition for decreasing the overall number of private cars. This would in turn directly address the problems of oil dependency, pollution, promote higher utilization rates and reduce parking lot sprawls. [22]. However, deploying these new systems also brings about new challenges to fleet operators which requires development and evaluation of robust and novel techniques. For example, the security of Mobility-as-a-Service (MaaS) systems against cyber-attacks was investigated in a recent study [23] where the authors proposed a tractable block-coordinate descent algorithm to compute attack strategies in the Manhattan road network.

To date, few studies have dealt with the implications of AMoD systems. Some of the studies of particular relevance to this research are described below.

7.2.1 Lisbon

The Lisbon study [24] examined the potential impacts that would result from the implementation of a shared and fully autonomous vehicle fleet. To perform this assessment, the researchers developed an agent-based model to simulate the behavior of all entities in the system: Travelers, as potential users of the shared mobility system; Cars, which are dynamically routed on the road network to pick-up and drop-off clients, or to move to, from, and between stations; and Dispatcher system tasked with efficiently assigning cars to clients while respecting the defined service quality standards, e.g. with regard to waiting time and detour time. The analysis was based on a real urban context, the city of Lisbon, Portugal. The simulation used a representation of the street network, using origin and destination data derived from a fine-grained database of trips on the basis of a detailed travel survey. Trips were allocated to different modes: walking, shared self-driving vehicles or high-capacity public transport. A set of constraints were established (e.g. that all trips should take at most 5 minutes longer than today's car trips take for all scenarios, and assumed all trips are done by shared vehicles and none by buses or private cars). The study also modeled a scenario which included high-capacity public transport (Metro in the case of Lisbon). The study modeled two different car-sharing concepts, "TaxiBots", a term the researchers coined for self-driving vehicles shared simultaneously by several passengers (i.e. ride sharing), and "AutoVots", cars which pick-up and drop-off single passengers sequentially (car sharing). For the different scenarios, the researchers measured the number of cars, kilometers travelled, impacts on congestion and impacts on parking space. The results indicated that shared self-driving fleets can deliver the same mobility as today with significantly fewer cars. When serviced by ride-sharing TaxiBots and a good underground system, 90% of cars could be removed from the city. Even in the scenario that least reduces the number of cars (AutoVots without underground), nearly half of all cars could be removed without impacting the level of service. Even at peak hours, only about one third (35%) of today's cars would be needed on the roads (TaxiBots with underground), without reducing overall mobility. On-street parking could be totally removed with a fleet of shared self-driving cars, allowing in a medium-sized European city such as Lisbon, reallocating 1.5 million square meters to other public uses. This equates to almost 20% of the surface of kerb-to-kerb street area (or 210 football pitches!). These findings suggest that shared self-driving fleets could significantly reduce congestion. In terms of environmental impact, only 2% more vehicles would be needed for a fleet of cleaner, electric, shared self-driving vehicles, to compensate for reduced range and battery charging time.

7.2.2 Stockholm

In the Stockholm study [25], the assessments included both a fleet consisting of currently in use gasoline and diesel cars as well as electric cars. The results showed that an autonomous vehicle-based personal transport system has the potential to provide an on-demand door-to-door transport with a high level of service, using less than 10 % of today's private cars and parking places. In order to provide an environmental benefit and lower congestion the autonomous vehicle would require users to accept ride-sharing, allowing a maximum 30% increase of their travel time (15% on average) and a start time window of 10 minutes. In a scenario where users were not inclined to accept a lower level of service, i.e. no ride-sharing and no delay, empty vehicle drive will lead to increased road traffic increasing environmental impacts and congestion. In a scenario which looked at electric cars, an autonomous vehicle-based system and electric vehicle technology seemed to provide a "perfect" match that could contribute to a sustainable transport system in Stockholm.

7.2.3 Austin

The Austin case study [26] investigated the potential travel and environmental implications of autonomous shared mobility systems by simulating a 12-mile by 24-mile area in Austin, Texas. The Multi-agent transport simulation (Matsim) software was used for conducting this experiment using 100,000 randomly drawn person-trips out of 4.5 million Austin's regional trips. The study claimed that each autonomous shared car would almost replace around 9 conventional vehicles within the 24-mile by 12-mile area while providing the same level of service, but would generate approximately 8 percent more vehicle-mile travelled. Their study also confirmed that this system would decrease the emissions by not only replacing the heavier vehicles with higher emissions rates, but also by cutting down on the number of cold starts.

7.2.4 New York

The New York case study [27] introduced the Expand and Target algorithm which was integrated with three different scheduling strategies for dispatching autonomous vehicles. The study also implemented an agent-based simulation platform and empirically evaluated the proposed approaches using New York City taxi data. Experimental results demonstrated that the algorithms significantly improve passengers' experience by reducing the average passenger waiting time by around 30% and increasing the trip success rate by around 8%.

8. MODELING FRAMEWORK

This research will apply the Commuter model, which is an agent-based simulation tool, to model an AMoD system for the city of Melbourne. A brief overview of the agent-based models and why they are suitable for this research is provided next.

8.1 Agent-Based Modeling

Transport professionals today have access to powerful modeling tools which can be applied at a number of levels depending on the application and modeling need. At the highest level are macro-simulation (or macroscopic simulation) tools which model traffic on a network as a time-varying flow on each link and assume that traffic streams generally follow behaviors similar to fluid streams. These tools are useful for building strategic, regional or city-wide models without attention to individual traveler behavior. At the next level are dynamic simulation tools which include mesoscopic, microscopic and hybrid models. These dynamic models allow greater levels of detail than a strategic model. In the Mesoscopic approach, the vehicles are modeled as individual entities with simplified behavioral models (car following and lane changing) with a slight loss of realism resulting in an event-oriented simulation approach. Microscopic simulation offers the highest level of detail and allows for distinguishing between the different types of vehicles and drivers. It also enables a wide range of network geometries (e.g. freeways, arterials) and traffic control (e.g. traffic signals, give-way intersections and ramp metering) modeling. The behavior of each vehicle is continuously modeled using detailed car following, lane changing, and gap acceptance models. In the Hybrid approach, the simulation concurrently applies the microscopic models in certain selected areas and the mesoscopic models in the rest. This approach can be used in large-scale networks where there is a need in specific areas to have a level of microscopic detail but with a global network evaluation. While these modeling tools have served the transport profession very well in previous years, the recent digital disruptions in mobility solutions (e.g. app-based on-demand car sharing and ride-sharing) and the anticipated arrival of autonomous vehicles over the next few years have created visions for a very different future based on shared autonomous mobility. Fleets of autonomous vehicles, to be owned by commercial companies, would pick up passengers on demand and offer both car-sharing and rider-sharing services. [25]; [27]; [28] This research builds on previous studies and will investigate how these disruptions are likely to impact on utilization of vehicles, car ownership, congestion, emissions and pollution. Modeling the impacts of such scenarios requires a level of detail much greater than what is offered by the above modeling tools. Agent-based or nanoscopic modeling offers a number of features which would allow for modeling network performance using end-to-end trips made by travelers over multiple modes of transport, rather than single-mode trips made in a vehicle or walking. This approach allows for modeling individual traveler behavior including dynamic decision processing incorporating a dynamic mode-choice function of individual travelers. This provides capabilities to allow a traveler in the model to make instantaneous choices between available modes as well as choices between available routes. Although existing micro-simulation tools can model dynamic route choice within a mode, the demand is specified by an (O-D) matrix of mode-specific trips making it impossible to model a person dynamically switching from one mode of transport to another. A nano-simulation model can represent dynamic mode switching by allowing each individual agent to choose a new mode of transport during its trip. [29]

8.2 Data Requirements

The travel demand data for this study will be sourced from the Victorian Integrated Survey of Travel and Activity (VISTA), which is an ongoing survey of travel and activity in Victoria. It includes 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 11,400 households for the metropolitan Melbourne. VISTA data for the period between 2012 and 2013 have recently been published on the department of Economic Development, Jobs, Transport and Resources website for which a following dataset allowing more detailed analysis is to be published later in 2016. [30] Households who complete the surveys are randomly selected from a listing of all residential addresses in the study areas. They 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. [31] Collecting this information provides detailed picture of 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. The traffic data, including traffic counts and signal timings, are available to the University through a Virtual Private Network (VPN) connection to VicRoads.

8.3 Pilot Study

To develop a proof-of-concept, a pilot study has been conducted on a real transport network located in Melbourne (See Figure 1). The pilot explored the feasibility of using Commuter for this project. It also helped the research team to develop a better understanding of the capabilities of the tool and the various functionalities required to enable investigations of a vast range of AMoD scenarios across a much larger study area under real activity-based data sourced from VISTA.

Figure 1. Pilot study area

8.3.1 *Scenario 1: autonomous shared mobility with zero passenger waiting times*

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

Table 1. Total number of trips between different ODs during AM-Peak (7:00am-9:00am)

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

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

An initial analysis of the autonomous mobility scenario (Table 2) shows that people travelling in groups and being dropped-off by the self-driving cars result in both decreased number of required vehicles (more than 40% compared to the base scenario) and parking space (around 58% compared to the base-case scenario). This frees up a substantial amount of land and space which can be used for different purposes. However, the simulation also showed that the total vehicle-kilometers travelled (VKT) by the autonomous vehicles increased by around 29% because the vehicles needed to reposition. The increase was largely due to the privately owned vehicles which were assumed to return to their origin. Finally, it was assumed in this analysis that no public parking space was needed for the privately owned cars because they would wait at home rather than at a public parking space.

Table 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 (BCS)	2,136	4.04	35,885
Autonomous mobility scenario (AMoD1)	1,217	5.20	15,238
Percent difference between BCS and AMoD1	43% decrease	29% increase	58% reduction

8.3.2 *Scenario 2: autonomous shared mobility with maximum 5 minutes passenger waiting times*

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

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

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 the base case scenario, it was assumed that all trips originated from home (where required on-street parking space is zero assuming all vehicles were parked on-site) towards destinations where off-street parking was also available. All trips were assumed to be undertaken during the period 07:00 am - 09:00 am using single-occupant traditional privately owned vehicles (therefore waiting time for travelers is zero).

In this second scenario (AMoD2), the waiting times for passengers were assumed to be longer than in AMoD1 (Table 3). This reflected situations in which the driverless vehicle would need some time to travel to the customer location. The only constraint was that the waiting times should not exceed 5 minutes. It was assumed that all origins and destinations have at least one taxi rank in their near proximity and one drop-off lane at their destinations. In this scenario, an AMoD vehicle would pick-up the 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 also a heuristic rebalancing strategy to reduce the empty travel and idle times for AMoD vehicles.

8.3.3 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 base case scenario such that passengers would not wait more than 5 minutes for their pick-up vehicle. To achieve this, the area (3km x 2km) was divided into two equal blocks of 1.5km by 2km (See Figure 2).

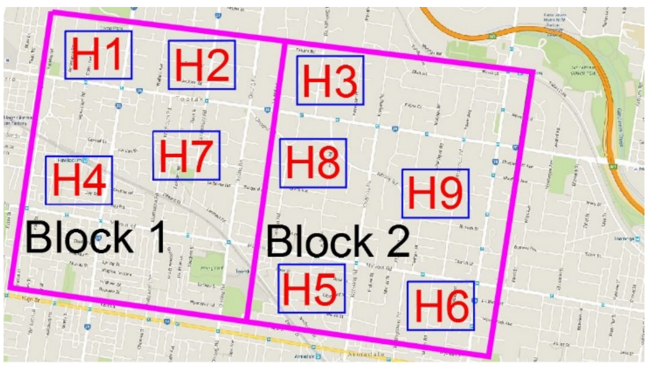

Figure 2. Dividing the pilot area into two equal blocks namely block 1 and block 2 for AMoD rebalancing purposes

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 were calculated for each origin. If the number of outgoing vehicles exceeds the number of in-coming AMoD vehicles, that number was chosen as the initial required number of vehicles for the origin at the start of simulation. For the first simulation run, no AMoD vehicles were allocated for the origins in which the number of attracted trips were greater than the generated ones. The premise was that as the trip attraction rate for these areas are higher, AMoD vehicles leaving other areas with greater trip generation rates will have enough time to arrive to these taxi ranks. Then, vehicles were released into the model within 30 minutes and afterwards no new vehicle were generated and the fleet size remained fixed until the end of simulation time (7:00am-9:00am). After the first run, waiting times for all passengers were calculated and the number of initial AMoD vehicles for the taxi ranks where passengers experienced waiting times more than 5 minutes within the first 30 minutes of the simulation were increased proportional to the amount of waiting times. This process was repeated until all traveler's waiting times were less than 5 minutes during the first 30 minutes of simulation period. Thereafter, it was attempted to reduce the waiting times with rebalancing the AMoD vehicles between various taxi ranks rather than generating new vehicles to meet the demand.

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

The results, shown in Table 4, illustrate that deploying the AMoD system led 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 spaces (83% compared to base case scenario) at the expense of 10% increase in total VKT incurred by empty vehicles repositioning themselves to better serve the demand in the taxi ranks. This demonstrates that the same demand can be met using only 12% of total number of vehicles required in the base case scenario with an average waiting time of 1 minutes and a maximum waiting time of 4 minutes (lower than 5 minutes constraint).

Table 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 (BCS)	2059	4660.38	34591
Autonomous mobility scenario 2 (AMoD2)	247	5204.16	6048
Percent difference between BCS and AMoD2	88% decrease	10% increase	83% reduction

To sum up, as shown in Table 5, using the AMoD system resulted in a significant reduction in both the number of vehicles on the road (43% in scenario 1, and 88% in scenario 2), and 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 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 (BCS)	43%	29%	58%
Scenario 2 (AMoD2) compared to base case (BCS)	88%	10%	83%

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

In Scenario 2, a homogeneous population of travelers was assumed where all travelers had identical mode-choice preferences and used only car sharing with single occupant driverless cars 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. [30]; [31] It would therefore be expected that the preference towards car sharing versus ride sharing will differ between travelers based on the increased travel time required to rideshare.

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

To develop a better understanding of the impacts of mode choice preferences, three scenarios were simulated in which the proportion of ride sharing travelers varied between 40% and 90% as shown in Table 6.

Table 6. Proportions of ride-share and car-share travelers in Scenarios AMoD 3-5

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

The simulation results are reported in Figure 3. As expected, the results show marked reductions in the total number of vehicles, total VKT traveled and parking spaces 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 travelers (from 90% to 40%). However, the number of vehicles in AMoD5 was still substantially lower (69% less) than the BCS.

Comparison of the results for AMoD5 and BCS also suggest 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 spaces.

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

Table 7. Mean and maximum waiting times

Scenario	Proportion of ride-sharing travelers	Percentage of vehicles compared to Base Case 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

8.3.5 Dynamic pricing

This work highlights the impact of market segmentation (between ride sharing and car sharing) for a fleet of autonomous vehicles based on values of travel time. Given that mode choice preferences are largely dictated by the cost of the service, its convenience and comfort [34], the cost of the trip could be the determining factor as to whether a traveler chooses to rideshare or car share.

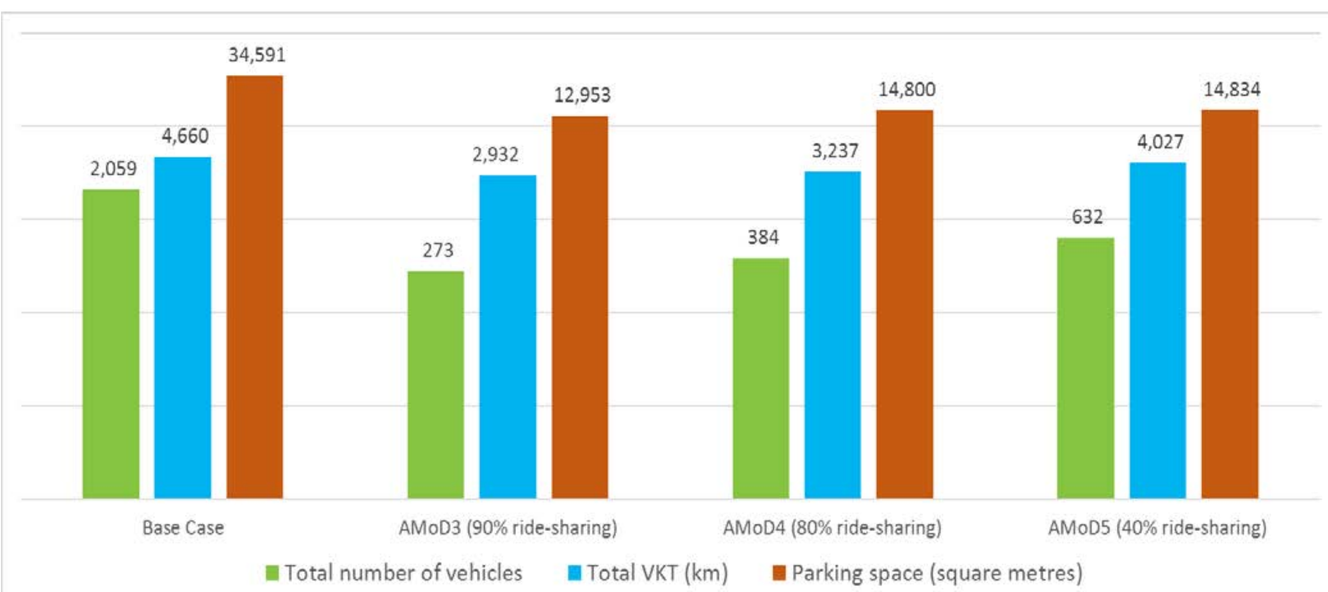

Figure 3. Impacts of variable proportions of ride-share and car-share

In that context, dynamic pricing could be a feasible mechanism to influence the mode split between car sharing and ride sharing to efficiently allocate the vehicle fleet across the road network. Dynamic pricing is implemented as a demand management technique during periods of excess demand and is currently used by mobility-on-demand companies, for example Uber's Surge Pricing and Lyft's Prime Time. [35]; [36] The increased price of a trip eliminates the shortage of available vehicles by offering a higher charge rate to drivers thereby increasing supply of vehicles where the demand is high. It also has an added benefit in that it may encourage travelers to reconsider their travel needs or shift to other modes of transport [34] where and when possible.

For a fleet of autonomous mobility-on-demand vehicles, the dynamic pricing could take this simple form as an example:

$$Dynamic\ Price = \frac{Vehicle\ Demand\ in\ Area}{Vehicles\ Available\ in\ Area} * fare\ rate$$

This measure would allow prices to increase when demand exceeds supply within a region, and would also allow prices to be discounted when there is a surplus of vehicles in the area. This could be used to manage the modal split between car sharing and ride sharing on a regional basis. For example, if there is a shortage of autonomous vehicles within one region, this could cause the fare price to increase and thereby provides an incentive for passengers with a lower value of travel time to choose ride sharing instead of car sharing. The dynamic pricing could be used in reverse for regions that have a surplus of vehicles, where the price could be further discounted to encourage better utilization of idle vehicles. Such pricing could also see vehicles travel from areas where there is a surplus to areas where there is a shortage based on the marginally higher price paid for the same service in areas where there are shortages. [37] In this case, dynamic pricing could be used as a rebalancing mechanism by providing incentives to underutilized vehicles to relocate to regions where there are shortages. Dynamic pricing has not been investigated in this simulation study and will be explored in future implementations of the simulation models.

9. SUMMARY AND FUTURE DIRECTIONS

The pilot study reported in this paper demonstrated the feasibility of using the agent-based approach for evaluating the impacts of autonomous shared mobility-on-demand systems. A base case scenario (current situation relying on traditional privately owned vehicles) and five autonomous shared mobility scenarios were simulated on a real transport network in Melbourne, Australia. The results showed that incorporating shared driverless-cars 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 would free up this space for other purposes. The results, however, also showed that there are likely to be some negative impacts such as increased total kilometers of travel due to repositioning, but these were less significant and can potentially be mitigated if all future self-driving vehicles are electric.

Although the pilot study has demonstrated the feasibility of the approach, there are still a large number of challenges that will need to be addressed in this research. These include:

- Undertaking stakeholder consultation to develop a better understanding of the drivers of travel behavior given emerging information technology solutions.
- Development of models for demand forecasting and understanding the demand for travel in the age of autonomous mobility.
- Development, calibration and validation of real-life models which include a large network representative of demands from the VISTA data. The models will also be tested on a large number of scenarios including ones which assume reduced or zero car ownership, and scenarios which assess the impacts under provision of light and heavy rail, public transport buses etc.
- Development of a methodology to address the re-balancing strategy through development of optimization techniques for determining the minimum fleet size using real-time rebalancing strategies and dynamic pricing measures which aim to reduce the total kilometers of empty travel and optimize travel costs for users.

10. REFERENCES

[1] Retrieved May 20, 2016 from Deloitte website: http://www2.deloitte.com/au/en.html

[2] Bruun, E., and Givoni, M. 2015. Sustainable mobility: six research routes to steer transport policy. *Nature*, 523, 7558 (Jul. 2015), 29-31. DOI=10.1038/523029a.

[3] Zipcar's Annual Millennial Survey Shows the Kids Are All Right. Retrieved September 3, 2015, from Zipcar: http://www.zipcar.com/press/releases/fourth-annual-millennial-survey

[4] Urban world: mapping the economic power of cities. MGI. Retrieved January 29, 2016, from McKinsey Global Institute http://www.mckinsey.com/mgi/

[5] Retrieved January 29, 2016, from United Nations Road Safety Collaboration: http://www.who.int/roadsafety/en/.

[6] Retrieved August 25, 2015, from World Health Organization: http://www.who.int/mediacentre/factsheets/fs358/en/

[7] Autonomous driving. Regulatory issues. Retrieved August 25, 2015, from International Transport Forum: http://www.internationaltransportforum.org/cpb/pdf/autonomous-driving.pdf

[8] Transport outlook 2010. Retrieved August 20, 2015, from International Transport Forum: http://www.internationaltransportforum.org/pub/pdf/10Outlook.pdf

[9] Delivering sustainable urban mobility. Final report. Retrieved November 25, 2015, from Australian council of learned academies: http://www.acola.org.au/PDF/SAF08/SAF08_FullReport_web.pdf

[10] Dia, H. 2013. How to save €300bn a year. *Thinking Highways*, 8, 3, 74-76.

[11] Retrieved September 25, 2015 from Access Economics: http://www.accesseconomics.com.au/

[12] Smart 2020: Enabling the low carbon economy in the information age. Retrieved September 20, 2015, from Global e-Sustainability Initiative (GeSI): http://www.smart2020.org/_assets/files/02_smart2020Report.pdf

[13] Pavone, M. 2015. Autonomous mobility-on-demand systems for future urban mobility, in M Maurer, JC Gerdes, B Lenz., & H Winner (Eds.), *Autonomes Fahren*, Springer Berlin Heidelberg, Berlin. DOI= 10.1007/978-3-662-45854-9.

Retrieved August 25, 2015, from: http://link.springer.com/book/10.1007%2F978-3-662-45854-9

[14] Manyika, J., Chui, M., Bughin, J., Dobbs, R., Bisson, P., and Marrs, A. 2013. Disruptive technologies: advances that will transform life, business, and the global economy. Retrieved August 26, 2015, from McKinsey Global Institute: http://www.mckinsey.com/insights/business_technology/disruptive_technologies

[15] Rose, G. 2006. Mobile phones as traffic probes: practices, prospects and issues, *Transport Reviews*, 26, 3 (Feb. 2007), 275-291. DOI= 10.1080/01441640500361108

[16] Wu, X., Zhu, X., Wu, G.Q., and Ding, W. 2014. Data mining with big data. *Knowledge and Data Engineering. IEEE Transactions on*, 26, 1 (Jan. 2014), 97-107. DOI= 10.1109/TKDE.2013.109

[17] Pozdnoukhov, A. 2016. Demand forecasting and activity-based mobility modeling from cell phone data. *ITSBerkeley, Institute of Transportation Studies*, eScholarship, University of California, Retrieved from: http://escholarship.org/uc/item/4hc9r218

[18] Kitchin, R. 2014. The real-time city? big data and smart urbanism. *GeoJournal*, 79,1 (Feb. 2014), 1-14. DOI= 10.1007/s10708-013-9516-8

[19] Mell, P., and Grance, T. 2011. The NIST definition of cloud computing. *National Institute of Standards and Technology (NIST)*, U.S Department of Commerce.

[20] Li, Z., Chen, C., and Wang, K. 2011. Cloud computing for agent-based urban transportation systems. *Intelligent Systems, IEEE*, 26, 1 (Jan-Feb. 2011), 73-79. DOI= 10.1109/MIS.2011.10

[21] Iaz-González, F., Sumper, A., Gomis-Bellmunt, O., and Villafáfila-Robles, R. 2012. A review of energy storage technologies for wind power applications. *Renewable and sustainable energy reviews*, 16, 4 (May 2012), 2154-2171. DOI= 10.1016/j.rser.2012.01.029

[22] Zhang, R., Spieser, K., Frazzoli, E., and Pavone, M. 2015. Models, algorithms, and evaluation for autonomous mobility-on-demand systems. *In Proceeding of the IEEE, American Control Conference* (Chicago, IL, USA. July 01-03, 2015). 2573 – 2587. DOI= 10.1109/ACC.2015.7171122

[23] Yuan, C., Thai, J., and Bayen, A.M. 2016. ZUbers against ZLyfts apocalypse: an analysis framework for DoS attacks on mobility-as-a-service systems. *In Proceeding of the ACM/IEEE 7th International Conference on Cyber-Physical Systems (ICCPS)* (Vienna, Austria. April 11-14, 2016) 1-10.

[24] Urban mobility system upgrade: how shared self-driving cars could change city traffic. Retrieved September 10, 2015, from International Transport Forum: http://www.internationaltransportforum.org/Pub/pdf/15CPB_Self-drivingcars.pdf

[25] Rigole, P. 2014. *Study of a Shared Autonomous Vehicles Based Mobility Solution in Stockholm.* Master of Science Thesis. KTH University. Retrieved from: http://bit.ly/1Qig7Cu

[26] Fagnant, D. J., Kockelman, K. M., and Bansal, P. 2015. Operations of a shared autonomous vehicle fleet for the Austin, Texas market. *Transportation Research Board (TRB)*, 2536. DOI= http://dx.doi.org/10.3141/2536-12

[27] Shen, W., and Lopes, C. 2015. Managing autonomous mobility on demand systems for better passenger experience. *Principles and Practice of Multi-Agent Systems. Springer International Publishing*, 20-35. DOI= 10.1007/978-3-319-25524-8_2

[28] Fagnant, D. J., and Kockelman, K. M. 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, 40 (March 2014), 1-13. DOI= 10.1016/j.trc.2013.12.001

[29] Duncan, G. 2010. From microsimulation to nanosimulation: visualizing person trips over multiple modes of transport. *Transportation Research Board (TRB)*, 2175,15, 130-137. DOI= http://dx.doi.org/10.3141/2175-15

[30] Victorian Integrated Survey of Travel and Activity (VISTA), Retrieved April 10, 2016, from Department of Economic Development, Jobs, Transport and Resources, State Government of Victoria, Australia: http://economicdevelopment.vic.gov.au/transport/research-and-data/statistics/vista#data

[31] Victorian Integrated Survey of Travel and Activity 2007 (VISTA 07). Retrieved September 19, 2015, from Department of Economic Development, Jobs, Transport and Resources, State Government of Victoria, Australia: http://economicdevelopment.vic.gov.au/__data/assets/pdf_file/0004/1092217/VISTA-07-Summary-Brochure.pdf

[32] Cirillo, C., Axhausen, K. 2005. Evidence on the distribution of values of travel time savings from a six-week diary. *Transportation Research Part A*, 40, 5 (Jun. 2006), 444–457. DOI= 10.1016/j.tra.2005.06.007

[33] Brownstone D., Small K. 2005. Valuing time and reliability: Assessing the evidence from road pricing demonstrations. *Transportation Research Part A*, 39, 4 (May 2005), 279-293. DOI= 10.1016/j.tra.2004.11.001

[34] Corpuz, G. 2008. Public transport or private vehicle: factors that impact on mode choice. *Proceedings of the 30th Australasian Transport Research Forum.* Retrived May 20, 2016 from: http://www.bts.nsw.gov.au/articledocuments/82/public-private-choice-factors.pdf.aspx

[35] Gurley, B. 2014. A deeper look at Uber's dynamic pricing model. Retrieved May 19, 2016 from: http://abovethecrowd.com/2014/03/11/a-deeper-look-at-ubers-dynamic-pricing-model/

[36] Griswold, A. 2016. Lyft has quietly eliminated its surge 3x cap on surge pricing. Retrieved May 25, 2016, from: http://qz.com/665093/lyft-has-quietly-eliminated-its-3x-cap-on-surge-pricing/>

[37] Sowell, T. 2011. Basic economics a common sense guide to the economy. New York, USA: Basic Books.