Simulation-Based Design of Integrated Public Transit and Shared Autonomous Mobility-on-Demand Systems

By

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Abstract

The autonomous vehicle (AV) is poised to be one of the most disruptive technologies in the transportation industry. The advent of three major trends in transportation: automation, on-demand mobility and ride-sharing, are set to revolutionize the way we travel. The forthcoming adoption and commercialization of AVs are expected to have extensive impacts on our road networks, congestion, safety, land use, public transportation (PT) and more. Rapid advances in AV technology are convincing many that AV services will play a significant role in future transportation systems. The advancement of AVs presents both opportunities and threats to transportation. It has the potential to significantly impact traffic congestion, traffic accidents, parking and VMT (vehicle miles traveled), especially for people that are not able to drive such as children and elderly people. Motivated by the potential of autonomous vehicles, authorities around the world are preparing for this revolution in transport and deems this an important research direction that requires significant investigation.

This thesis tackled and contributed to three main research questions related to the impact of autonomous vehicles on transportation systems. First, this thesis proposes a simulation-based approach to the design and evaluation of integrated autonomous vehicle and public transportation systems. We highlight the transit-orientation by respecting the social-purpose considerations of transit agencies (such as maintaining service availability and ensuring equity) and identifying the synergistic opportunities between AV and PT. Specifically, we identified that AV has a strong potential to serve first-mile connections to the PT stations and provide efficient and affordable shared mobility in low-density suburban areas that are typically inefficient to serve by conventional fixed-route PT services. The design decisions reflect the interest of multiple stakeholders in the system. Second, the interaction between travelers (demand) and operators (supply) is modeled using a system of equations that is solved as a fixed-point problem through an iterative procedure. In this, we developed demand and supply as two sub-problems. The demand will be predicted using a nested logit model to estimate the volume for different modes based on modal attributes. The supply will use a simulation platform capable of incorporating critical operational decisions on factors including fleet sizes, vehicle capacities, sharing policies, fare schemes and hailing strategies such as in-advance and on-demand requests. Using feedback between demand and supply, we enable interactions between the decisions of the service operator and those of the travelers, in order to model the choices of both parties. Finally, this thesis systematically optimizes service design variables to determine the best outcome in accordance to AV+PT stakeholder goals. Optimization objective functions can be formulated to reflect the different objectives of different stakeholders. In this paper, we specifically propose and develop a simulation-based service design method where we quantify various benefits and costs to reflect the objectives of key AV+PT stakeholders. We simulate the service with different sets of system settings and identify the highest performing set. We employ a case study of regional service contracting to showcase the ability of this method to inform AV+PT service design.

We tested our approach with a case study area in a major European city on an agent-based simulation platform, amod-abm. Agent-based simulation has the advantage of capturing individual (agent) behaviors and the interactions of the various individual agents in a realistic synthetic environment where the intent is to re-create a complex phenomenon of mobility on demand service delivered by AV. Although this thesis will focus on a major European city, the general framework and methodologies proposed here can be widely applicable.

The thesis concludes that the demand-supply interaction can be effective for designing and assessing the role of AV technology in our mobility systems. Moreover, simulation-based optimization can be an effective method for transit agencies to make decisions that support their overall AV related transport strategy as well as operational planning.

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Preface

The contents of chapter 3, 4, 5, and 6.1 in this thesis are closely related to the research paper "Transit-Oriented Autonomous Vehicle Operation with Integrated Demand-Supply Interaction" by Jian Wen, Yu Xin Chen, Neema Nassir, and Jinhua Zhao. This paper is currently under review at Transportation Research Part C. Chapters 6.2 go beyond this paper and extends this research to include the use of simulation-based optimization for autonomous vehicle service design.

Section 1

1.0 Introduction

The autonomous vehicle (AV) is poised to be one of the most disruptive technologies in the transportation industry. The advent of three major trends in transportation: automation, on-demand mobility and ride-sharing are set to revolutionize the way we travel. The forthcoming adoption and commercialization of AVs are expected to have extensive impacts on our road networks, congestion, safety, land use, public transportation (PT) and more. Many companies ranging from large technology companies like Google and car original equipment manufacturers (OEMs) like Ford to smaller startups like Nutonomy are aggressively exploring opportunities in this area. These rapid advances in AV technology are convincing many that AV services will play a significant role in future transportation systems. The advancement of AVs presents both opportunities and threats to transportation. It has the potential to significantly impact: traffic congestion and fuel consumption, traffic accidents, the need for parking, and demand for transport and VMT (vehicle miles traveled), especially for people that are not able to drive such as children and elderly people [1]. Motivated by the potential of autonomous vehicles, authorities around the world are preparing for this revolution in transport.

It is essential to integrate autonomous vehicles (AV) with public transportation (PT) and other active modes to realize urban transportation planning goals of affordable, sustainable, and seamless urban mobility. This is because for a transportation network to be effective, it needs both the efficiency of mass transportation to move large amounts of people as well as the flexibility of personal transport to get travelers to their unique destinations. However, the interplay between AV and PT is understudied, and the extent and nature of AV's impacts on public transit are uncertain. There is a concern that AV may adversely impact the ridership, revenue, and general viability of public transportation systems. However, in a study done in 2015 [2], only 2 of the 25 largest MPO in the US mentioned autonomous vehicles in their official long-range regional transportation plans, indicating perhaps that these MPOs are uncertain of how to prepare for this technology.

In the past few years, the online-enabled on-demand mobility services have attracted considerable mode share from PT in hundreds of cities around the world. The convenience of hailing from a smartphone, ease of transactions, and economic efficiency of crowd-sourcing the rides have made these services very attractive to consumers. It is anticipated that AV technology may further improve the economics of such services by reducing the operational costs. More travelers may leave PT for autonomous on-demand mobility services of the future. This can be considered a threat to not only public transportation itself but also the social values it protects in our societies such as equity, accessibility, and environmental sustainability.

To identify and create synergistic opportunities between AV and PT, and to plan, regulate and leverage the AV technologies towards supporting the PT systems are essential for cultivating an affordable, equitable, sustainable and efficient urban mobility system in the future. However, existing research on autonomous on-demand mobility systems [3, 4, 5, 6, 7, 8, 9, 10, 11] have provided little insight into the future of PT systems. Studies on integrated autonomous vehicle and public transportation (AV+PT) solutions have just begun very recently [12, 13, 14]. The design and operation of such a system is therefore an important research direction that requires significant investigation.

The research questions in this thesis, as a result, are 1) the design and evaluation of integrated autonomous vehicles and public transportation services, 2) the modelling of the interaction between travelers (demand) and operators (supply), and 3) the systematic optimization of fleet size and fare in the design of such an AV+PT mobility service.

First, this thesis proposes a simulation-based approach to the design and evaluation of integrated autonomous vehicle (fully autonomous level 4 and 5 as defined by the Society of Automotive Engineers International Taxonomy) and public transportation (AV+PT) systems. We highlight the transit-orientation by respecting the social-purpose considerations of transit agencies (such as maintaining service availability and ensuring equity) and identifying the synergistic opportunities between AV and PT. Specifically, we identified that AV has a strong potential to serve first-mile connections to the PT stations and provide efficient and affordable shared mobility in low-density suburban areas that are typically inefficient to serve by conventional fixed-route PT services. The design decisions reflect the interest of multiple stakeholders in the system.

Second, the interaction between travelers (demand) and operators (supply) is modeled using a system of equations that is solved as a fixed-point problem through an iterative procedure. In this, we developed demand and supply as two sub-problems. The demand will be predicted using a nested logit model to estimate the volume for different modes based on modal attributes. The supply will use a simulation platform capable of incorporating critical operational decisions on factors including fleet sizes, vehicle capacities, sharing policies, fare schemes and hailing strategies such as in-advance and on-demand requests. Using feedback between demand and supply, we enable interactions between the decisions of the service operator and those of the travelers, in order to model the choices of both parties.

Third, this thesis systematically optimizes service design variables to determine the best outcome in accordance to AV+PT stakeholder goals. Optimization objective functions can be formulated to reflect the different objectives of different stakeholders. In this thesis, we specifically propose and develop a simulation-based service design method where we quantify various benefits and costs to reflect the objectives of key AV+PT stakeholders. We simulate the service with different sets of system settings and identify the highest performing set. We employ a case study of regional service contracting to showcase the ability of this method to inform AV+PT service design.

In this thesis, we test our approach with a case study area in a major European city on an agent-based simulation platform, amod-abm [15]. Agent-based simulation has the advantage of capturing individual (agent) behaviors and the interactions of the various individual agents in a realistic synthetic environment where the intent is to re-create a complex phenomenon of mobility on demand service delivered by AV. Although this thesis will focus on a major European city, the general framework and methodologies proposed here can be widely applicable.

1.1 Organization

The thesis is structured as follows:

- Section 2 presents a literature review of the most relevant works and identifies the research gaps. It begins with a review of the state-of-the-art large-scale agent-based autonomous vehicle simulation models. It follows with a discussion on simulation-based design and logsum as a utility measure of consumer welfare. Finally, it presents the existing literature on preference for AVs and traveler responses.
- Section 3 presents the AV+PT service design in three aspects: operating mode, fleet management, and fare policy. It also outlines the key stakeholders, their interests and associated performance indicators.

- Section 4 proposes the methodology for formulating the supply-demand interaction as well as the agent-based simulation tools.
- Section 5 presents the case study area in a major European city. The analysis of the area's current travel demand relies on an annually sampled travel demand survey of local households. Consequently, the data is used for the construction of the nested-logit mode choice model and the specification of a new AV+PT mode.
- Section 6 uses the case study area in a major European city to evaluate the performance of the transportation system based on design decisions. In the first subsection, we test the decisions variables: hailing policy, fleet size, vehicle capacity, and preference to service. For each of these we selected a subset of simulation scenarios to test the viability of the proposed service. The second subsection will describe the formulation of the objective function and how each benefit and cost will be quantified. Then it will detail simulation results from a case study of regional service contracting to showcase the ability of this optimization method to inform AV+PT service design.
- Section 7 concludes and discusses future research questions.

Section 2

2.0 Literature Review

2.1 Agent-based Simulation

Spieser et al. [16] are among the first to conceptualize the shared AV system as an enabling technology for future urban mobility. Based on the analytical models, they prove that ideally shared AVs would reduce the total number of vehicles in the system to one third, assuming all modes of personal transportation are replaced by AVs that are shared. Moreover, it is also argued that shared AV reduces the trip cost by half since it eliminates the time consumed for active driving, parking, and maintenance.

Agent-based simulation has recently become popular in AV research for its advantages in capturing individual behaviors, enabling dynamic operations and accounting for stochasticity. The successive works by [3] are representative of agent-based simulation applications, in which issues such as dynamic ride-sharing, fleet sizing, and operational costs have been discussed from the perspective of operators [3, 4]. Similar simulation frameworks could also be found for applications in Singapore [5], Lisbon [6], Toronto [7], New Jersey [8], Delft[9], Berlin[10], Zurich[11], Shanghai[17], Seoul [18], and New York [19]. The scale and scope of research are being gradually expanded to include emissions, congestion and parking implications.

The aforementioned research papers demonstrate that AVs have the potential to engender better system performance. On the supply side, many studies have assumed a station-based system to reduce the complexity of dispatching and routing. More recent simulations use a free-floating system with door-to-door service. If electric autonomous vehicles are considered, the placement of charging locations becomes an important supply side discussion.

Meanwhile, some other researchers take a different perspective by investigating travel behavior from the demand side. Martinez and Viegas [20] investigate travel behavior using a nested logit mode choice model to predict mode shares – they include non-shared AV as a competing mode in their model. Levin and Boyles [21] adopt the four-step model to include non-shared AV as a competing mode. A nested logit model is used to predict its mode share. The results indicate that AV trips will sharply increase while transit ridership declines and road congestion increase. Childress et al. [22] use activity-based travel demand simulation and reach the same conclusion. Azevedo et al. [23] also use an activity-based travel demand Model (SimMobility) to study the effects of implementing an on-demand shared AV service while restricting private transport use in the case study region in Singapore. They found that of 38% of private transport mode share, only 4% goes to public transport while the vast majority (32%) goes to the new shared AV mode. Correia and van Arem [9] found a 17% VMT increase when all private vehicle is replaced with automated ones in the city of Delft using a mode choice model between private vehicle and public transit. Chen and Kockelman [24] and Qiu et al. [25] argue that, if shared AV is used instead and pricing strategies are designed deliberately, on-demand shared AVs could capture significant market share to be profitable without inducing extra traffic. A summary of the large-scale agent-based simulation applications in literature is provided in Table 2.1.

However, none of the existing papers incorporate the demand model into the AV+PT simulation, nor do they model the interaction between demand and supply as traveler behavior changes in reaction to the level-of-service change. Also, existing works apply generic AV system design and ignore the uniqueness of transit system and its social-purpose considerations, such as maintaining service availability and ensuring equity and affordability.

2.1.1 Agent-based Simulation – Transit Considerations

As shared AV's availability grows, it will take some of the market share of public transportation, unless planned on a mutually complementary basis. The idea of integrated AV+PT systems is first illustrated by Lenz and Fraedrich [26] as "broadening service options of public transport" by providing multimodal service in less dense areas. Liang et al. [12] use integer programming models to study AV as a last-mile connection to train trips. Vakayil et al. [13] then develop an AV+PT hybrid system and emphasize its potential for reducing total vehicle miles traveled and the corresponding negative externalities such as congestion and emissions. Shen et al. [14] use agent-based simulation to explore the idea of supporting bus operations and planning with AV service as a complement. In their paper, high-demand bus routes are preserved while low-demand ones are re-purposed and shared AV comes in as an alternative for first mile trips. Results indicate that the integrated system would benefit both AV and PT operators.

The service design of the work in this thesis reflects transit considerations. First, the mode choice model includes the creation of a new AV and PT combined mode. Second, the service focuses on transit-specific trips such as first-mile connections to public transportation. Third, the design framework embodies the considerations of transit agencies through including high service availability and seeks to make the service more equitable through in-advanced requests for underserved areas.

Furthermore, in the simulation-based optimization design section, the benefits and costs quantified in the objective function include welfare, decongestion due to single-occupancy vehicle reduction, lost public transit revenue, and health considerations due to active mode share decrease and emissions. These reflect the considerations of many cities and transit agencies.

Table 2.1 Large-scale Agent-based Simulation Applications in Literature

Paper	Assumptions			Research Study Objective
	Study Area	AV Demand Prediction	Supply	
[3]	gridded map	random trips	AV	fleet size, system performance, emissions, energy consumption
[4]	Austin	2-10% of all trips	AV (station-based)	fleet size, system performance
[6]	Lisbon	all taxi trips	AV (station-based)	fleet size, vehicle capacity, system performance, cost
[20]	Lisbon	all taxi trips	AV (station-based)	fleet size, system performance, modal shift, emissions
[17]	Shanghai	mode choice model	AV (station-based)	system performance, charging strategy
[5]	Singapore	car trips in CBD	AV	fleet size, system performance
[18]	Seoul	all taxi trips	shared AV	fleet size, system performance
[19]	New York	all taxi trips	shared AV	fleet size, vehicle capacity, system performance
[9]	Delft	all modes trips in City	AV	system performance
[10]	Berlin (2)	all car trips	AV	fleet size, system performance
[11]	Zurich (3)	all car travel trips	shared AV	fleet size

2.2 Simulation-Based Optimal Service Design

Given all the potential opportunities of AV systems, it is important to optimize the benefits that AVs can provide. From an urban transportation perspective, public agencies focus on delivering the most benefit to the transportation system when developing an AV+PT service. This goal can be identified as specific objectives - some of the most prominent are improving cost-efficiency and providing travel alternatives to single occupancy automobile.

In this subsection, two areas of literature will be reviewed for simulation-based design. The first is focused on the systematic optimization of mobility service decision variables (e.g. fare, fleet size) in large scale agent-based simulations in literature. The second is based on one of the benefits quantified in the objective function discussed in section one, utility-based welfare. This includes a review of the measure of logsum as a utility-based welfare measure. The use of the logit model allows us to use the logsum as an evaluation measure, a method applied to quantify the impact of transportation projects, transportation policies, and to measure accessibility. This section will review the measure, existing practices, and its potential to serve as a reflection of welfare as an objective function in simulation-based design.

Majority of the existing research in simulation of AV's assume a priori design characteristics for service design areas such as fare, vehicle size, etc. This is true even for fleet size, a design variable that should be heavily tailored to a particular study area as it has a particularly strong effect on the system performance. Some of the existing experiments have used decision rules when choosing the fleet size. Zachariah el al. [27] simulated an area wide autonomous taxi system in New Jersey where they used an infinite fleet size. In Boesch et al.'s [28] case study in Zurich, the size of AV fleets was determined based on the number of cars that was required to serve at 95% of all requests within 5 min. When Martinez et al. [6] assessed the impacts of shared self-driving taxis and taxi buses in Lisbon, they replaced current car, taxi, and bus trips and found the fleet size as an output of the simulation by measuring the number of vehicles that are required in the simulation to satisfy a predefined service (defined using service characteristics like vehicle availability, waiting time, etc.). Finally, Zhang et al. [29] explored the impact of shared autonomous vehicles on urban parking demand. The final ideal fleet size in their model is determined by the change of average waiting time in the system.

2.2.1 Simulation-Based Design in Large-Scale Agent-Based Simulation

In the studies that explicitly optimize AV supply characteristics, the literature has been heavily focused on fleet sizing. Fagnant and Kockleman [30] simulated SAV with varying fleet size and defined optimal fleet size from the economic perspective using fare, SAV capital and operational cost, and wait time penalty cost. Spieser et al. [31] assess the optimal fleet size by taking the cost of vehicles, customer walk away, and the expenses derived from moving empty. Wang et al. [32] determine optimal fleet size as the one that produces the least aborting, least vehicles, and most ride-sharing. This was done through continuously allowing for the generation of new vehicles to meet customer demand and for vehicles to be eliminated if it is "rarely used". More recently, transportation policy optimization was tackled in Zurich [33]. This paper sought to optimize fare policy of AVs based on two performance indicators as opposed to a single objective function. The indicators used are accessibility to represent the positive contribution of the transport system and the total vehicle kilometer traveled to represent the cost and externalities produced.

In this thesis, we seek to extend the existing literature through optimizing the service design variables according to a set of objective functions that represent various different stakeholders in urban mobility and then comparing the performance of transportation system to show the difference in service design variables using various objective functions.

2.2.2 Utility Based Approach to Consumer Welfare Assessment

Utility based measures have been popular in the past to evaluate the impact that transportation alternatives will have on the welfare of citizens. Specifically, the logsum of random utility choice models have been used to quantify user benefits resulting from transportation projects [34], policies [35, 36], and accessibility [37, 38, 39, 40, 41, 42, 43]. In this section, we provide a brief background and review of the logsum as a measure of consumer benefit.

The main purpose of generalized extreme value (GEV) models [44] is to predict the future choices of users by processing the past choice observations. However, the GEV models (including the logit family) can also be used for statistical estimation of the total benefit (e.g. consumer surplus or welfare) perceived from the set of alternatives available to the users. More specifically, the logsum term is a measure that estimates the expected maximum utility that a user in the system would perceive from the set of alternatives that are available to him/her. In this section, we outline how the logsum can be used to quantify: (1) the additional travel welfare gained from addition of a new travel modes, such as AV+PT, to the existing set of travel modes, and (2) various service designs that may result in different values of benefit perceived from the service. In order to discuss the logsum, we will first provide a background on random utility theory and discrete choice logit models.

Utility in transportation is an assessment of the value an individual derives from some set of travel options; it represents satisfaction experienced by the individual. Generally, we think about utility as being derived from different attributes of each alternatives. The attractiveness of each alternative can then be modeled as a linear function of its attributes, called the 'utility function'. The utility function can be decomposed into two main portions. The first is the observable portion of the utility that is constructed based on the observed attributes of the alternative. The second is the difference (or error) between the systematic expectation of utility (based on observed attributes) and the actual utility experienced by the traveler [45]. Such difference may relate to error in measurement of attributes, missing attributes in the utility function, and/or anomaly in individual behaviors, etc.

$$(1)\begin{cases} U_{in} = V_{in} + \varepsilon_{in} \\ V_{in} = \Sigma\beta_{ik} * \mathrm{X}_{ink} \end{cases}$$

In equation 1, U_{in} is the actual utility of choice i perceived by person n, V_{in} is the systematic utility of person n, and ε_{in} is the difference between the actual utility of choice and systematic utility, or also known as the random error term. $\beta_{ik}$is the is the parameter which defines the direction and importance of the effect of attribute k on the utility of an alternative and X_{ink} is the value of attribute k for alternative i perceived by person n.

The individual i is assumed to choose an alternative if the utility is greater than that of any other alternative. Using some assumptions, utility models can be used to represent measure the consumer surplus. These assumptions are that consumers have consistent and transitive preferences over the alternatives available in their choice set, there is translationally invariant distribution of the random elements of utility, and error terms are identically and independently distributed Gumbel distributions [46].

The basic multinomial logit model (a very common application of GEV) can be formed if we assume (1) the error components are extreme-value (or Gumbel) distributed, (2) the error components are identically and independently distributed across alternatives, and (3) the error components are identically and independently distributed (iid) across observations/individuals. This model gives the choice probabilities of each alternative as a function of the systematic portion of the utility of all the alternatives, shown in equation 2 [46].

$$(2)\ \Pr(i) = \frac{\exp(V_i)}{\sum_{j=i}^{J} \exp(V_j)}$$

Where Pr(i) is the probability of the traveler choosing alternative i. The whole set of choices i is represented by J and the set of traveler's n is represented by N. In this equation, the logsum equals to the denominator $\sum_{j=i}^{J} \exp(V_j)$.

While, the multinomial logit model is commonly used and excels in ease of estimation and interpretation, it is commonly criticized for the independence of irrelevant alternatives property (IIA). The IIA property dictates that the likelihood of choosing any two alternatives is not related to any other alternatives in the choice set because they are deemed to be irrelevant – a direct result of the independence of error terms assumption in the utility of alternatives. This property creates a major limitation as it implies equal competition between all pairs of alternatives. It is difficult to justify this when some alternatives compete more closely with each other than they do with the rest of the alternatives in the choice set. Other models can be derived through different assumptions on the error distribution of alternative utilities. One of the simplest and commonly used is the nested logit model, where the alternatives are considered as ordered in a nested tree structure. The utilities of alternatives choices in separate nests are deemed to be iid but not within a nest. This allows for substantially more flexibility in representing differential competitiveness between pairs of alternatives through complex tree structures. The formulation of the nested logit is show in equation 3 and 4 [46].

$$(3)\ \Pr(i|C) = \frac{\exp(\mu_m V_i)}{\sum_{j \in C_m} \exp(\mu_m V_j)} \frac{\exp(\mu V_m')}{\sum_{k=1,\dots,M} \exp(\mu V_k')}$$

where

$$(4)\ V_m' = \frac{1}{\mu_m} \ln \sum_{j \in C_m} \exp(\mu_m V_j)$$

$\Pr(i|C)$ is the probability of choosing mode i $\in C_m$. V_i is the utility of mode i from choice set C. C_m is a nested mode set with utility V_m', m = 1, …, M if M nested sets are available.

The consumer surplus in general logit models can be calculated using the systematic utility of the mode choice model or the denominator of the choice model (Logsum).

$$(5)\ B_n = E\left[MAX_{i\in C_n} U_{in}\right] = \frac{1}{\mu} ln \sum_{i\in C_n} \exp\left(\mu V_{in}\right) + C$$

$$(6)\ E[CS_n] = \frac{1}{\alpha_n} \frac{1}{\mu} ln \sum_{i\in C_n} \exp\left(\mu V_{in}\right) + C$$

In equation 5, the perceived utility benefit by a general traveler n is represented by B_n, μ is the scale parameter of the error term, and C_n is the set of all alternatives available to person n. In equation 6, CS_n is the consumer surplus of traveler n and α_n is the marginal utility of money. The consumer surplus is assumed to be equal to the expected maximum utility of all available choices which equals to the logsum term (denominator of the logit model). The monetized equivalent of the consumer surplus can then be found by dividing the expected maximum utility by the marginal utility of money. The absolute values of changes are not important when comparing different service scenarios, the change in logsum then will represent the utility gained or lost.

The logsum is especially appropriate in this research because welfare of citizens when considering new transportation is an especially salient consideration of the transit. Moreover, the utility of different transport modes, especially AVs, are subjective and perceived differently among users. Logsum is able to capture the random nature of user preferences through considering all alternatives available to the user as well as all measurable attributes. As a result, the logsum can act as a cumulative measure of the desirability of all travel choices available to travelers. Moreover, the strength of the logsum also lies in its ability to encapsulate a variety of attributes of the alternative in a single term that is easily computed [46].

2.3 Preference for AVs and Traveler Responses

In order to accurately capture the performance of autonomous mobility on demand services, it is essential to understand the demand response of consumers to the AV technology. Currently, the research focused on demand for AVs have been opinion studies, focus groups, and stated preference survey studies. This subsection aims to give an overview of research to understand traveler's preference for AVs. Specifically, traveler's preference for AV adoption, willingness to pay for AV use, and preference for AVs in relation to transit will be covered.

AVs promise to solve many problems that face today's travelers. First, riders will not have to be engaged with the task of driving and they will be able to devote their travel time to other activities. Second, new segments of the population that were previously restricted from driving, such as youth, will gain access to vehicles. Third, it will reduce the cost of travel and induce more demand for travel. Lastly, self-driving cars will likely lead to a redesign of the interior of cars, allowing a shift in the way vehicle space is used and again affecting travel experience. Considering all the potential advantages, one of the main obstacles in the adoption of this technology will be people's willingness to trust such a technology and accept new travel paradigms. In particular, people do not feel comfortable using a new technology that has not been proven to be safe [47, 48].

When considering preference for the use of AVs, studies have found a wide range of opinions among users. Schoettle & Sivak [49] found that people have high levels of concern about riding AVs in China, India, Japan, U.S.A, U.K., and Australia. As well, Alessandrini et al. [50] showed that users do not perceive automation to be valuable when there is not savings in travel time and fare. However, in a mode choice experiment, Bansal and Kockelman [51] found that 40% of the respondents in their online survey are willing to use a private AV and this figure rose to 50% in Zmud et al.'s [52] Austin sample. Studies when considering people's decision to buy or use AVs as taxi service showed that there is support for replacing ownership of private vehicles with AVs as a second vehicle but very little support for full reliance on AVs as taxi service. In studies, it was shown that few respondents would fully rely on taxi services, 50% of the respondents in Silberg et al. would give up the household's second car [53] and 23% would reduce vehicle ownership in Zmud et al. [52]. Moreover, socio-demographic variables have a strong impact on preference for AVs. The strongest tendency towards AVs are shown among male and youth. As well, it was shown that people with higher income were more willing to pay for autonomous technology [54].

In Bansal, Kockleman, and Singh [55], it was found that 41% of respondents would pay 1 USD per mile, a very competitive price. However, Kyriakidis et al. [56] found that from data collected from 109 countries, 22% of respondent stated that they would not pay more for AVs but 5% said that they would pay more than $30,000 extra for autonomous capabilities.

One of the first surveys of the preference of travelers regarding the integrated AV+PT system is done by Yap et al. [57]. Based on a mode choice model, they found that the VOT for AVs is higher when compared to manually driven vehicles as an egress mode on train trips. One of the main factors contributing to this is that egress trips are short, many people may not mind driving for short distance, some may even enjoy it. However, for longer trips people may be more concerned with capitalizing on many of the benefits that AVs can bring such as allowing for people to use their time productively. Moreover, it is found that first class train travelers prefer to use AV when compared to other non-private vehicle options (bike/bus/tram/metro), concluding that this segment of the market has the highest potential especially at the early stages of the technology. A study done by Dong et al [58] focusing on perception of buses shows that a significant proportion of people will be willing to ride an attended driverless bus. This study shows that the road to acceptance (if achievable) will involve an intermediary phase. It is worthwhile to note that even if only a very small proportion of people do not agree with the use of AVs, transit authorities risk alienating that segment of the population.

Much has been learned from these studies about the perception of AVs and there were some intuitive and not intuitive results. However, we would caution in full acceptance of even the most intuitive results. This is a result of a shift in the entire travel paradigm and interactions of forces; anything from an operational system factor to human psychology like car pride could dramatically shift people's opinions on the technology.

In these results, we notice that the conclusions vary significantly across geographical locations. Moreover, it also varies significantly across time showing that people's opinions are very susceptible to change based on information given. We should then note that there is a strong likelihood that people's opinions of this technology will be significantly altered when the vehicles actually come to market and impact the day-to-day life of people. It is also unclear whether the shift will be positive or negative. However, in every study there is a significant proportion of people that are expected to be willing to adopt the technology, giving it a good base and ability to capture some market share right at the beginning. In our demand prediction, we address the uncertainty through the testing of a variety of alternative specific constants (ASCs).

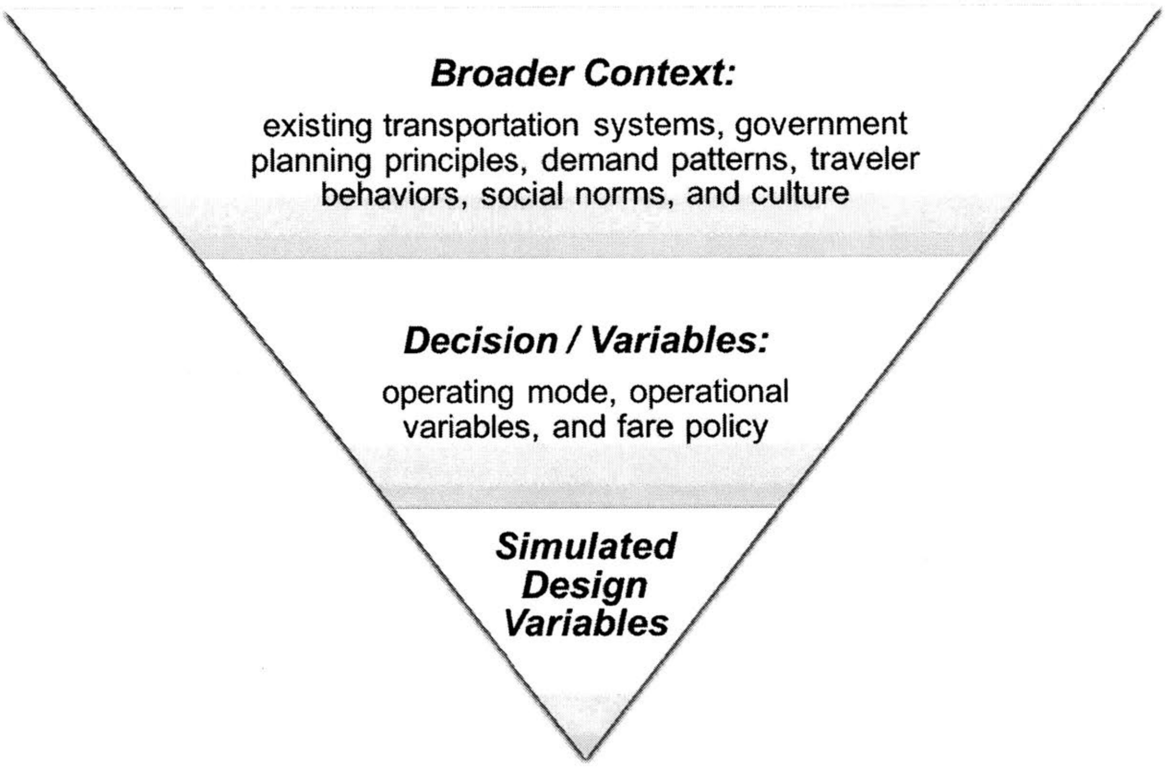
Section 3

3.0 Service Design and Evaluation Framework

3.1 Service Design

Depending on existing transportation systems, demand patterns, traveler behaviors, social norms, and culture, AV services may take different forms to fit the unique travel needs of each individual city. When AV and PT are integrated as a public mobility service, system design becomes even more challenging since government organizations often have more considerations such as focusing on system-level performance, enhancing sustainability and caring for the connectivity of all citizens [59]. A detailed discussion of the institutional settings and organizational relationships among the AV technology provider, AV operator, PT systems, and travelers in an integrated AV+PT system is presented in Freemark and Zhao [59]. Specifically, it is argued that local governments should leverage the period of time prior a full-sale AV rollout to establish a regulatory relationship with AVs to cultivate cities' planning objectives. Based on local government's current available regulatory mechanisms, the authors identify seven policy instruments that are feasible to promote normative principles of equitable, environmentally sustainable, efficient, and livable cities: centralized data collection and distribution; distance- and congestion-based road pricing; income-based subsidies; minimum level-of-service provisions; zero-emission vehicles; lowered parking provision; and a rethinking of the use of street space. In this thesis, it is assumed that the AV operator for the AV+PT service is part of the integrated system, fully respects regulatory mechanism laid out by governments (such as minimum level-of-service provisions), and behaves in the interest of the overall system objectives. This context paves the way for the discussion of specific decisions/variables. Figure 3-1 below diagrams how the broader context under which AV operates in leads to the decisions and variables that need to be considered and made, which subsequently impacts the specific simulation-based design variables that are considered.

Figure 3-1: AV simulation-based design relationship pyramid.



* This pyramid outlines how the broader context under which AV operates in leads to the decisions and variables that need to be considered and made which subsequently impacts the specific simulation-based design variables (discussed in Section 6) that are considered.

This section summarizes the AV+PT service design decisions/variables and outlines how they can be used to help achieve a city's planning goals. These decisions/variables are outlined in this section in three parts: operating mode, operational variables, and fare policy.

The operating mode decisions relate to two modal characteristic decisions: sharing policy and hailing policy. The sharing policy involves determining whether sharing is optional and how rides are paired. These decisions will affect the system efficiency at large, and the level-of-service as experienced by the users, such as wait time and travel time. Hailing policy includes the choice between on-demand and/or in-advance requests. On-demand services are desirable for users because it provides absolute flexibility both in time and space. However, the dispatching of vehicles would be more efficient if the requests are known in advance. Therefore, there is a tradeoff between service flexibility and system efficiency that can be captured in service design via hailing policy decisions. In addition to the two operating modes reflected in the proposed framework, other modal decisions can also be incorporated and tested similarly to achieve other social goals. For example, to guarantee that services will be provided to all and especially the disadvantaged, para-transit services can also be incorporated as another operating mode.

Operational variables consist of fleet size, vehicle capacity and dispatching strategies of the AV service. The choice of vehicle capacity and fleet size can dramatically impact system performance as well as operational cost. Traditional operators tend to use larger vehicles such as buses to minimize driving cost. The AV technology eliminates the cost of driving, therefore enables the usage of smaller vehicles and larger fleet for more flexible service when compared to traditional buses. This also raises the question of whether door-to-door service or trunk service (or a mix) would be more beneficial. In addition, AV provides another major advantage over human drivers since it fully complies with dispatching directions. This is not always the case with human drivers. As a result, it is possible to improve overall efficiency through the implementation of sophisticated real-time dispatching algorithms that optimize request-vehicle assignment, routing and rebalancing at the system level.

Fare policy is an extremely powerful tool to promote certain service goals. On one hand, the generated revenue from the farebox can, partially or even fully, pay the operational cost and even the capital cost of the AV fleet. On the other hand, service pricing could be used as leverage for demand management to promote active and sustainable modes of transport or achieve certain system objectives such as accessibility [60]. Due to the uncertainty with respect to operational costs, there is great ambiguity when considering AV+PT fares. Cost-based structure like ride-hailing fares appears to be most realistic and as such, in this paper, the fares will be structured with three components: base fare, per-unit-distance fare, and per-unit-time fare. To leverage pricing and promote sustainable travel behavior, sharing discount and transit transfer discount could also be applied. A high base or minimum price is also implemented as a strategy to discourage short AV trips which are usually made by active modes like walk and bike.

Each of the three parts in the AV+PT service design can be effectively modeled and simulated with our proposed tools and methodology.

In addition, it is worthwhile to note two other areas relevant to AV+PT service design. The first is that operators see AV's ability to execute exact orders as a major advantage over human drivers. Operators can improve overall efficiency through the implementation of specific and sophisticated dispatching, routing, assignment, and rebalancing algorithms. It should be noted that regulatory constraints should be taken into consideration, especially with respect to empty running. As well, when running an AV+PT service, there is the question of how the service will interface the customer and how it will cooperate with the current public transportation system. The payment platform could take shape in many different ways, but it should integrate with existing payment infrastructure to effectively combine the two services. As well, the AV+PT problem will be heavily focused on rail stations. As large batches of people get on/off the trains simultaneously, it is likely that this demand pattern will stress the capacity of the limited infrastructure that transit stations have for pickup/drop-off. Hailing strategy can be tailored to support this type of demand and information can be provided to operators in-advance so that they can better plan for such occurrences. These elements are not explicitly modeled and compared in our simulations.

3.2 Performance Evaluation Metrics

Performance metrics should be selected to evaluate the extent to which the interests of each stakeholder are met. In this thesis, we evaluate the performance with a series of indicators. For travelers, the level-of-service indicators include availability and total travel time. Availability is represented by service rate; the percentage of travelers being served given their time constraints. Total travel time consists of wait time and in-vehicle travel time. The in-vehicle travel time, when shared, is proportional to the detour factor, defined as the ratio of actual in-vehicle travel time to shortest travel time. As for the AV operator, the supply performance is evaluated by the operational cost. Specifically, the cost of operating one vehicle is represented by average vehicle distance traveled, which indicates the service and rebalancing distance traveled by a single vehicle within an hour. Another indicator related to supply performance is the distance-based average load, which measures the average load (number of travelers on board) weighted by the distance it travels (average occupancy). Based on these indicators, the design decisions such as fleet size, vehicle capacity, fare scheme and sharing/hailing policies can be simulated and evaluated. The indicators and the mode shares from the mode choice model also shed light on the transport performance of the city as a whole.

The design decisions reflect the interest of multiple stakeholders in the system, see Table 3.1. This table identifies the key indicators useful for the evaluation of simulation results in this thesis and is not intended to represent an exhaustive list of interests for all stakeholders.

Table 3.1: Stakeholders, Interests, Metrics and the Indicators Used in This Paper

Stakeholder	Interests	Performance Metrics	Indicators
Traveler	level-of-service	availability	service rate
		reliability	average wait time
		temporal cost	average wait time
			average detour factor with respect to time
	travel cost	fare	fare
AV Operator	financial viability	revenue	AV mode share
		cost	total vehicle distance traveled distance-based load
		market share	AV mode share
PT Operator	performance	ridership	PT mode share
		availability	denied boarding rate*
		punctuality	on-time rate*
	financial viability	cost/revenue	profit/subsidy*
Government	public equity	availability	service rate
		accessibility	wait time variability*
	sustainability	motorized traffic	average vehicle distance traveled
		non-motorized trips	active mode share
		shared trips	distance-based average occupancy
	total travel welfare	consumer surplus	logsum

* "*" implies indicators not applicable in the scope of this simulation.
** We assume PT operator to be not profit-driven.

Section 4

4.0 Simulation Framework

4.1 Simulation Framework

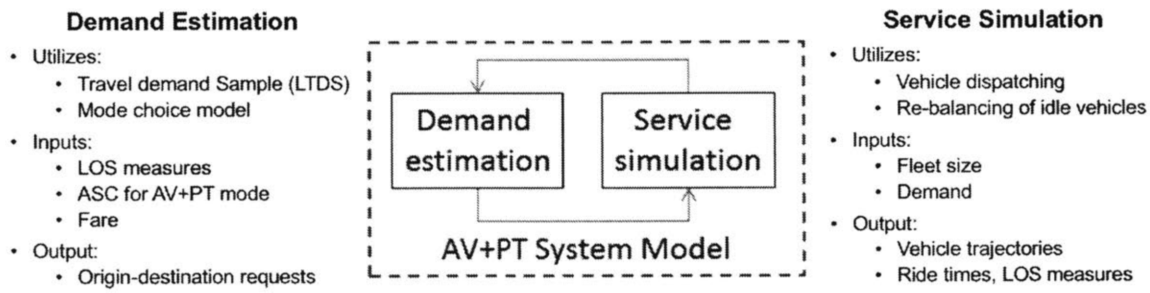
This section presents the methodology for the simulation framework and the demand-supply interaction. The level-of-service provided to travelers has a significant effect on mode choice (demand). Level-of-service is largely a result of system design and operational strategies; it should be studied together with supply provision. Figure 4-1 shows the process in which the interaction between demand and supply of shared AV services is modeled. The interaction process consists of two main areas, as shown in Figure 4-1. The left section represents the choices of travelers and also represents the fixed-point problem for demand prediction equilibrium. This section uses the travel demand data sample and mode choice model to process inputs (level-of-service, preference to AVs (ASC), and fare) and outputs the origin and destination requests. When level-of service indicators are unknown, they will be initialized with an empirical value. The right section represents the choices of the operators where the supply performance is used to support the service design choices of the shared AV service. This section uses vehicle dispatching and re-balancing algorithms to process fleet size and demand specifications to output vehicle trajectories, ride times, and level-of-service measures.

In the agent-based simulator, the level-of-service indicators are used as feedback between supply and demand. The system enables interaction between the decisions of the service operator and those of the travelers to model the choices of both parties. The simulation begins with empirically determined values of level-of-service indicators, assumed fare and shared AV preference, and historical travel data to determine the demand volumes of each OD pair. Then a set of supply assumptions and predefined system settings such as dispatching and rebalancing strategies will be applied. Using this information, the simulation is then able to evaluate the system performance by outputting level-of-service indicators for travelers and supply performance indicators for operators. The level-of-service indicators are then reflected in the mode choice model to update the demand prediction. This process establishes the demand-supply interaction process.

The formulation of the problem is presented as below:

$$(1)\begin{cases} \boldsymbol{D} = MODECHOICE(\boldsymbol{T}, \boldsymbol{L}, \boldsymbol{V}_d, \boldsymbol{S}_d) \\ \boldsymbol{L} = SIMULATION(\boldsymbol{D}, \boldsymbol{V}_s, \boldsymbol{S}_s) \end{cases}$$

Figure 4-1: The demand and supply interaction process.



In equation 1, MODECHOICE is the demand prediction sub-problem and SIMULATION is the simulation sub-problem. MODECHOICE takes the matrix of total current trips **T**, level-of-service indicators **L**, demand decision variables $\mathbf{V_d}$ (e.g. fare), and other demand assumptions $\mathbf{S_d}$ (e.g. alternative specific constant for AV) as input.

The matrix of total current trips **T** that is used as an input in MODECHOICE subproblem is derived from the sample of trips on all modes recorded in the household travel survey and expanded to match the population. The MODECHOICE output **D** is a vector of predicted OD-specific demand for AV+PT service. Symmetrically, SIMULATION takes in predicted demand **D**, supply decision variables **Vs** (e.g. vehicle capacity, fleet size, hailing policy) and system assumptions $\mathbf{S_s}$ and gives estimates of level of service **L** and supply performance **P.**

To find the solution to the system of equations in (1), we apply an iterative fixed-point solution approach. The pseudo code to the proposed algorithm is shown in Algorithm 1. To update the solution from one iteration to the next, we use the method of successive averages (MSA) [61] as shown in line 9 of the algorithm. The procedure keeps updating **D, L,** and **P** iteratively until **D** converges to a fixed-point solution and the demand-supply reaches balance and SOLVEFIXEDPOINT returns the estimated performance indicators at convergence, for travelers and operators.

Algorithm 1 Fixed-point Solution

procedure SOLVEFIXEDPOINT ($\mathbf{T}, \mathbf{V_d}, \mathbf{S_d}, \mathbf{V_s}, \mathbf{S_s}$)
    let level-of-service indicators be arbitrary values $\mathbf{L}^{(0)}$
    $\mathbf{D}^{(0)}$ = MODECHOICE ($\mathbf{T}, \mathbf{L}^{(0)}, \mathbf{V_d}, \mathbf{S_d}$)
    let step counter $i = 0$
    do
        $i = i + 1$
        $\mathbf{L}^{(i)}, \mathbf{P}^{(i)}$ = SIMULATION ($\mathbf{D}^{(i-1)}, \mathbf{V_s}, \mathbf{S_s}$)
        $\mathbf{D}^{(i)}$ = MODECHOICE ($\mathbf{T}, \mathbf{L}^{(i)}, \mathbf{V_d}, \mathbf{S_d}$)
        $\mathbf{D}^{(i)} = \frac{1}{i}\mathbf{D}^{(i)} + \frac{i-1}{i}\mathbf{D}^{(i-1)}$
    while $\|\mathbf{D}^{(i)} - \mathbf{D}^{(i-1)}\| > \delta$
    return $\mathbf{D}^{(i)}, \mathbf{L}^{(i)}, \mathbf{P}^{(i)}$

According to the discussion in Section 3, designing an AV+PT service involves multiple stakeholders and the system design decisions should be made to reflect the interest of each party. In practice, the comprehensive performance metrics should be defined and examined on a case-by-case basis. Due to limited space, this thesis only evaluates the most important system design decisions from the perspective of key stakeholders summarized in Table 4.2.

Table 4.2 reports the parameters and variables in the AV+PT system simulation and design model. “Input” and “output” parameters represent the inputs and outputs of the simulation model. “Demand decisions” and “supply decisions” refer to variables that users of the software are able to control. These variables will be either studied, explicated or assumed. “Assumption” outlines the variables with assumed values. “Intermediate” represents intermediate variable in the formulation of demand-supply fixed-point problem.

Table 4.2: Parameters and Variables

Vector	Parameter/Variable	Type
level-of-service (**L**)	AV service rate (SR_{av}) AV wait time (WT_{av}) AV detour factor (DF_{av})	output output output
supply performance (**P**)	AV vehicle distance traveled (VMT_{av}) AV distance-based load (L_{av})	output output
supply decision variables (**Vs**)	AV vehicle capacity (K_{av}) AV fleet size (V_{av})	decision decision
Supply assumption ($\mathbf{S_s}$)	AV maximum wait time (MWT_{av}) AV maximum detour factor (MDF_{av}) period of simulation (T) period of study (T_s) period of warm-up (T_w) period of cool-down (T_c) interval of assignment (T_a) interval of rebalancing (T_r)	assumption assumption assumption assumption assumption assumption assumption assumption
demand decision variables ($\mathbf{V_d}$)	AV base fare (c_{base}) AV per-unit-time fare (c_{time}) AV per-unit-distance fare (c_{dist}) AV leg minimum price (MP_{av}) discount for sharing ($DC_{sharing}$) discount for transfer ($DC_{transfer}$)	decision decision decision decision decision decision
predicted demand matrix (**D**)	(see section 5.2 for more details)	intermediate
total current trips (**T**)	(see section 5.2 for more details)	input
demand assumptions ($\mathbf{S_d}$)	preference to AV (ASC) penalty wait time (PWT) (see section 5.2 for more details)	assumption assumption assumption
supporting variables	cost of a shared AV trip (C) actual travel time (TT) shortest travel time (ST) shortest travel distance (SD) adjusted wait time (AWT)	intermediate intermediate intermediate intermediate intermediate

* Types "input" and "output" represent the inputs and outputs of the model respectively.
** SR, WT and DF require being initialized to start the iteration.

4.1.1 SIMULATION Sub-Problem

In our simulator, the level-of-service indicators in **L** that serve as the feedback values between supply and mode choice are service rate SR, wait time WT, and detour factor DF. We incorporate the demand-supply interaction into the simulation sub-problem. The sub-problem **L** = SIMULATION (**D**, $\mathbf{V}_s$, $\mathbf{S}_s$) is implemented within a continuous-time agent-based simulation platform. The pseudo code for SIMULATION is shown in Algorithm 2.

Algorithm 2 Agent-based Simulation

procedure SIMULATION (**D**, $\mathbf{V}_s$, $\mathbf{S}_s$)
    initialize the system according to $\mathbf{V}_s$ and $\mathbf{S}_s$
    $t = 0, t_a = 0, t_r = 0$
    while $t < T$ **do**
        generate next request with arrival interval $\boxed{\Delta t}$ and push into queue
        $t = t + \boxed{\Delta t}$
        if $t > t_a$ **then**
            assign pending requests in queue to vehicles
            $t_a = t_a + T_a$
        if $t > t_r$ **then**
            rebalance the idle vehicles
            $t_r = t_r + T_r$
        route the vehicles to t
    return L, P based on service performance during T_s

The variable **K** represents vehicle capacity and the variable **V** represents fleet size.

In this platform, the demand is drawn from a predefined set of origins and destinations in list **D.** The arrival of the requests was assumed to follow a Poisson process of constant arrival rate, which is proportional to the OD-specific demand volume. The requests can be subcategorized as on-demand or in-advance depending on the settings of the user. All requests are subjected to a maximum wait time (MWT) and maximum detour factor (MDF). A thorough discussion of MODECHOICE can be found in subsequent section 5 along with the case study area in which the model was constructed for.

The central dispatcher dynamically assigns requests to vehicles using insertion heuristics. If any requests cannot be served within the maximum wait time then it will "time out" and the user is assumed to disengage with the shared AV service. The service rate is defined as the percentage of requests being served. The dispatcher also rebalances idle vehicles periodically to regain the balance between demand and supply and plan for the coming requests in the short future. The request-vehicle assignment is performed every T_a simulated seconds (30s here) and rebalancing is performed every T_r seconds (150s here).

After dispatching, the routing server updates the shortest routes in real-time using the Open Street Routing Machine (OSRM). OSRM is an open-source routing engine that applies contraction hierarchies or multilevel Dijkstra algorithm to calculate shortest paths using data from OpenStreetMap. The travel time between the two locations is static. In section 6.1 and all subsections of 6.1, the travel time is based on the average morning peak-hour travel time provided by OpenStreetMap. However, in section 6.2 and all subsections of 6.2, the travel time is based on values provided by a preprocessed Google API lookup table while the route is still generated using OSRM– for further details on the Google API routing times please refer to section 6.2

The simulation runs for T seconds, of which T_s seconds makes the period of study. Requests generated during T_s are used in the evaluation to calculate level-of-service L and supply performance P. L includes service rate, wait time and detour factor. P consists of vehicle distance traveled and distance-based load. The rest of the simulation time before and after T_s are warm-up and cool-down buffers. To summarize, $T = T_w + T_s + T_c$.

4.1.2 Vehicle Request and Assignment

The static version of the vehicle-request assignment problem is the vehicle routing problem. Typically, due to limitations in time and computational concerns, heuristic methods are often chosen in literature for dynamic ride-sharing problems. Most studies on dynamic ride-sharing consider one of the following specific objectives when assigning requests to vehicles: minimize the system-wide vehicle miles travelled for vehicles, minimize the system-wide travel time for the travelers, maximize the profit/benefit for the entire system assuming profit-driven or publicly-owned operator [62]. In this thesis, we propose to minimize the system-wide travel time for travelers.

The optimization of the system-wide travel time is a mixed integer linear programming problem. The insertion heuristic is applied to tackle this problem. The insertion heuristic approximates the solution by considering each new request independently from other passenger requests. The proposed method serves each request in a first-come-first-serve basis. It then searches for the best available vehicle for each request. The insertion heuristic takes the travel time value from OpenStreetMaps in section 6.1, but this was not feasible in section 6.2 due to the large volume of simulations. As a result, in section 6.2 the travel time was taken from a lookup table generated from OpenStreetMaps in advance. This lookup table consisted of the travel times between all trip origins and destinations, but when vehicles are not traveling on these known ODs, an approximation using Euclidian distance with constant vehicle speed is used to generate the travel time value.

In our simulator, rides are given on both an on-demand and in-advance basis. These differ in that the in-advance requests are known beforehand. Travelers will be notified of their assignment 30 minutes before the earliest departure time. Please refer to Wen's work [63] for further details.

4.1.3 Rebalancing

The rebalancing problem is considering how a vehicle can reposition itself when it is not actively in use. Repositioning vehicles allows for us to better match vehicle supply to demand. The objective of rebalancing is to maximize the service availability while limiting the rebalancing cost. Service availability is evaluated by the average wait time of requests emerging within the period and rebalancing cost is represented by total vehicle rebalancing distance traveled. There are two types of rebalancing applied in our simulations. The first is called the "simple anticipated rebalancing", where every vehicle uses local knowledge on the neighboring areas to predict the best zone it can rebalance to. The probability that a vehicle moves to a new zone is proportional to the number of predicted requests in that zone. The approach is less computationally intensive in comparison to more sophisticated algorithms. Due to this, it was adopted in section 6.2 to accommodate for the large amount of simulations needed. The second is the "optimal rebalancing problem" where an objective function is set to maximize service availability by maximizing total expected number of requests that can be served. The optimal rebalancing problem is a Mixed Integer Nonlinear Programming problem. Although it achieves better performance, it is computationally burdensome. To tackle this issue, Wen proposed a combination of incremental optimal and branch-and-bound methods to give a close approximation to the optimum [63]. This is referred to as heuristic optimal rebalancing (HOR) and was employed in section 6.1. Please refer to Wen's work [63] for a case study comparing the performance of both methods and further details.

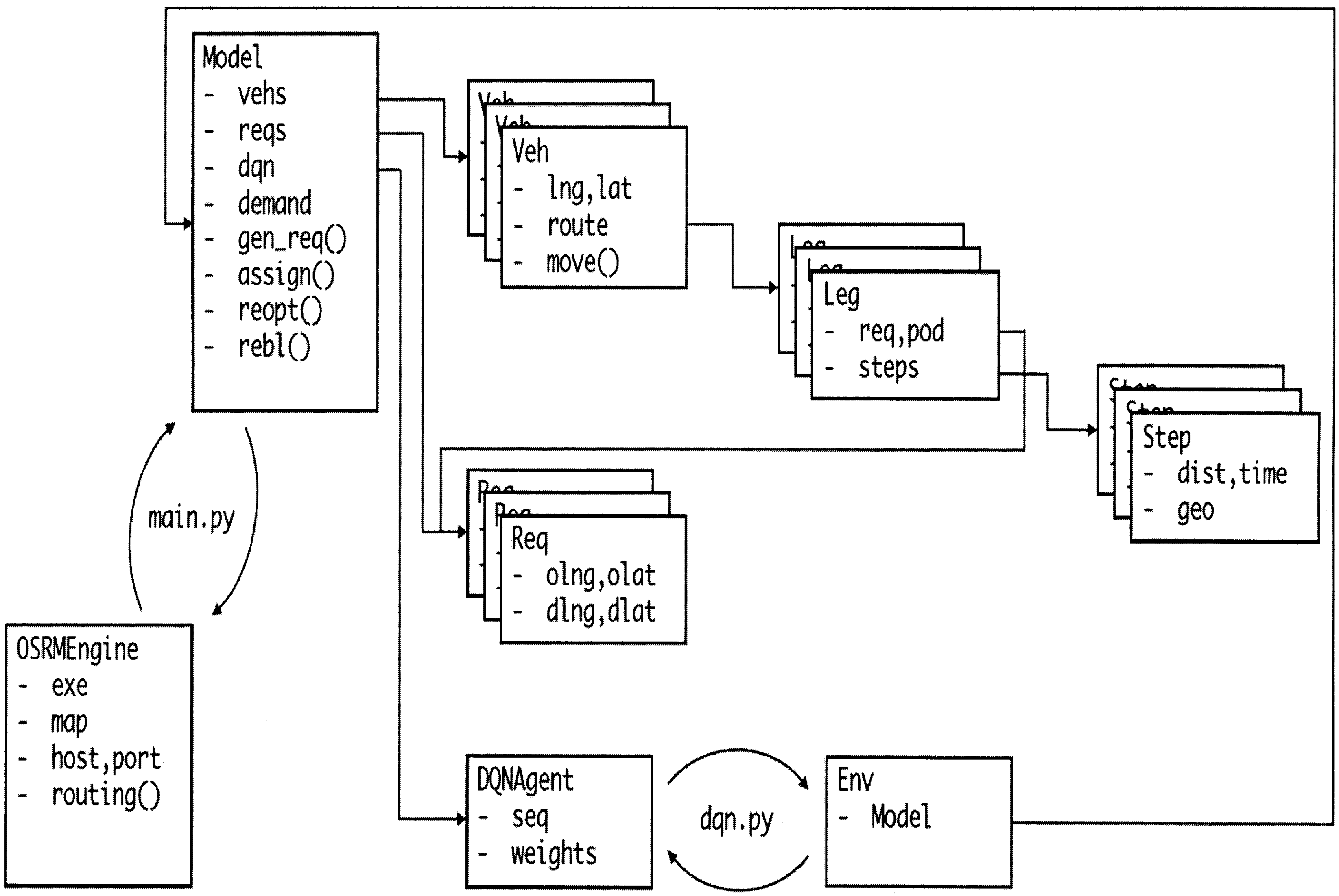
4.1.4 Platform Overview

The simulation is an agent-based simulation platform coded in Python 3. The platform is able to simulate door-to-door shared AV service. It services generated requests with a fixed fleet size of autonomous vehicles with predefined operational methods and dispatching strategies. An open source version of the code can be found in [15]. The following is a list of classes and data structures currently available in the simulation platform:

- Class Model for shared AV systems, with central dispatcher and fleet of autonomous vehicles
- The demand matrix **D** from MODECHOICE sub-problem, with demand volumes for a list of OD pairs - the demand is time-invariant
- Class Veh for shared AVs that can accommodate vehicle capacities from 1 to 4
- Class Req for processing requests (on-demand or in-advance) generated based on the demand matrix
- Class OSRMEngine for connecting the OpenStreetMap database with the Open Source Routing Machine (OSRM) [64]
- Class Leg and class Step for processing route information;
    - Each route assigned to a vehicle can have a single or several legs and each leg consists of multiple steps
    - Each step is denoted by a connected sequence of straight line segments (polyline) and travel speed within a step is constant

Figure 4-2 shows the dependency between classes.

Figure 4-2 Class dependency in simulation platform.



Section 5

5.0 Case Study and Demand Model

5.1 Case Study Area

In order to support the presentation of the mode choice model and demonstrate its capability in a real urban setting, we select a case study area in a major European city. This city has an extensive and developed transportation network in which public transport has a high mode share (45% in 2015). Commuter rail travel has shown strong growth over the past decade, providing good service from the outskirt of the city to the downtown area.

The case study area is a spread-out residential area located about 25 kilometers outside the downtown area. It is centered around a commuter rail station with frequent and high-speed train service to downtown. However, bus service in this area is infrequent and not economically efficient as a result of the low residential density. Consequently, local trips are particularly car-dependent. The area is chosen as the case study area because (a) it possesses a significant first-mile demand to the train station, (b) the inefficient bus service requires improvement, and (c) it has an appropriate density for initial AV trials. The local administrative boundary was enlarged to include all significant bus routes originating from the rail station. This enlarged area, 15km by 10km and home to around 159 thousand people, will be referred to as the Case Study Area (CSA).

5.1 Current Trips

The analysis of current travel demand relies on an annually sampled travel demand survey of local households. Pseudonymized historical trips made by households in CSA during the morning peak (6:30am to 9:30am) from 2005 to 2014 are used. This proportion contains 2709 respondents (1.7% of the population) and 1639 trips. It accounts for around 74,000 trips made by all residents after expansion (the expansion factor of a specific survey zone is the ratio of the number of residents to the number of completed surveys).

Seven modes are defined: walk, bike, car, taxi, bus, rail and park/kiss+ride (P/K+R). The multimodal trips are classified based on their distance-based main mode, except for rail and P/K+R. Rail is defined as all bus and rail trips that involves a rail leg and P/K+R is listed separately to target first-mile travelers with car access. Table 5.1 outlines the current mode share. "Trips to Downtown" represents trips that have origins in CSA and destinations in downtown (account for 11% of all trips). "Intrazonal Trip" represents trips that have both origins and destination in CSA (account for 54% of all trips). Note that "All Trips" consists of trip segments other than "Intrazonal Trips" and "Trips to Downtown", e.g. the trips from CSA to another area.

Table 5.1: Current Mode Share in CSA

Mode	All Trips	Trips to Downtown	Intrazonal Trips
Walk	20%	0%	32%
Bike	1%	0%	1%
Car	58%	10%	57%
Taxi	0%	0%	0%
Bus	8%	0%	10%
Rail	11%	74%	0%
P/K+R	2%	16%	0%

It can be noticed that CSA is very car-dependent with 58% of all trips and 57% of intrazonal trips using car. Trips to downtown are dominated by rail service because of the fast and direct rail connection. 74% of downtown trips are using rail as main mode, another 16% rely on car as the first-mile access. The mode share of bus is very small this is due very space demand and low level-of-service planned on bus route. The worst is the bus routes has only one planned run for every hour and has almost no ridership. Walk is popular for short intrazonal trips. Bike and taxi trips are very rare for all trips.

In this thesis, we denote the current trip origin and destination table by **T. T** and this is an input of the mode choice sub-problem MODECHCHOICE.

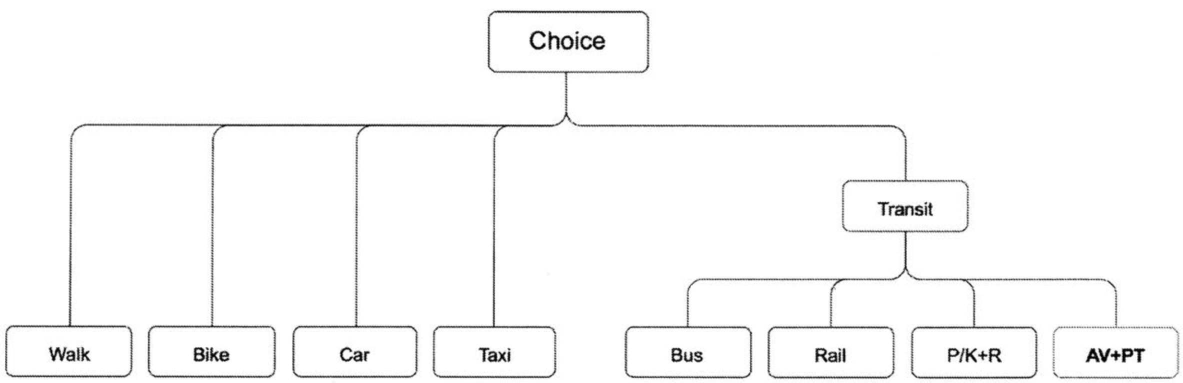
5.2 Mode Choice Model

The mode choice sub-problem $\mathbf{D} = \text{MODECHOICE}\ (\mathbf{T}, \mathbf{L}, \mathbf{D})$ is built upon a nested logit model. MODECHOICE is driven by historical trip data **T** and responsive to the level-of-service **L** as well as supply characteristics defined in **V** and **D**. The sub-problem is for the purpose of understanding the sensitivity of demand to modal attributes in CSA and allowing the demand estimation to be responsive to supply factors.

We suppose that individual traveler chooses among the available transportation modes for a specific trip and the discrete choice behavior follows the Logit model. The probability of shifting from any existing mode to AV+PT depends on the attributes of the new mode as well as the competence of the existing modes. We also assume no latent demand in this research.

After testing various model specifications with different variables both with and without nesting structures, we chose to apply a nested logit structure for MODECHCHOICE. This is shown in Figure 5-1. This structure was selected based on the model's performance when considering goodness of fit, likelihood ratio test as well as significance of coefficients and nest parameters.

Figure 5-1: Nested logit structure for mode choice model.



The existing choice set $\mathrm{C} = \{\mathrm{w}, \mathrm{k}, \mathrm{c}, \mathrm{t}, \mathrm{b}, \mathrm{r}, \mathrm{p}\}$ contains all seven modes. w, k, c, t, b, r *and* p are short for walk, bike, car, taxi, bus, rail and P/K+R respectively. V_i is the utility of mode i from C. C_m is a nested mode set with utility V_m', m = 1, …, M if M nested sets are available. Based on the utilities, the probability of choosing mode i $\in C_m$ is as below:

$$(2)\ \Pr(i|C) = \frac{\exp(\mu_m V)}{\sum_{j \in C_m} \exp(\mu_m V_j)} \frac{\exp(\mu V_m')}{\sum_{k=1,\dots,M} \exp(\mu V_k')}$$

where

$$(3)\ V_m' = \frac{1}{\mu_m} \ln \sum_{j \in C_m} \exp(\mu_m V_j)$$

The utility equations are defined as follows:

$$(4)\ U_w = ASC_w + \beta_{T,w}T_w$$
$$(5)\ U_k = ASC_k + \beta_{T,k}T_k$$
$$(6)\ U_c = ASC_c + \beta_{T,c}T_c + \beta_C C_w + \beta_N N_c$$
$$(7)\ U_t = ASC_t + \beta_{T,t}T_t + \beta_C C_t + \beta_{D,t}D_t$$
$$(8)\ U_b = ASC_b + \beta_{T,b}T_b + \beta_W W_b + \beta_C C_b + \beta_X X_b$$
$$(9)\ U_r = ASC_r + \beta_{T,r}T_r + \beta_W W_r + \beta_C C_r + \beta_X X_r$$
$$(10)\ U_p = ASC_p + \beta_{T,b}T_p + \beta_W W_p + \beta_C C_p + \beta_X X_p$$

ASC_i represents the alternative specific constant of mode i; T_i is the total travel time for all non-transit-related modes in 10-minute units; for bus, rail, and P/K+R, the walking time (for access and egress) is separated from the total travel time and is represented by W_i, and it is also measured in 10-minute units. C_i is the equivalent cost in U.S. Dollars ($); X_i is the number of transfers; D_i is the total travel distance in kilometers and N_i is the number of cars that the household owns. The mode-specific coefficient for travel time is denoted as $\beta_{T,i}$. The coefficient for walking time in transit modes is listed as β_W. Similarly, $\beta_{D,t}$ is the coefficient for taxi travel distance. β_C, β_X and β_N are the generic coefficients for cost, transfer and car ownership respectively. Also, $\mu_{transit}$ is denoted as the scale parameter of the transit nest (bus, rail, P/K+R and in the future AV+PT). Walking time and travel time for walk, bike, car, bus and rail are generated based on the fastest path during the morning peak using Google Maps API. Taxi and P/K+R times are estimated using car and transit respectively with an additional 3-minute wait for taxi mode.

Other attributes including travel costs are determined under the following assumptions:

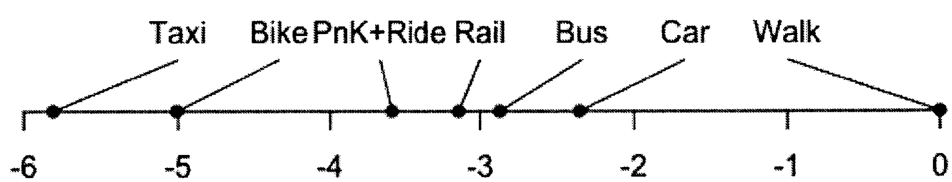
- The scale parameter μ in Equation 2 is set to 1.
- Walk: As the reference mode, ASC is set to 0.
- Car: Parking cost reflects the morning, commuting, and on-street parking cost. Congestion charging is $15.30 if a trip has origin or destination in the zone. Gas cost is $6.96/gallon with an average car fuel economy of 76.17km/gallon.

- Taxi: Cost is estimated based on workday, day-time price fares.
- Bus/Rail: Bus trips are defined as "bus-only" and the cost is \$1.73 per trip. Non-bus-only trip alternatives are dominated by rail and are as such classified as rail. Rail trips have distance-based fare based on a predefined fare scheme.
- P/K+R: Cost is assumed to be equivalent to transit travel cost.

The final model coefficients are estimated using PythonBiogeme [66]. With 1639 observations, the model has an adjusted rho-squared of 0.613. Grouping transit alternatives in the nesting structure produces a robust model and matches our intuition that transit modes should be correlated. The results are shown in Table 5.2.

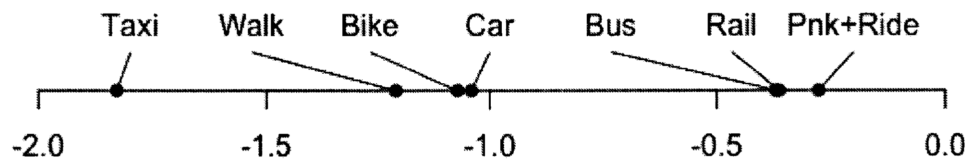
The ASC of walk is set to 0, whereas for all other modes ASCs are found to be negative. This indicates that in the absence of significant difference in other travel attributes (which is probably only true for short distance trips), walking is likely to be the first choice. The ASCs of all transit modes (bus -2.87, rail -3.14, P/K+R -3.58) and car (-2.35) are almost similar and less negative than others. The automobile network infrastructure and transit service provision have probably made these four modes dominant travel alternatives. Taxi and bike have very negative ASCs (-5.74 and -4.99), likely due to limited availability for taxi and necessary physical requirements for bike. Figure 5-2 shows the relative value ASC of each mode.

Figure 5-2: Number line of ASCs.



The coefficients for travel time (per 10 minutes) are almost similar for car (-1.04), bike (-1.07) and walk (-1.20). This is probably because in either of these modes the traveler has to be actively engaged and cannot make use of that time to engage in other activities such as reading, writing, etc. In contrast, the coefficients for transit related travel time are about a third of the previous group. In these modes, travelers are free to use that time for other activities. The transit parameter value for walking is slightly more negative than travel time for other aspects of transit travel. This is likely due to walking being viewed as more onerous. Figure 5-3 shows the relative value of travel time coefficient of each mode.

Figure 5-3: Number line of travel time coefficients.



Furthermore, the value of time of transit modes is about $20/hour. P/K+R has a slightly lower value of time at about $15/hour and walking time in transit has a slightly higher value of time at roughly $30/hour.

For the remaining three variables used in the mode choice model, it is shown that there is a negative correlation between number of transfers and utility. Roughly one transfer is equal to 12 - 16 minutes in transit, which is consistent with findings from the literature [67]. The positive value of car ownership correctly reflects the fact that people are more likely to choose car if it is available. Taxi distance is positive since the model already considers cost and travel time, showing that taxi with higher speed is preferred.

Table 5.2: Estimation Results of Mode Choice Model

Coefficient	Value	Standard Error	t-test	p-value
ASC_k	-5.01	0.42	-11.81	0.00
ASC_c	-2.35	0.20	-11.87	0.00
ASC_t	-5.81	1.12	-5.18	0.00
ASC_b	-2.87	0.23	-12.30	0.00
ASC_r	-3.14	0.30	-10.47	0.00
ASC_p	-3.58	0.49	-7.27	0.00
$\beta_{T,w}$	-1.20	0.08	-15.21	0.00
$\beta_{T,k}$	-1.07	0.23	-4.66	0.00
$\beta_{T,c}$	-1.04	0.11	-9.55	0.00
$\beta_{T,t}$	-1.83	0.90	-2.03	0.04
$\beta_{T,b}$	-0.37	0.07	-5.56	0.00
$\beta_{T,r}$	-0.36	0.08	-4.31	0.00
$\beta_{T,p}$	-0.28	0.08	-3.43	0.00
β_W	-0.54	0.11	-5.06	0.00
β_C	-0.11	0.03	-4.16	0.00
β_X	-0.45	0.17	-2.64	0.01
$\beta_{D,t}$	0.44	0.11	4.14	0.00
β_N	0.75	0.08	9.03	0.00
$\mu_{transit}$	3.23	1.19	2.71	0.01
$\overline{R}^2$	0.613			

The results of this model were then validated using a 5-fold Cross-Validation technique. Here we compare the predicted mode defined as the mode with the maximum probability of being chosen with traveler's actual choice. The results showed that over 60% predication was able to be consistently achieved, these can be found in Table 5.3.

Table 5.3: Proportion of Traveler's Choice that was Able to be Predicted Using Mode Choice Model

Trail Number	Proportion Predicted
1	0.631
2	0.626
3	0.639
4	0.682
5	0.631

5.3 Assumptions and Decision Variables

As for the assumptions $\mathbf{S_d}$, when AV+PT mode becomes available in CSA, it can serve both first-mile trips to the rail station and intrazonal trips that replace car and bus. As such, one typical AV+PT trip may have both AV and PT legs and we put AV+PT in the transit nest of the model. The coefficient for AV travel time ($\beta_{T,av}$) is assumed to be the same as bus, as travelers are not engaged. The coefficient for PT travel time ($\beta_{T,pt}$) is same as rail. The coefficients for cost (β_c) and number of transfers (β_x) also apply.

ASC reveals the intrinsic preference of travelers to the proposed AV+PT service when all independent variables such as travel time and travel cost are controlled. However, due to the lack of existing services, our knowledge of the AV preference is still limited. To tackle this in this research, we tested a wide range of ASCs in section 6.1.6 to show its potential effects on system performance. Since the AV+PT mode inherently takes characteristics of both car and transit modes, in this case, three ASCs are chosen to reflect this range: -3.58 (lower bound benchmarked by P/K+R), -2.35 (upper bound benchmarked by car) and -3.00 (the midpoint case, average of bus and rail).

Decision variables $\mathbf{V_d}$ in the AV+PT utility function include fare, which is important for AV operator as well as other stakeholders as discussed in Section 4.0. Here, the fare structure using base fare, per-unit-distance, and per-unit-time is also adopted:

$$(11)\ C_{av} = c_{base} + c_{time} T_{av} + c_{dist}\, D_{av}$$

C_{av} is the cost of the AV leg. T_{av} and D_{av} are travel time and distance. c_{base}, c_{time} and c_{dist} are per-trip-base, per-unit-distance, and per-unit-time parameters respectively.

Practically, in our simulation we benchmark the proposed AV+PT product with current market prices for similar services as follows: Zipcar currently rents cars to Uber drivers at the fare of \$3.658/hour (or \$0.061/min) and \$0.289/km [68]. These values can be used as proxies for the capital cost and the operating (fuel, insurance, depreciation, etc.) cost of the AV's. However, if the AV service is operated by a third-party contractor, the operational cost of the vehicle dispatch platform has to be taken into account too. For this purpose, we use the Uber revenue model. Uber has a fare of \$3.325/trip, \$0.199/min and \$1.033/km while taking 25% profit [67, 68]. This makes Uber's portion \$0.831/trip, \$0.050/min and \$0.258/km. Using the sum of these two prices, we can estimate the cost of providing the vehicle and insurance, taking into account the profit of the operators. In this case, we have:

$$(12)\ c_{base} = \$0.83, c_{time} = \$0.11/min, c_{dist} = \$0.55/km$$

To promote service goals relating to traffic congestion and sustainability and to reflect the transit-oriented principle, we assume that if any trip has a chance to be shared, the traveler cannot refuse sharing. In addition, a universal sharing discount DC_{share} is applied to remunerate travelers. In this case, T_{av} and D_{av} in fare computations are replaced by ST_{av} and SD_{av}, the shortest travel time and distance instead of the actual ones as below:

$$(13)\ C_{av} = (c_{base} + c_{time} ST_{av} + c_{dist}\, SD_{av})(1 - DC_{share})$$

A minimum trip price MP_{av} is also added to discourage short trips. As well, discount $DC_{transfer}$ is given if transfers are involved. The total fare for an AV+PT trip is therefore:

$$(14)\ C_{av+pt} = max(C_{av}, MP_{av}) + max((C_{pt} - DC_{transfer}), 0)$$

where C_{av+pt} is the total travel cost of the trip and C_{pt} is the cost of the PT leg.

5.4 Level-of-Service Indicators

The level-of-service of the AV leg is the missing piece of the demand estimation puzzle. As discussed in section 3.3, the indicator vector **L** could be determined using an agent-based simulation platform.

Assuming that indicators from SIMULATION are ready, average wait time and detour factor can jointly update the travel time of an AV leg. Since the service rate cannot always be 100%, we also introduce a penalty wait time for those who walk away, and we propose to use the adjusted wait time instead:

$$(15)\ AWT_{av} = WT_{av} \times SR_{av} + PWT_{av} \times (1 - SR_{av})$$

and

$$(16)\ T_{av} = AWT_{av} + ST_{av} \times DF_{av}$$

AWT_{av} represents the adjusted wait time, which is calculated using the following components: the average wait time WT for those served, the service rate SR_{av}, and the penalty wait time PWT_{av} for those rejected. In addition, DF_{av} represents detour factor and we therefore have T_{av}, for the travel time for AV leg.

Consequently, the AV+PT utility of any specific OD pair would be:

$$(17)\ U_{av+pt} = ASC_{av+pt} + \beta_{T,av}T_{av} + \beta_{T,pt}T_{pt} + \beta_C C_{av+pt} + \beta_X X_{av+pt}$$

T_{pt} is the travel time for PT leg. C_{av+pt} and X_{av+pt} are cost and number of transfers respectively. Based on U_{av+pt} for each of the OD pairs, the mode choice model is able to predict its demand volume. The output list of OD-specific demand volumes is noted as **D**. To start the interaction and solve the fixed-point problem, we initiate service rate, wait time and detour factor in **L** with arbitrary values. Arbitrary values are chosen because we have shown through experiments that the choice of initial values has limited impact on the convergence after a couple of iterations, this can be found in Wen et al. [71]. MODECHOICE takes **L** as input and outputs **D**. SIMULATION then takes **D** for **L** and **P**. The demand-supply interaction continues iteratively. Iterations reaches the balance and stops when the MSA condition is satisfied.

Section 6

6.0 Simulation Based AV and PT Design

In this section, we will cover simulation-based AV and PT service design. This will be done through a series of simulation experiments in two parts – shared AV+PT design experiments and simulation-based design. In the first, we will seek to study the performance of the AV+PT service in a set of simulation experiments. The second will seek to develop a systematic method of making supply decisions through optimization based on stakeholder interests.

6.1 Shared AV+PT Design Experiments

In this section, we will seek to explore the rules of AV+PT design in a set of simulation experiments.

6.1.1 System Settings

To study the performance of a shared AV system, we used an agent-based simulation platform [15]. The shared AVs will be modelled as a fixed-size fleet of taxi-like vehicles. For each vehicle, there is a potential to have up to 4 passengers on board at a time. Every trip has a chance to be shared if it meets the sharing criteria outlined in Table 6.2.

This section of the research is structured to test the viability of a first-mile shared AV service. Here, we focus on two segments of trips - those going to downtown and those that stay within CSA. As a result, all modes are included for trips going to downtown and only those that are bus and car are selected for intrazonal trips for simulation. Assumed values and demand decision variables in the simulation are listed in Table 6.1. These values are determined empirically and remain constant throughout the rest of the section.

Table 6.1: System Assumption Variable Values and Demand Decision Variable Values

Variable	Value
maximum wait time (*MWT*)	10 minutes
maximum detour factor (*MDF*)	1.5
period of simulation (T)	7200 seconds
period of study (T_s)	3600 seconds
period of warm-up (T_w)	1800 seconds
period of cool-down (T_c)	1800 seconds
interval of assignment (T_a)	30 seconds
interval of rebalancing (T_r)	150 seconds
penalty wait time (*PWT*)	20 minutes
base fare (c_{base})	\$0.83
per-unit-time fare (c_{time})	\$0.11/min
per-unit-distance fare (c_{dist})	\$0.55/km
discount for sharing (*DC*)	25%

The purpose of this section is to test the performance of the developed simulation model in capturing the fundamental relationships between the simulation input variables/parameter and the simulated results intuitively. We present a subset of scenarios in Table 6.2 for our simulation experiments. In each scenario, the ASC, fleet size, vehicle capacity, fare, and hailing policy are fixed.

A demand-supply interaction loop will be applied to capture the feedback between travelers (demand) and operators (supply). We define the convergence of the demand-supply interaction to be when the relative change of total demand from one iteration to next is less than 0.5%. We initiate the first demand estimation based on an assumption of 100% service rate, 300 seconds of wait time, and 1.00 detour factor for the demand-supply interaction.

The rest of this section is organized as follows. First, it will present the tradeoff between improving level of service and traveler experience, and the cost of larger fleet size and low occupancy. Second, it will outline how sharing capacity will impact level-of-service and fleet size. Third, it will explore how fare policy can impact the mode choice of travelers. Fourth, it will explore implications that hailing policy may have on customer experience. Fifth, it will detail the impact of intrinsic preference of traveler for AVs on system performance. Finally, it will conduct a thorough analysis of the effects that the AV+PT service has had on the mode choice of the CSA.

Table 6.2 System Settings and Simulation Scenarios

Simulation	Parameters/Variables					Scenarios for Target
	Fleet Size	Vehicle Capacity	Fare Policy	Hailing Policy	ASC_{AV+PT}	
Fleet Sizing (6.1.2)	See target variable	4	as in 6.1.1	as in 6.1.5	-3.00	200, 220, 240, 260, 280
Vehicle Capacity (6.1.3)	dependent	See target variable	as in 6.1.1	as in 6.1.5	-3.00	capacity = 1: fleet = 520, 560, 600, 640, 680 capacity = 2: fleet = 280, 300, 320, 340, 360 capacity = 3: fleet = 220, 240, 260, 280, 300 capacity = 4: fleet = 200, 220, 240, 260, 280
Fare Policy (6.1.4)	220	4	See target variable	as in 6.1.5	-3.00	original fare as in section 6.1.1 vs. no minimum price/no transfer discount
Hailing Policy (6.1.5)	220	4	as in 6.1.1	See target variable	-3.00	on-demand requests vs. in-advance requests
Preference to AV (6.1.6)	dependent	4	as in 6.1.1	as in 6.1.5	See target variable	ASC = -3.58: fleet = 100, 120, 140, 160, 180 ASC = -3.00: fleet = 200, 220, 240, 260, 280 ASC = -2.35: fleet = 350, 400, 450, 500, 550

* A parameter/variable being "target" indicates it's isolated and tested with a range of scenarios

** A parameter/variable being "dependent" indicates the choice of its value is dependent on that of the target

6.1.2 Fleet Sizing

This section evaluates the passenger level-of-service and performance of the system with respect to different fleet sizes. The level-of-service factors that are evaluated are service rate, wait time, and detour factor. The system performance indicators evaluated are vehicle distance travelled, load factor of vehicles, and final demand volume.

We have found that there is a tradeoff between benefits to travelers and operators with respect to fleet size. Results show that larger fleet sizes improve the level-of-service, but larger fleet size is known to boost operational costs. This tradeoff is shown in Figure 6-1. As fleet size increases, wait times get shorter and service rate increases (Figure 6-1c), producing a better level-of-service. This, however, comes at a price of increased service distance travelled (Figure 6-1b) and decreased average load, dropping from 1.30 to 1.16 in the blue curve in Figure 6-1d.

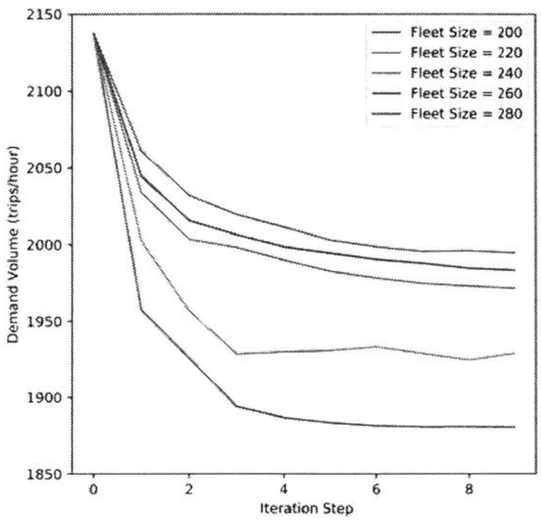
Moreover, we found that even when we initialized demand to be the same, demand volume converged to different levels with different fleet sizes. The smallest fleet size, 200, converged to the lowest demand volume - the demand volume monotonically increased as fleet sizes got larger. This confirms our hypothesis that larger fleet sizes lead to higher demand volumes, as induced by higher levels-of-service. This illustrates the demand supply interaction. Typically, the D-S interaction is able to balance in 10 steps.

Figure 6-1d also shows that the detour factor remains constant for various fleet size. The detour factor is stable at a very low level around 1.15. Similarly, average travel time also remains constant at around 520s regardless of fleet size.

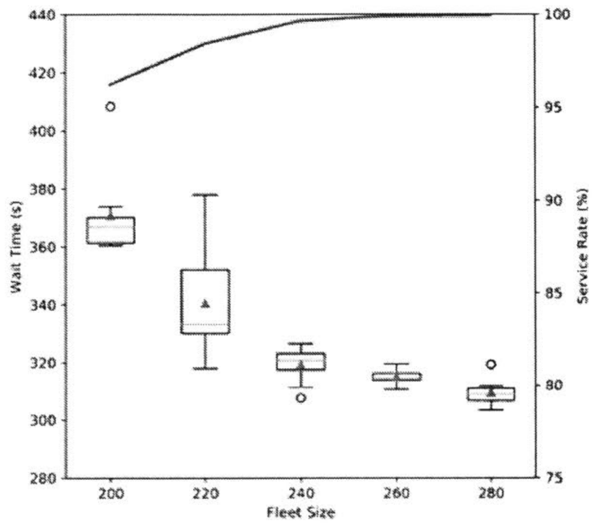
Consider a hypothetical operator that is contracted by a public agency. If this operator is required to provide a high service rate (99%+) and would like to limit the cost as much as possible, then we recommend that this operator choose a fleet size of 230. At this fleet size, the rebalancing distance will be 10% of travel distance and we will have a demand of 1950 trips per hour.

Figure 6-1: Impact of fleet sizes on travelers and the operator (case ASC = -3.00).

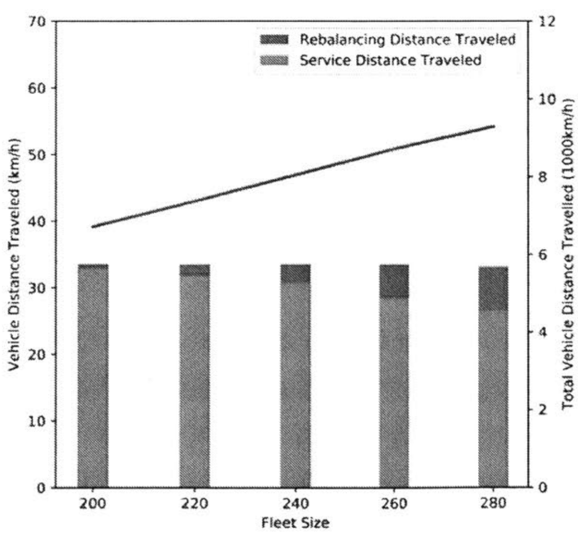
(a) Demand volume converges to different levels when fleet size varies.



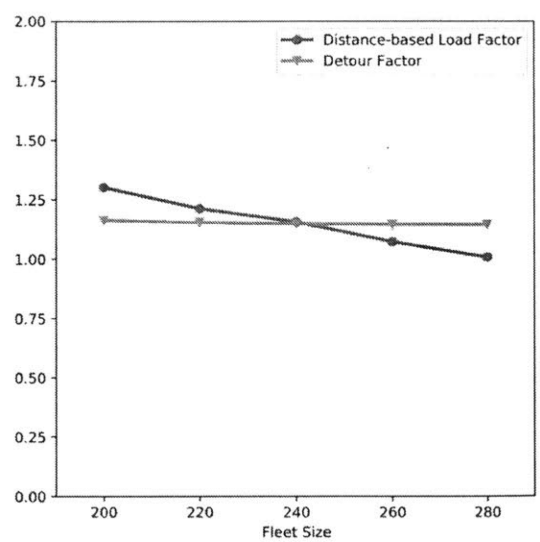
(b) A larger fleet leads to higher service rates and shorter wait times.



(c) Providing more vehicles results higher total vehicle service distance traveled.



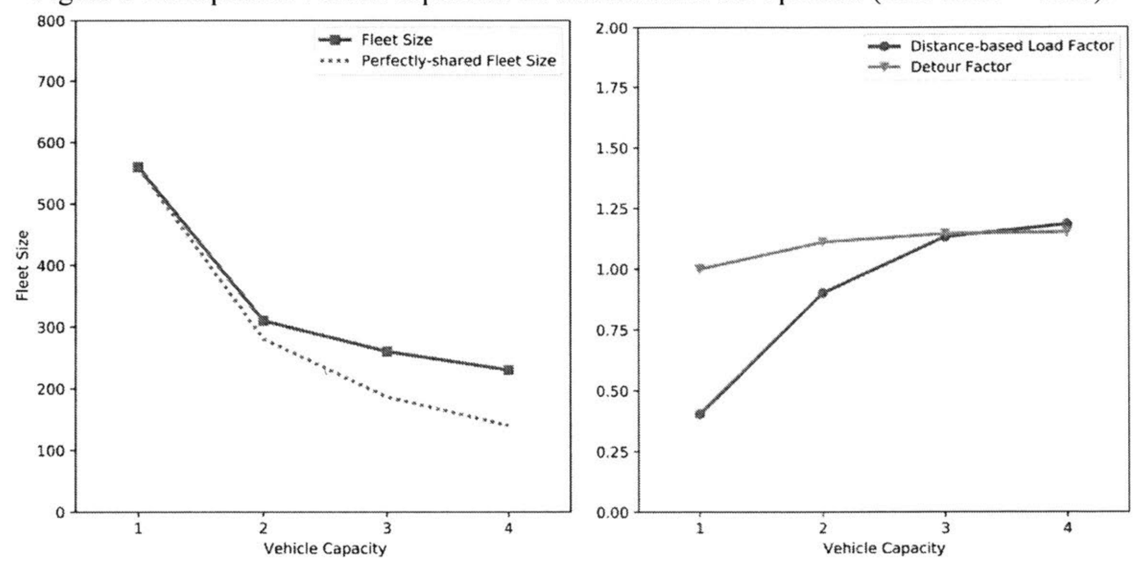
(d) Load decreases when fleet size increases; detour factor remains steady.



6.1.3 Vehicle Sharing Capacity

When passengers share trips, several passengers can concurrently share the costs for a single ride. This makes trips more affordable and decreases the number of vehicles on the road, improving traffic and reducing emissions. Sharing between many travelers, however, does have side effects on the travel experience: less space, higher uncertainty in travel time, and higher travel time due to pickups and drop-offs. As a result, the operator needs to balance the positives and negatives of sharing capacity. In this section, we explore how sharing affects service performance and fleet size required. We have assumed that the same discount for sharing (25% off) still applies.

Figure 6-2: Impact of vehicle capacities on travelers and the operator (case ASC = -3.00).



(a) The vehicle capacity-fleet size curve is decreasing and above the ideal curve

(b) Both load factor and detour factor increase as vehicle capacity increases

In Figure 6-2 we explored the impact of vehicle capacities on traveler's experience and fleet size. Figure 6-2a shows that for a 99% service guarantee, the number of vehicles required significantly reduces. Our demand model has taken into consideration of the price discount, waiting time change, and travel time change due to the detour; but has not taken into account the uncertainty in travel time or the privacy and social interaction preference. When we increased the vehicle sharing capacity from 1 to 4 at increments of 1, number of vehicles required will decrease from 560 vehicles to 310 to 260 to 230 - this is shown in the blue curve in Figure 6-2a. Our experiments have shown that allowing sharing has a significant impact on the system performance: the number of AVs on road can be reduced by more than half when a maximum of 4 passengers can share the trips.

Moreover, the increased sharing capacity corresponds to an increase in vehicle load factor (or occupancy). This means that there was a more efficient use of road infrastructure (reducing traffic) and vehicle resources (reducing emissions and cost). When there was no sharing, the average load was 0.40. This means that the vehicle was carrying one passenger half the time. If the vehicle's sharing capacity is increased to 2, 3, 4, the load factor increases to 0.77, 1.14, 1.18 respectively indicating that the vehicle can carry more than one passenger on average if sharing capacity was greater than 3. It should be noted that the low vehicle occupancy may stem from first-mile access to a rail station. This demand is highly asymmetrical and reduces the efficiency of vehicle use.

Although sharing brings many advantages to operators and travelers, it leads to a less attractive service for passengers because of the possible detours. In Figure 6-2b, the orange curve shows that the detour factor increased to values from 1.10 to 1.15 when sharing is activated. This means that travelers would experience about a 10% to 15% increase in their trip's in-vehicle travel time.

6.1.4 Fare Policy

We compared the initial fare policy with the minimum trip price ($1.73), sharing discount (25%), and transfer discount ($1.33) with two alternative policies: no discount for transfers $DC_{transfer} = 0.00$, and no minimum trip price $MP_{av} = 0$. Table 6.3 shows the comparison of the modal shift to the AV+PT mode in the three fare policy scenarios. The modal shift is defined as the percentage of trips leaving the existing mode for the AV+PT mode over the total trips by the existing mode before the introduction of the AV+PT mode. It is clear that the price schemes significantly impact the choice of travelers. When the discount for transit connection is removed, there is a significant decrease in modal shift towards AV+PT in the downtown trips since they often involve first-mile access and transfers. In contrast, the minimum trip price has virtually no effect on the mode choice of the simulated trips. This implementation could discourage short-distance walk/bike trips from shifting to AV+PT, however, these trips are not the focus of section 6.1 but will be discussed in section 6.2.

Table 6.3: Predicted Modal Shift to AV+PT Service under Different Fare Policies

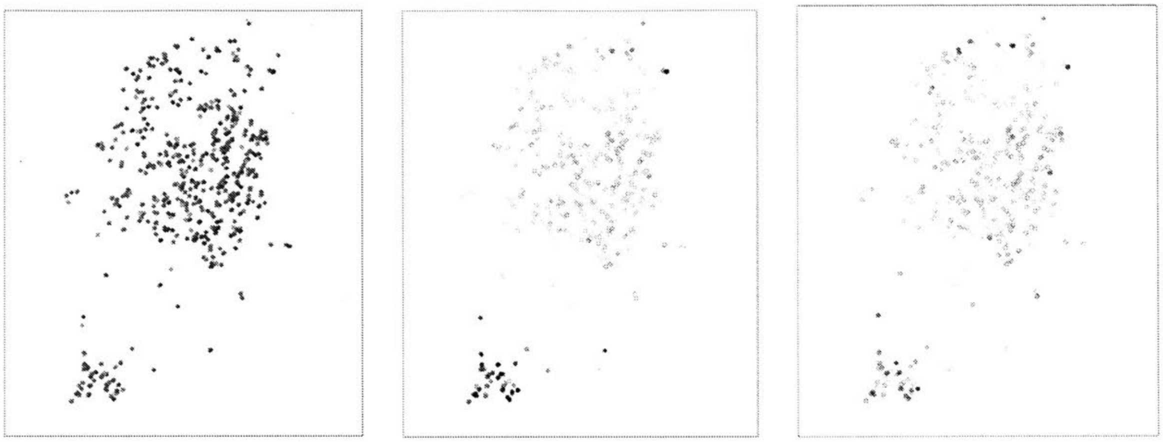
Trip Type	Mode	Original Fare	$DC_{transfer} = 0$	$MP_{av} = 0$
Downtown	Car	43%	36%	43%
	Rail	39%	31%	39%
	P/K+R	43%	36%	43%
Intrazonal	Car	10%	10%	10%
	Bus	14%	14%	14%

* No observations for walk, bike, and taxi

6.1.5 Hailing Policy

Due to the asymmetrical nature of the first-mile trips, an on-demand service would need an immense amount of resources to ensure 100% service rate. The origins of the predicted trips are shown in Figure 6-3a. In the bottom, left corner there is a patch of demand that is distant from the main pocket of demand in the center; this area will be referred as SA. Considering the limitations of the service, it is reasonable to assume that customers may choose to not use the service as a result of the long wait time. Figure 6-3b shows the likelihood of people choosing not to use the service as a result of long wait time. It can be seen that in SA there is a particularly large number of dark markers (higher chance of walking away).

Figure 6-3: Impact of hailing policy on service availability.



(a) Scatter of the origins of the predicted trips. The satellite town is the agglomeration in the southwest.

(b) Likelihood of walking away assuming on-demand requests only. **Dark marker** indicates high chance.

(c) Likelihood of walking away if in-advance requests are allowed in satellite town.

There is also a particularly low service rate when compared to the rest of the CSA, 35% vs. 99%. Such low availability in this area is potentially bad for people that live there. In response to this, we assumed that in-advance requests are sent for travelers from SA. In-advance requests in our simulation are known to the dispatcher beforehand and the travelers will be notified of their assignment 30 minutes before the earliest departure time. When we assumed that half of the people request in advance, we found that the service rate improved to 85.5%. The cost of fulfilling this is that the rest of the CSA experienced a small decrease in availability (0.7%). This shows that there is potential to achieve a significantly higher service rate in underserved areas at a small cost to the overall service rate.

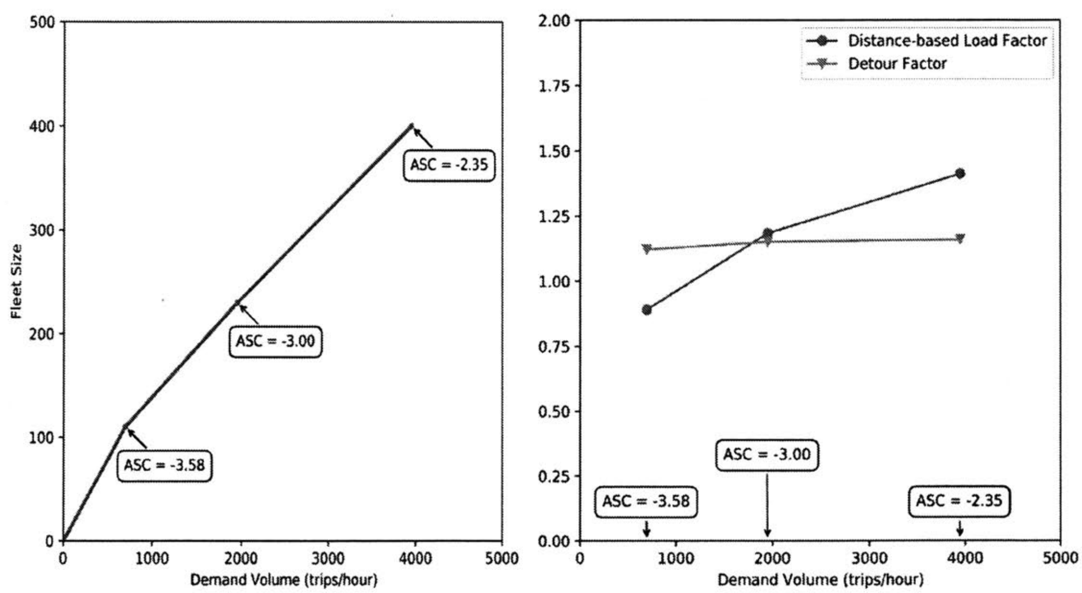
In this section, we assumed that half of the travelers choose to request in advance. However, it can be seen that hailing policy can impact the service characteristics of various groups. There can be many more dimensions with respect to the service attributes that are associated with hailing policy that can be considered here in future tests. Some factors that can be tested for in-advance requests are: differentiated fare policies, variations in window of time for in-advance requests, whether services are guaranteed when a request is in-advance, etc.

This section shows the significant implications that hailing policy may have on a shared AV service. When choosing a set of hailing policies, the agency or private operator should test to determine the implications that different hailing policies can have for the availability of service and consider the optimal strategy to fit their objectives in their specific service context (e.g. demand distribution, etc.).

6.1.6 Preference to AV

In the shared AV's utility equation, the alternative specific constant (ASC) reveals the intrinsic preference of travelers for the mode. As discussed in the literature review, there is no conclusive evidence for the exact preference of AVs. Thus, to reflect the uncertainty in travelers' intrinsic preference for the AV+PT service in our experiments, we tested 3 ASCs: -3.58 (lower bound), -3.00 (midpoint) and -2.35 (upper bound). The reason we bound AV's ASC to these values is because we believe the AV+PT mode should have an ASC value between public transit (-3.58) and car (-2.35).

Figure 6-4: Impact of preference (ASC) on system scale and performance.



(a) The relation between demand and fleet size indicates the economies of scale.

(b) A higher volume lead to higher load. Detour factor remains steady.

Simulation results shown in Figure 6-4 indicates that when ASC becomes less negative (increase), the utility of travelling by AV increases and the demand volume grows exponentially from 700 for the lower bound ASC to 1950 for the midpoint to 3950 for the upper bound.

To maintain the same level-of-service when considering different intrinsic preferences for AVs (ASC), the operator should expect to need a much larger fleet if the service rate is to be maintained over 99%. At the lower bound ASC, the fleet size required is 110. An additional 120 vehicles are needed when the ASC increases to the midpoint bringing the fleet size to 230, and when the ASC is at the upper bound, the fleet size needed will need to be increased by another 170 vehicles bringing the fleet size to 400. As well, the results show the economies of scale of the system. As the volume of demand increases due to higher ASC, we see a decrease in the number of vehicles needed per traveler. Moreover, load factor increases as ASC increases. These two findings likely reflect that people are more likely to get paired together when more requests occur at the same time. However, the detour factor remains at a constant level throughout.

6.1.7 Before-and-After Mode Shares

As discussed in section 4, the CSA is a car dominant area. The shared AV service will significantly draw travelers away from this market, where 44% of all shared AV trips will come from cars, which had mode share of 10% for downtown trips and 86% for intrazonal trips prior to the introduction of shared AV. Moreover, for downtown trips 72% of shared AV travelers used rail and 17% of travelers use park/kiss and ride. Table 6.4 shows the mode shares and total trips made before and after the launch of AV+PT service. "Shift to AV+PT" shows the number and percentage of trips shifted from car, bus, rail, and P/K+R to the AV+PT service.

Table 6.4 Shared AV Ridership and Mode Share Analysis

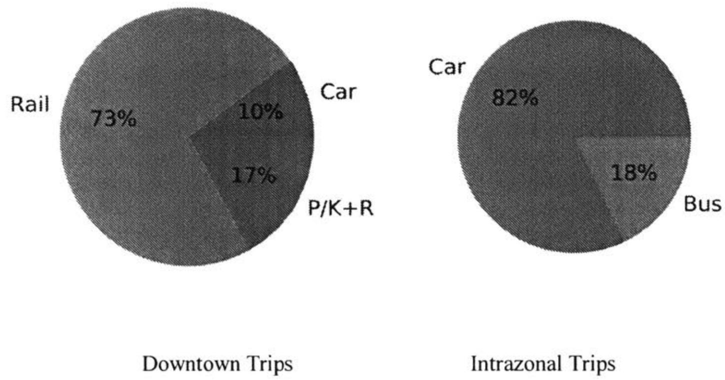
Trip Type	Mode	Before		After		Shift to Shared AV	
		Trips	Share	Trips	Share	Trips	% Shift
Downtown	Car	775	10%	441	5%	334	43%
	Rail	5968	74%	3661	46%	2307	39%
	P/K+R	1277	16%	723	9%	554	43%
	Shared AV	0	0%	3195	40%	N/A	N/A
	Total	8020	100%	8020	100%	3195	40%
Intrazonal	Car	22715	86%	20373	77%	2342	10%
	Bus	3629	14%	3109	12%	520	14%
	Shared AV	0	0%	2862	11%	N/A	N/A
	Total	26344	100%	26344	100%	2862	11%

* No observations for walk, bike and taxi – they will be analyzed in the next section.
** All of the downtown AV+PT trips use AV for rail connection, while only 10% of the intrazonal AV+PT trips involve bus or rail. The rest of them are AV-only.

The mode share of the direct car trips to downtown drops from 10% to 5%. The long-haul portion of the downtown trips is dominated by rail but the access to the stations changed the mode composition significantly. Walking trips to the stations decreased by 39%, and P/K+R trips reduced by 43%. Downtown trips have a high mode shift to AV+PT because there is a direct high-speed train service to central business district at the CSA's train station, consequently making AV as a first-mile connection to transit an attractive mode. For this segment, AV serves as a first-mile connection to rail and does not cause the rail service to lose ridership. Rather, it gains as AVs will bring other modes to rail for this segment of trips. The total rides that use rail predicted will be 6856 vs. 5968 previously, up by 888.

For intrazonal trips, the AV+PT service captures 11% of the mode share; car trips drop by 10% and bus trips decreases by 14%. In terms of intrazonal trips, conversion of car is smaller than bus (10% vs. 14%). However, in the CSA, car travel is more frequent. This resulted in a greater absolute number of trips, 22,715 trips by car vs. 3,629 trips by bus. As a result, 82% of all shift actually came from car. A summary of the percentage of AV+PT trips converted from each existing mode for each trip segment is shown in Figure 6-5.

Figure 6-5: Percentage of AV+PT trips from each existing mode: left: downtown trips; right: intrazonal trips.



Moreover, this number is likely to increase in the long term, as the new service may reduce the need for private ownership of vehicles. It is likely that attitudes towards AVs may change once people try the service and develop trust in it. Finally, a 14% decrease in bus ridership as a result of AVs would negatively impact the revenue of the bus operator. This impact will be accounted for in simulation-based design in section 6.2 as a part of the objective function.

6.2 Simulation-Based Optimization for AV+PT Service Design

This section proposes a simulation-based design module to utilize the abilities of the tool and support decision makers when designing an AV+PT service. This model will utilize the simulation model to optimize the choice of system design variables while reflecting the interests of stakeholders through the benefit-cost formulation of the objective function. This model will help agencies to make decisions that support their overall AV+PT transport strategy as well as operational planning For strategic decisions, the tool is able to show a well performed scenario for the proposed service. As well, it gives an evaluation of the overall performance of a given design scenario. This will inform decision makers on the "if", "where", and "when" questions with regard to AV related decisions. For operational decisions, the model can help the decision makers optimize the choice of design variables such as fleet size and fare to best reflect the stakeholder interests.

Using system-based optimization model, we can simulate a range of alternative scenarios and identify the highest performing scenario in terms of the defined objective outcomes. The current simulation provides flexibility to test a large set of decision variables. In this section, decision variables are defined as elements of the simulation that could be tested to optimize for system performance and constraints are elements that act as a limitations or restrictions to what the system can and cannot do – it is possible for one element to play either roles. A list of possible variables and constraints are shown in Table 6.5.

Table 6.5 Possible Decision Variables in Simulation

LOS Feedback Variables	Simulation Rules	Algorithms	Fare	Other
Wait Time	Route Cost Calculation Method	Routing Algorithms	Base Price	Hailing Policy*
Detour Factor	Condition for Rejecting Requests *	Rebalancing Algorithms	Per Unit Distance	ASC
Number of Transfers*	Penalties for Rejecting Requests		Per Unit Time	Fleet Size*
Vehicle Size*	Queue Service Order/ Preferences		Transfer Discount	
	Generation of Requests		Sharing Discount	
	Vehicle Scheduling (Time in Service, Rotation of Vehicles)*			
	Assignment Rules			

* "*" represent the potential to be a constraint as well

It is anticipated that AV technology may further improve the economics of such services by reducing the operational costs. If the state of the transportation systems around the world stays similar to its current condition and if AVs are to become dramatically cheaper, then more travelers would be likely to leave PT and active travel modes for autonomous MoD services of the future. A scenario like this may increase congestion in cities by adding more vehicles to the streets. Moreover, this not only threatens public transportation itself, but could also undermine the abilities of agencies to protect social values such as equity, accessibility, and environmental sustainability. In order to identify ways to prevent such a future, this section proposes an optimization method for AV+PT service that quantitatively takes into account many of these issues as a first step to addressing some of these issues. The benefits and costs were chosen to represent the interests of the various key stakeholders: AV operator, PT operator, government, and travelers, as identified in Table 3.1. Specifically, we quantified the following benefits and costs resulting from the AV+PT service:

- Benefit derived from increased mobility opportunities through AV+PT - Travelers
- Operational profit (or subsidy if required) – AV operator
- Decongestion benefit (private vehicle use reduction) - Government
- Health impact from active travel mode share decrease - Government
- Environmental footprint (AV's) – Government
    - Global warming cost
    - Morbidity and mortality
- Lost bus revenue – PT operator

The rest of this section is organized as follows. First, it will outline how bus service contracting will be used to provide a case study that showcases the ability` of this tool to help inform the creation of a contracting process for shared AV on-demand service. Then it will describe the formulation of the objective function and how each benefit and cost will be quantified. Finally, it will detail simulation results to showcase the ability of this tool to help inform design decisions in the context of a similar shared AV on-demand service contracting.

6.2.1 Shared AV Contracting Case Study

This section draws upon competitive bus service contracting in a major European city to provide a case study that showcases the ability of this tool to help inform the creation of a contracting process for shared AV+PT service. This particular competitive contracting practice began in Great Britain in the mid-1980s and its practice since spread to much of the rest of Europe and also internationally. The success of this system using this process makes it a great case study example. Specifically, we will assume a market structure that is similar to the major European city's bus contracting method, meaning the chosen operator will have a monopoly of AV service in a defined area. As well, it is assumed that the government has enforced that AVs must integrate with transit.

The ability of the contracting system to provide a high level of service with reduced financial assistance from public funds is well known and has resulted in the adoption of this system by other countries around the world. It is certainly possible that other cities around the world may choose to pursue a similar structure in the future with AVs. Thus, we choose to use this as the case study to showcase the ability of this simulation-based design module.

When comparing to fixed route bus operations, an on-demand door-to-door AV service is significantly different and has many highly uncertain variables such as user preference for service, viability of technology, and costs of technology. As such, a flexible simulation approach may be a very cost-efficient way to construct the contracting specifications. The agency can define a set of goals in the simulation's objective function and identify the set of decision variables that best helps them accomplish its goals (social welfare, profit, active travel, etc.). The tool can then quickly produce a set of simulated results that can inform the agencies' decisions.

In this case study, we will optimize for the choice of fleet size and fare magnitudes. These two variables are extremely influential in the balance of demand-supply interaction. Larger fleet sizes directly improve level-of-service but also generate larger derived demand, resulting in an increase in cost and vehicle miles travelled. Similarly, although higher fare leads to greater revenue per trip, it also reduces the number of people who use the service. These tradeoffs are captured in the simulation, so that we can then find the "sweet spot".

For fares, we apply a "fare multiplier" to the base price, per unit distance price, and per unit time price to represent the variation in fare – the multiplier was not applied to the discounts or minimum fare.

The case study area, fare, demand, and system settings all remain the same as in section 6.1. Before we can present the result of the case study, we must first detail the current bus contracting process and how this tool can be used to help construct a new shared AV contracting service.

6.2.2 Bus Contracting Background

The transit agency in the CSA manages bus services in the city. It plans routes, specifies service levels and ensures service quality. The transit agency awards bus services through a tendering process to private operating companies. The tendering and contracting arrangements are designed to balance the expectations of passengers against the costs of providing a better service. About a fifth of the network is retendered or reviewed every year to help the network meet the changing travel needs of the city.

Drawing on the example of the contracting of a route in 2011, this tool can help in redefining several sections of the existing contract and revise it for an on-demand shared AV service. Specifically, it can help with the following sections: Service Specification, Proposed Changes, Requirements and Pinchpoints, Performance Statistics, Operational Considerations, and Incentive Structure. On-demand service is by nature different from bus service and as a result, some of the metrics that have been used in bus contracting such as headways may be replaced by similar metrics such as detour experienced by passengers.

In terms of the "Service Specifications" section, the tool is able to help the contract designer with determining the service details that will replace the current route information portion of the contract. The first is vehicle size - the tool can be used to test the performance of various vehicle sizes to determine the best performing vehicle size for the service area in question. Similarly, it is able to help determine the minimum performance standard, extension threshold, departing on time sections of the contract that are used to ensure timely service to the customers. The maximum wait time and detour factor metrics in the simulation can be used to supplement this area. Some newly relevant variables due to the on-demand nature of such a service could be: service rate, hailing policy (please see section 6.1.5), and fares. Fares in the contracts have previously been set by the transit agency. This type of top down pricing can be continued, or the transit agency may choose to implement operator pricing in such contracts with the transit agency playing the role of a regulator. the transit agency can use this tool to test and understand different feasible pricing schemes' impact on operations and customers. It can then use the results to determine what is the maximum price. As well, it can determine the fee that the transit agency wishes to collect as a part of the contract (if profitable) or the amount of subsidy (lump sum, per trip, ad valorem) required to ensure profitability for operators (if not profitable). Currently, the tool can vary base price, per unit time and per unit distance price, as well as sharing and transit connection discount. These can be extended to consider other imaginable fare structures such as a distance-based congestion pricing scheme.

The "Proposed Changes" section outlines the changes that the transit agency wishes to implement on the routes from the last iteration of the service. The transit agency's bus network is dynamic and constantly seeks to respond to the city's changing transport needs. These changes are due to be implemented before the new contract is set up. This tool can be used to test any proposed changes in performance, understand its feasibility, and detail the expected impacts on the system along any of the dimensions in Table 6.5.

The "Schedule Requirements & Pinchpoints" section details the schedules for the bus lines. When considering a fleet-based on-demand service, one of the most relevant specifications would be fleet size. The tool can be used to determine the optimal fleet size for the goals of the contract owner. Moreover, due to the variation in demand throughout the day as well as different days in the week, different fleet sizes may be considered optimal at different times or days. Under a similar framework, this module can be extended (through a deeper analysis of whole day or whole week demand) to determine the fleet size that maximize overall benefits for whole day or week.

The "Performance Statistics" section is used to give bidders an idea of the current performance of the route. This section reports the mileage operated, deductible mileage, nondeductible mileage, average excess waiting time, and long gaps in service for each route. The operators are assessed based on their performances on mileage and on-time performance. For the first time a service is tendered, the contract designer can use the simulation to output the same statistics to give bidders a benchmark of what to expect.

The "Operational Considerations" section is used by the organization to note out-of-ordinary considerations such as unexpected delays, unusual events like Olympics, etc. The simulation's results and visualizations can be used to try to foresee and understand potential trouble areas. Our simulations have already contributed to this with respect to hailing policy in SA outlined in section 6.1.5

Finally, we would expect that algorithms in this new AV+PT service will play a crucial role in the performance of the service. Thus, it is worth considering adding it in as a new section in the contract. The contract designer can identify "favorable" characteristics of the algorithms for passenger to vehicle assignment, rebalancing, and routing – more about these algorithms can be found in Wen's work [63]. Algorithms could be a very unique opportunity provided to a transit agency and operators to deliver better traffic performance. For example, algorithms could be designed to route vehicles to achieve system optimal performance rather than user equilibrium traffic (a classic problem transportation engineers face). It could also be designed to, for example, relieve overcrowded stations by dropping passengers off at alternative train stations or even to encourage traffic on main roads as opposed to local roads by assigning a travel score to trips depending on types of roads used on the trip– something that has been proposed by researchers at MIT in "Rules of the Road" by Ben Gilles [72].

6.2.3 Objective Function and Quantification of Benefits and Costs

This section will detail how each benefit and cost were quantified. The benefits and costs were chosen to represent the interests of the various key stakeholders: AV operator, PT operator, government, and travelers.

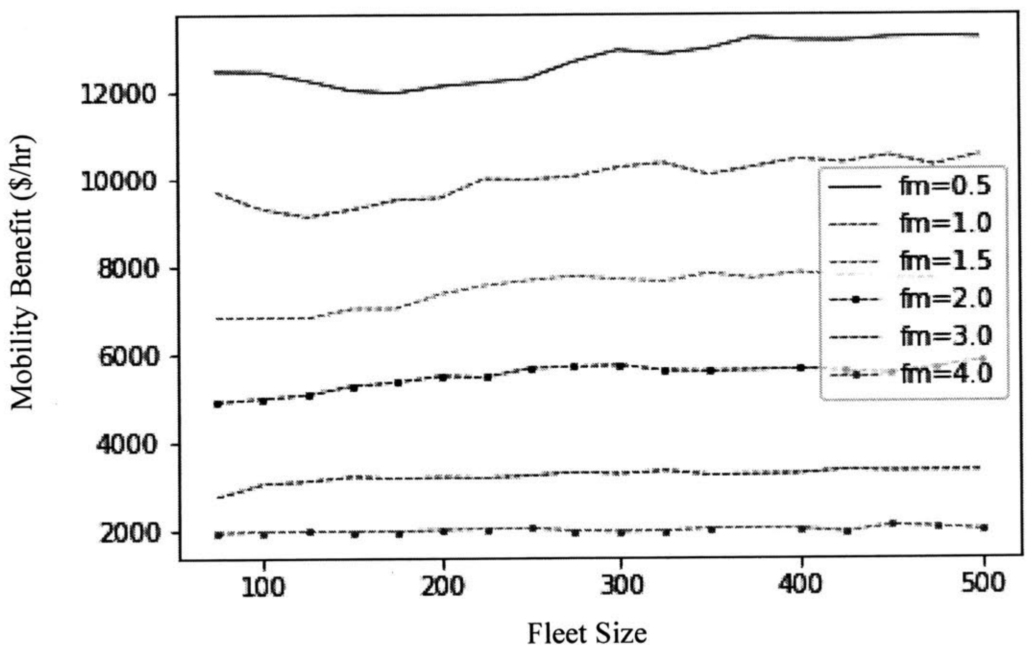
The first is mobility benefit. Mobility benefit uses the concept of logsum as described in section 2.2.2 to derive a monetary equivalent of the mobility benefit that travelers get from having the AV+PT service. The logsum represents consumer surplus (value that services provide) in nested logit models and agencies can use logsum to measure the increase in consumer surplus due to the addition of (1) new travel modes such as AV+PT and (2) different service designs that can be offered resulting from supply side changes such as increase in fleet size.

$$(18)\ MB = \frac{L_{AV} - L_{noAV}}{\beta_{Cost}}$$

- MB = monetary equivalent of mobility benefit derived from the difference in logsum before and after the availability of the AV service
- L_{AV}, L_{noAV} = Logsum (estimated expected utility) of the choice set for with AV service and without AV service respectively
- β_{cost} = 0.011 utils/$ same value of time coefficient as the case study's mode choice model

In this section, the change in utility perceived by travelers due to the addition of the AV+PT alternative was expanded using the travel demand survey's weekly expansion factor. The utility was then scaled to the hourly value, assuming 10 hours of operation a day. The value of time was used to convert the logsum to a dollar value – it was assumed to be the same as the cost parameter in the demand model. The resulting formulation is shown in equation 18.

Figure 6-6: Impact of fare and fleet size on mobility benefit.



*"fare multiplier" is a factor multiplied to the base price, per unit distance price, and per unit time price – it represents variation in fare magnitudes.

Looking at Figure 6-6, it can be seen that by increasing fare we are decreasing mobility benefit. When the service becomes more expensive, the utility of the AV+PT alternative decreases. The decrease in utility of this alternative causes the gain in expected utility of the choice set ($L_{AV} - L_{noAV}$) to also decrease, thus reducing the mobility benefit that travelers are able to receive from this new service. This effect can be observed in the big decrease in volume of the demand – this will be shown in Figure 6-12a.

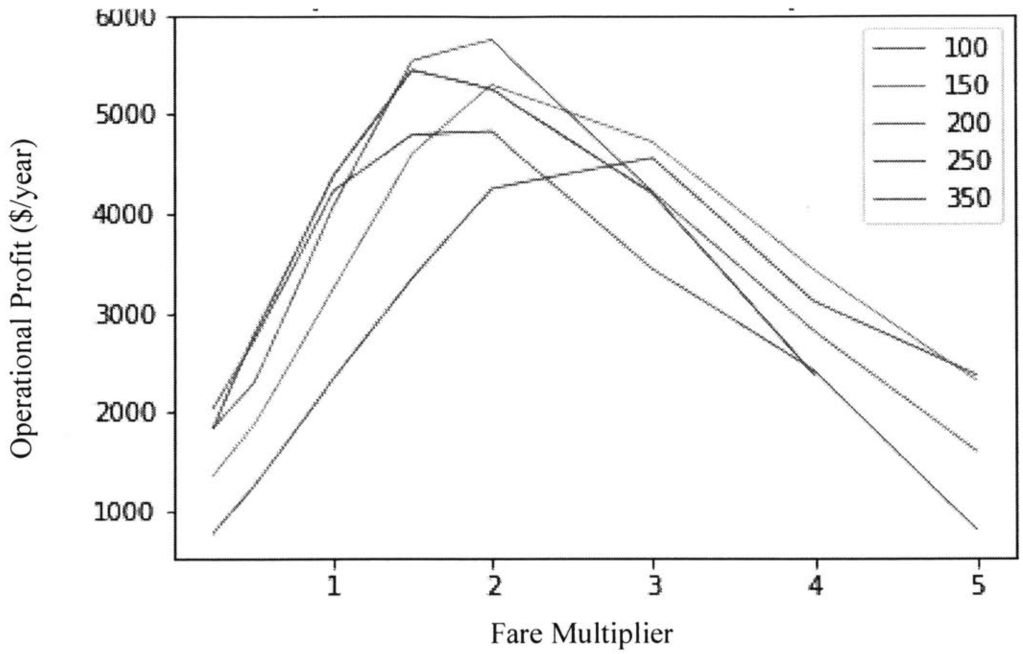
Also, it can be seen that the change in logsum generally increases monotonically with fleet size. This is due to the increase in level-of-service provided with greater fleet size, hence resulting in an increase in mobility benefit to travelers. Although both of these effects are significant in magnitude, it is clear that fare has a much greater effect than fleet size due to the fact that the lines never intersect.

The second is operational profit or subsidy. This takes into account the profit that operators can derive from the service. The revenue is calculated using the assumed fare structure and fare multiplier, while the cost of automated vehicles is assumed to have two components: capital and operating costs. For capital cost, a new car is assumed to be $30,000 [73] with an added purchase price of $10,000 for autonomous capabilities [74]. A vehicle is assumed to have 10 years vehicle useful life at 5 hours of use per day for 200 days a year. An interest rate of 10% per year is taken for net-present value calculation, which is 3% higher than that used by the Office of Management and Budget for federal projects and TIGER grant applications. This was done to reflect greater uncertainty in this technology [74]. This results in an equivalent annual cost of $6509 per year which scales down to $6.50 per hour (assuming 5 hours of operation per day). A $0 cost of infrastructure investment was also assumed. On the other hand, for operating cost, day-to-day fuel, maintenance and tires summed to $0.20 per km [73]. In addition, there is also insurance cost, where it was found by AAA (a federation of motor clubs) that the average insurance cost is $1170.40 [73]. It was also found in a study on autonomous vehicle by the Eno Center for Transportation that "costs may fall by 50 percent for insurance" [75]. Hence, this brings the insurance cost to $585.20 per year or $0.16 per hour. As such, the final costs sum up to $6.66 per hour & $0.20 per km.

$$(19)\ P = TR - TC$$

- P = Operational profit
- TR = Total revenue
- TC = Total cost

Figure 6-7: Impact of fare and fleet size on operational profit.



*each colored line represents one fleet size

Figure 6-7 shows that the maximum profit can be achieved at a fare multiplier of 2.0 and fleet size of 200. At a given fleet size, the results show that an operator can raise prices up to a critical point before the revenue falls. This points to a trade-off between raising fares to gain more revenue per trip and reduced demand volume as a result of a more expensive service. Moreover, this figure shows a rough pattern- given a smaller fleet size, the profit-maximizing price increases. In the next steps of this research, more fine-grained analysis can be used to map out this exact pattern. This can be done by testing fare multipliers in steps sizes of $\pm$ 0.1, $\pm$ 0.05 or even $\pm$ 0.01.

The third is decongestion benefit derived from taking cars off the road. Albrantes [76] uses welfare economics to find the economic contribution of bus networks in England. He estimates that each peak bus trip generates decongestion benefit of $3.59/trip when accounting for lost in productive time, environmental externalities, and traffic accidents. Since the shared AV+PT service will similarly reduce private vehicles on the road, we can estimate the decongestion benefit provided by the shared AV+PT service using the number of cars shifted away from private vehicle usage multiplied by the value provided by Albrantes – this is shown below in equation 20.

$$(20)\ B_{CarShift} = N_{CarShift} * \beta_{CarShift}$$

- $B_{CarShift}$ = Benefits resulting from mode shift away from private vehicle use
- $N_{CarShift}$ = Number of trips shifted away from private vehicle use
- $\beta_{CarShift}$ = \$3.59/trip

Figure 6-8: Impact of fare and fleet size on decongestion benefit.

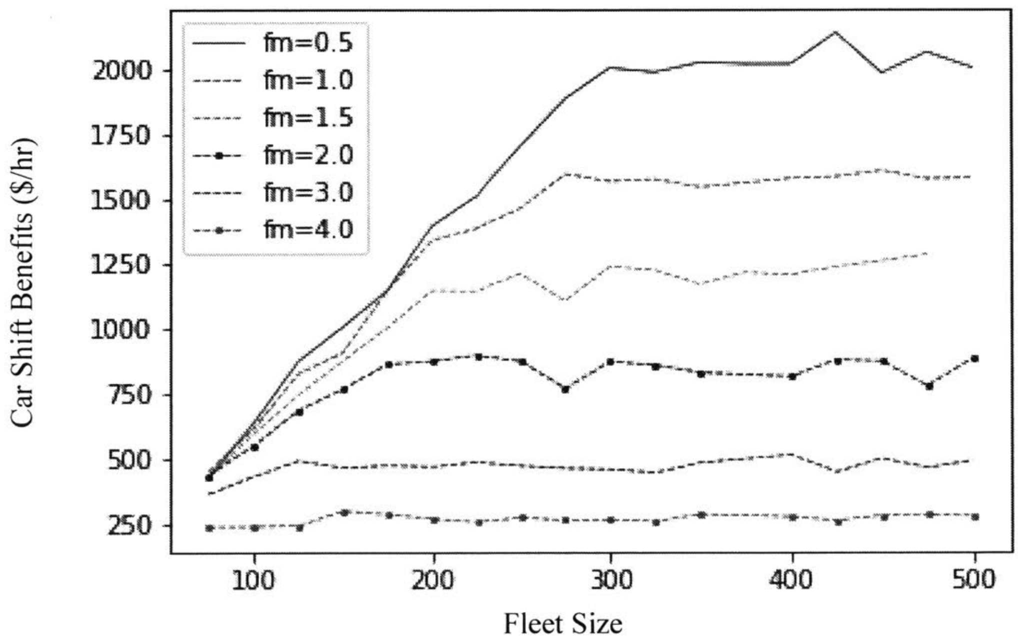


Figure 6-8 outlines the decongestion benefit that can be gained from reducing private vehicle use. The curved lines at low fleet sizes indicate that the system is not able to capitalize on the maximum potential to shift people away from private vehicles at lower fleet sizes. However, once reaching a "sufficient" fleet size (end of curved portion) there is no more incremental gain (flat tail at higher fleet sizes). Once at these "sufficient" fleet sizes, the difference in magnitude between different fare multipliers show more people shift away from private vehicles when the service is cheaper. This is a direct result of AV+PT being a more attractive service at lower fares.

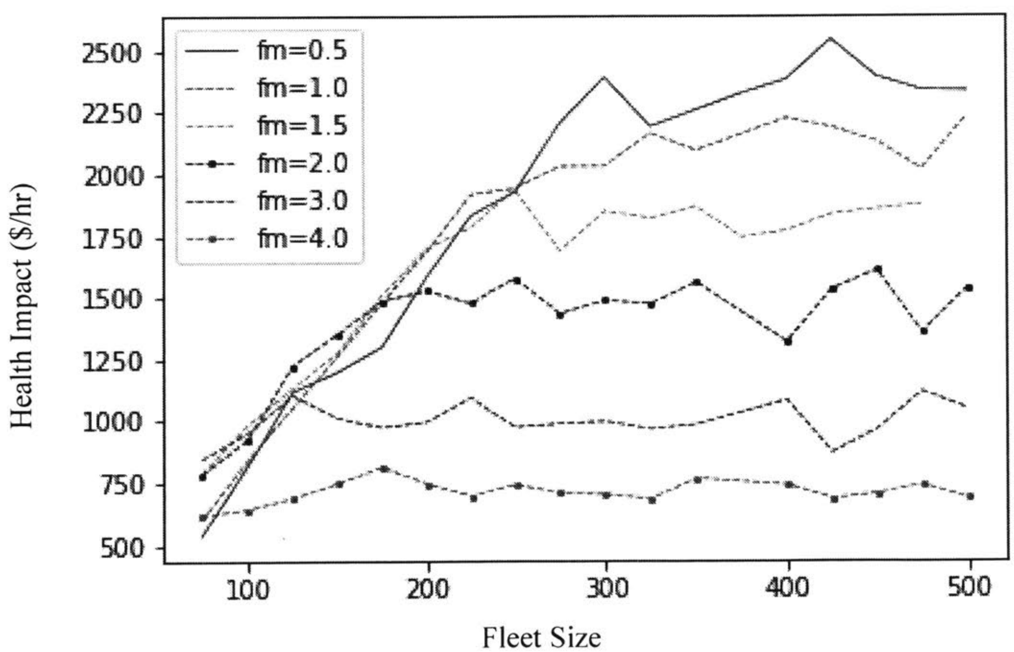
The fourth is the harm on health resulting from the decrease in mode share of active modes (cycling and walking). A tool called HEAT was used to quantify this. HEAT, which stands for Health Economic Assessment Tool, is developed by World Health Organization (WHO) to value the deaths prevented as a result of increased levels of cycling or walking [77]. HEAT applies a linear relationship between walking and cycling duration and mortality rate, hence it is able to quantify the positive benefits that active modes have on health. It uses this relationship to calculate the number of lives saved and multiply that value by the statistical value of life to convert it to monetary terms.

For our CSA, it was found using the tool that an average of one-minute decrease in walking and cycling cost \$980.82 and \$857.53 on a per hour (simulation time) basis respectively. The exact assumptions used to calculate these values can be found in Appendix A.

$$(21)\ HB = \mathrm{WT} * \beta_{\mathrm{Walk}} + \mathrm{BT} * \beta_{\mathrm{Bike}}$$

- HB = Health harm in monetary terms
- WT = Average loss in walking time over whole population
- BT = Average loss in bike time over whole population
- β_{Walk} = \$980.82/ average min (in CSA)
- β_{Bike} = \$857.52 / average min (in CSA)

Figure 6-9: Impact of fare and fleet size on harm to health due to decrease in active mode travel.



* Note that the kinks are artificial effects of the fluctuation in the simulation. If there are sufficient large simulation runs, the curves should smooth out

Figure 6-9 indicates that there is a greater health impact at lower levels of fare. Moreover, the negative effects to health plateaus as fleet size increases indicating that after a "sufficient" fleet size no additional harm is experienced. Please note that the kinks seen in the figure and future figures likely reflect the stochasticity in simulation experiments.

The fifth is the environmental footprint resulting from emissions. The health costs of vehicle emissions by a Ford Taurus (a mid-sized car) is estimated by Lemp et al. [78] to be \$0.0031/VMT. This was done using mainly Environmental Protection Agency's (EPA) 2008 air pollution indices and Ozbay and Berechman's estimates of morbidity and mortality costs of such emissions in their 2001 study. Lemp et al. [78] also estimates that \$0.0316/VMT of damage is done to the atmosphere for a Ford Taurus. This was derived using estimates of the amount of carbon emitted as a result of gasoline burnt in that car and also estimates of global warming's external cost in past studies. The case study in this section will assume this is the average vehicle emissions in the fleet. However, it is worthwhile to note that these numbers can be easily adjusted to meet future needs as more information about autonomous vehicles emerges. Moreover, the direct emissions resulting from vehicles can also be set to 0 if vehicles are assumed to be electric.

$$(22)\ EF = VMT * (\beta_{EH} + \beta_{GW})$$

- EF = Environmental footprint
- β_{EH} = \$0.0031/VMT
- β_{GW} = \$0.0316/VMT

Figure 6-10: Impact of fare and fleet size on environmental footprint.

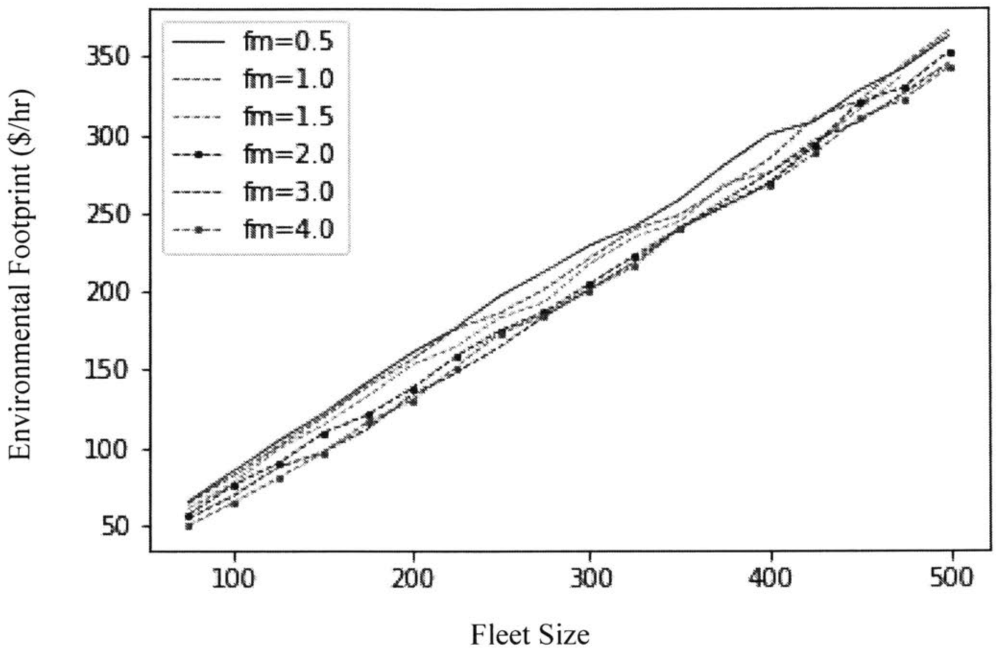


Figure 6-10 shows a near linear increases in environmental footprint with fleet size. This is due to a near linear increase in VMT as fleet size increases.

Lastly, there is the revenue loss from passengers shifting away from bus mode. Please note that the number of rail trips are not reduced and that there are no changes to existing bus operation.

$$(23)\ LR = N_{BusShift} * \beta_{BusShift}$$

- LR = Lost bus revenue
- $N_{BusShift}$ = Number of trips shifted away from bus use
- $\beta_{BusShift}$ = $1.72/ trip same as bus fare

Figure 6-11: Impact of fare and fleet size on lost public transit revenue.

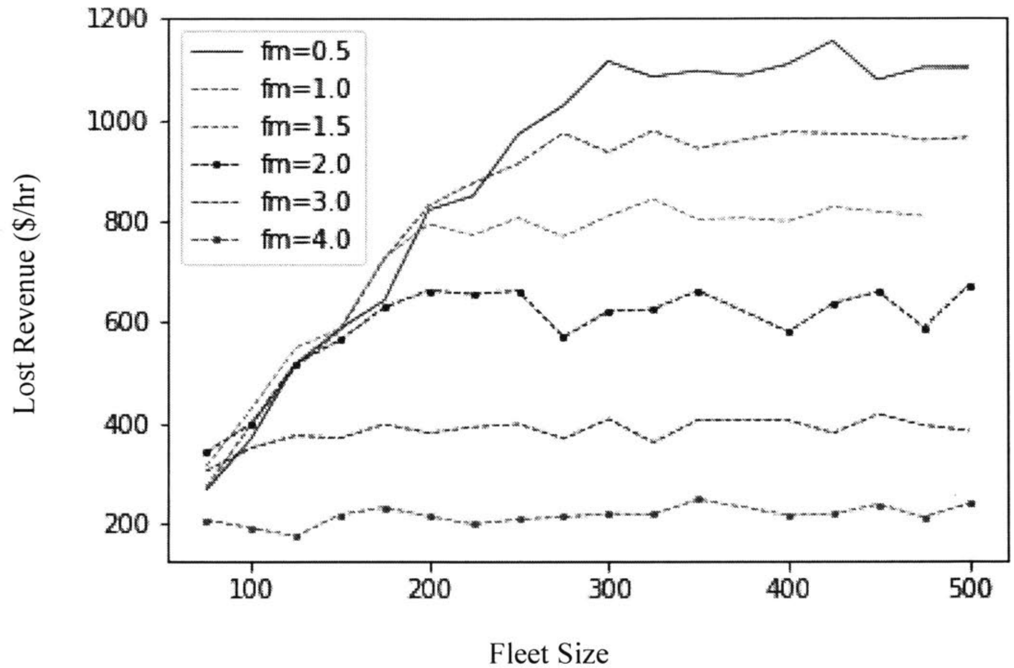


Figure 6-11 indicates that less people shift away from buses at higher fare levels. As well, the curvature of lines for a fare multiplier shows that when service is poor (not big enough fleet size), less people shift away from bus. This is because AV+PT demand is greater than the capacity of supply at lower fleet sizes- many people get rejected from the service and are not given the choice to shift away from buses.

The objective function seeks to quantify the concerns of AV service operators through operational profit, PT operators through lost bus revenue, and government through mobility benefit, decongestion, health impact from active travel mode share decrease, and environmental footprint. Thus, the cumulative objective function is as detailed below in equation 24. Through this objective function, we are able to simultaneously optimize service design for the concerns of all above stakeholders.

$$(24)\ Objective\ Function = MB + P + B_{CarShift} - HB - EF - LR$$

6.2.4 Enhancements to the Simulation Model

Some changes to the simulation were made from section 6.1.

First, the AV+PT service's simulated demand was increased to include all intrazonal trips. Previously in Section 6.1, we only included the intrazonal trips for car and bus. This was done to allow for the analysis of impacts of AV+PT on walk, bike, and taxi trips in simulation-based design.

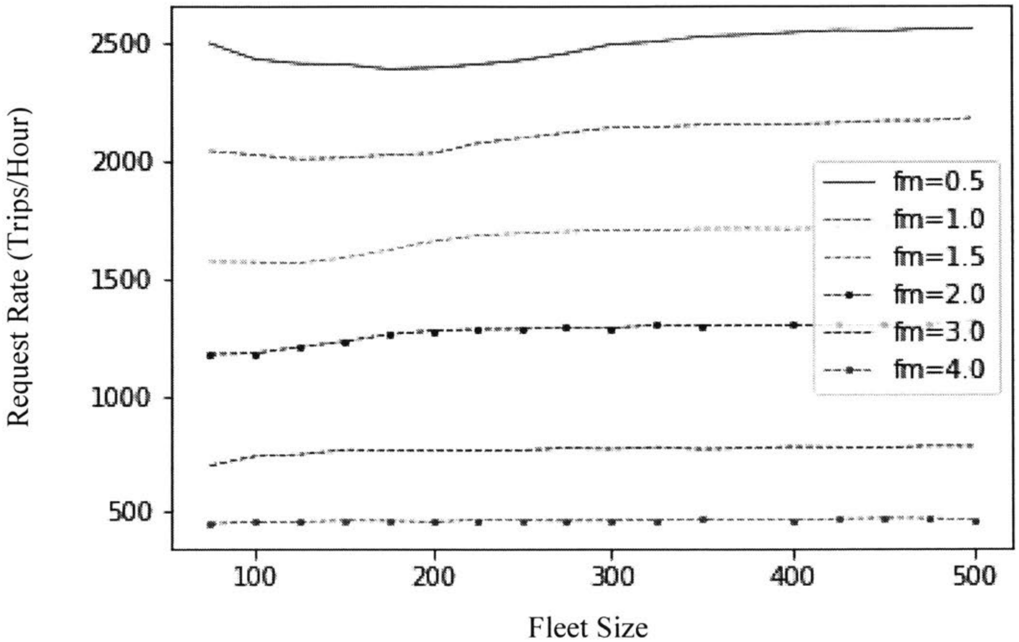
Second, the level-of-service metrics wait time and detour factor were changed to be trip specific. Within each simulation, a trip may be simulated multiple times. Subsequently, each trip was assigned as the average of all of the times in which that trip was simulated in the feedback loop for the level-of-service. Trips that were not simulated are assumed to take on the average of all the simulated values. This enhances the accuracy of the simulation by allowing for more accurate level-of-service feedback between demand and supply.

Third, as discussed in section 4.1.1 and 4.1.2, it was not possible to continue to use OpenStreetMaps to generate vehicle travel times due to the large volume of simulation. As a result, the travel time was taken from a pre-processed lookup table generated from OpenStreetMaps in the vehicle assignment module. This lookup table consisted of the travel times between all trip origins and destinations. This was generated through identifying origins and destinations in past runs of the simulation and recording the travel times from OpenStreetMaps. However, when vehicles are not traveling on these known ODs, an approximation using Euclidian distance with constant vehicle speed is used to generate the travel time value. Similarly, in the vehicle routing module, the travel time is derived based on values provide by a preprocessed Google API lookup table while the route is still generated using OSRM. The Google API is able to include on-road congestion in the travel times whereas OSRM did not -for further details on the Google API routing times please refer to Appendix B.

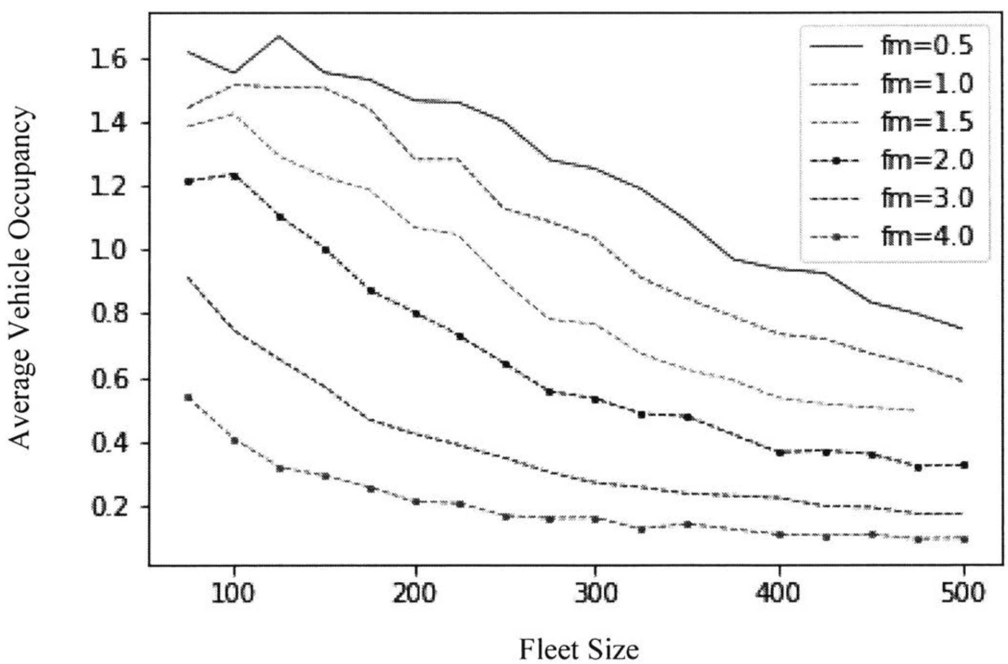
6.2.5 Simulation Results

This section will present the simulation-based design results. First, it will detail simulation experiment results on relevant performance characteristics for service contracting: request rate, average vehicle occupancy, and service rate. Then it will present the results of the objective function and identify the optimal solution space. Finally, it will provide recommendations on fleet size and fare in the CSA during the AM peak for a shared AV on-demand service.

Figure 6-12: Impact of fare and fleet size on average vehicle occupancy and service request rate.



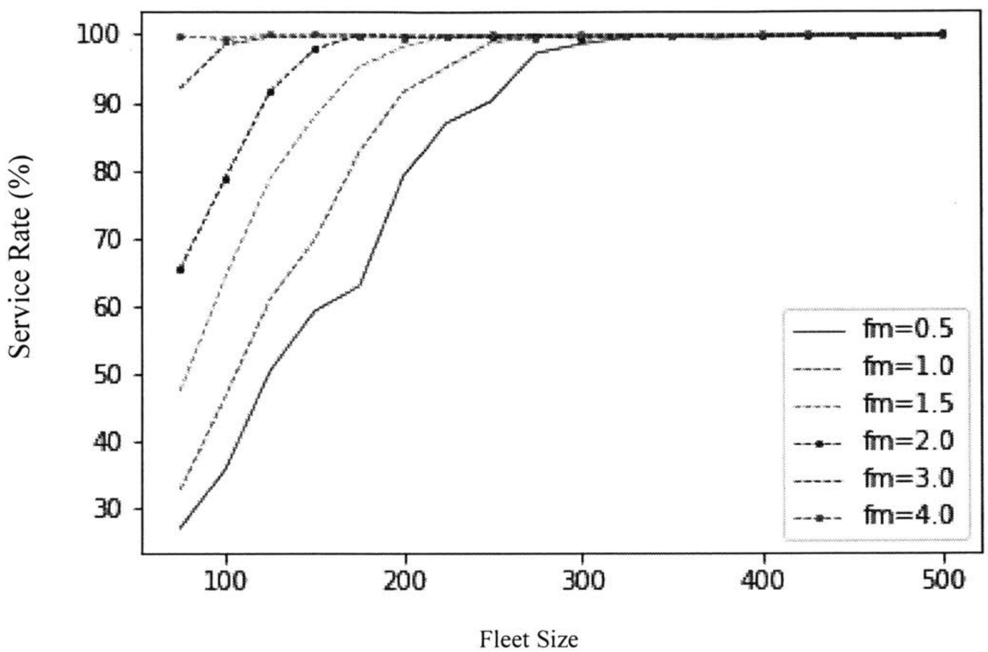
(a)



(b)

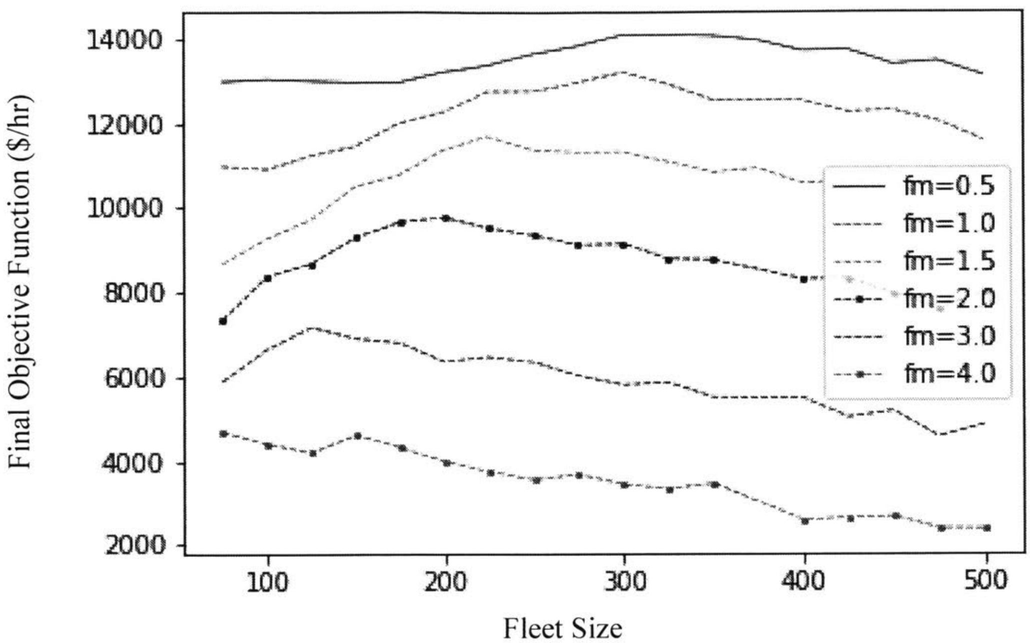
One of the most important considerations for transit agencies is the number of vehicles on the road. AVs may dramatically increase demand for travel by making travelling in personal vehicles cheaper, more convenient and thus more appealing. Figure 6-12a shows that a lower fare multiplier dramatically increases the number of service requests. In this figure, the lines do not intersect showing that any reasonable change in fleet size is not able to compensate for the impact of the fare. One way to combat an increase in demand is to encourage sharing. Figure 6-12b shows that the average vehicle occupancy increases with a decrease in fare. This is because lower fare leads to an increase in the density of demand, which in turn increases the likelihood that trips that are similar enough to be shared. Conversely, an increase in fleet size has the opposite effect on sharing in the simulation. A larger fleet size decreases the need to share thus reducing the average vehicle occupancy. This, however, increases the level-of-service because it reduces the need to detour and typically also means having to wait less. Thus, this makes the service more attractive for passengers and increases the demand, which has shown to increase sharing. The simulation's decrease in average vehicle occupancy with increase in fleet size shows that the effect of reducing the need to share overpowers the increase in attractiveness of service. The average vehicle occupancy represents the amount of sharing that is occurring in this mode. A more highly shared service will help reduce the number of vehicles that are needed to meet a certain travel demand, thus reducing single occupancy car travel. It has not been explicitly quantified in the objective function but should be an important consideration to decision makers when designing an AV transportation service contract.

Figure 6-13: Impact of fare and fleet size on service rate.



Another important consideration to transit agencies is availability of service to the public. Unlike private operators, transit agencies have a duty to provide a certain level of transportation service to people in the city whether its bus, rail, or AV. This means that a transit agency operated service should have high availability. Figure 6-13 shows that at about 300 vehicles, the service rate (equal to 1 minus proportion of denied boarding) is greater than 99% at any fare multiplier. It can be noticed that as the fare increases (resulting in reduced demand), the number of vehicles needed to reach 99% service rate decreases from 300 at fare multiplier of 0.5 to 100 at fare multiplier of 4.0. Similar to average vehicle occupancy, service rate is not explicitly quantified in the objective function but it should be an important consideration to decision makers when designing an AV transportation service contract. In the next phases of research, the quantification of service rate would be a valuable topic to explore.

Figure 6-14: Impact of fare and fleet size on objective function.



Evaluation of the final objective function for all fare and fleet levels indicate that fare has a significant and dominating effect on the overall performance of the service when all of the objective components are considered. The lower the fare, the higher the final objective function and the lines do not intersect, meaning that any reasonable change in fleet size is not able to compensate for the impact of the fare. It can be seen in Figure 6-14 that the optimal solution occurs at fleet 300 when fare multiplier is 0.5, i.e. fare is half of the proposed. However, there are various other possible fleet sizes where the solutions are almost as good. Results from fare multipliers below 0.5 were simulated but are not presented here because their results are very similar to that of 0.5. These results are similar because the fare multiplier was not applied to the minimum fare. Meaning, many trips have fares that are lower than the minimum at fare multipliers below 0.5 leading to the results to be similar. Considering that average vehicle occupancy, service rate, and level-of-service are all very important considerations in decision making but are not quantified in the objective function, it is wise to consider these factors along with the objective function. These factors are compared with the three of top performing fleet sizes in Table 6.6 – it will be referred to as the optimal solution space.

Table 6.6: Performance Characteristics of Optimal Solution Space for Fare Multiplier 0.5

Fare Multiplier	0.5			Trend
Fleet Size	300	325	350	
Objective Function ($)	14091	14084	14066	
AV Trip Rate (Trips/Hour)	2497	2508	2531	↗
Average Vehicle Occupancy	1.25	1.19	1.09	↘
Service Rate (%)	98.59	99.56	99.61	↗
Level-of-Service: average wait time (s)	376.11	373.30	357.67	↘
Level-of-Service: average detour factor	1.16	1.15	1.16	→
Active mode shift to AV+PT: walk (%)	60.40	58.34	59.85	→
Active mode shift to AV+PT: bike (%)	51.81	52.29	52.58	→

When comparing solutions in the optimal solution space, Table 6.6 shows that fleet size of 300 has the maximum objective function with the highest vehicle occupancy at 1.25. This solution, however, has the lowest service rate and wait time at 98.59% and 376.11s respectively. Fleet size of 325 has a slightly lower vehicle occupancy at 1.19, 0.06 lower than fleet size of 300, and a 1% higher service rate. Fleet size of 350 provides the best performance in terms of wait time at 357.67 seconds with a 20 second increase, but it has the lowest vehicle occupancy rate at 1.09, almost 13% lower than fleet size of 300. Detour factor and active mode shift remains constant among these 3 solutions. The active mode shift to AV+PT is very high at a conversion rate of more than half- this is an uncomfortably high amount as increasing active travel is among the top transport objective in many major cities, including the CSA. Strategies for retaining active mode share should be explored in future studies.

When considering service contracting, we would recommend fleet size 300 for fare multiplier of 0.5. Promoting sharing is among the most important objectives for agencies and fleet size of 300 has the highest average vehicle occupancy rate. This comes only at a cost of 1% decrease in service rate and about 1/3 of a minute in terms of wait time. It is worthwhile to note that this solution also has the smallest fleet size, making it easiest to manage.

When considering services provided by transit agencies, sometimes it is not feasible to lower fares by half – this could be a result of inter-organizational dynamics, politics, etc. Due to this, we also present the top solutions for fare multiplier 1.0 in Table 6.7. In the next steps of this research, more fine-grained analysis can be used to determine a more exact optimal point. This can be done by testing fare multipliers in steps sizes of ± 0.1, ± 0.05 or even ± 0.01.

Table 6.7: Performance Characteristics of Optimal Solution Space for Fare Multiplier 1.0

Fare Multiplier	1.0			Trend
Fleet Size	225	300	325	
Objective Function ($)	12751	13206	12922	
AV Trip Rate (Trips/Hour)	2076	2144	2146	↗
Average Vehicle Occupancy	1.28	1.03	0.91	↘
Service Rate (%)	95.18	99.95	99.95	↗
Level-of-Service: average wait time (s)	391.08	358.31	350.95	↘
Level-of-Service: average detour factor	1.15	1.13	1.13	→
Active mode shift to AV+PT: walk (%)	61.53	60.96	60.54	→
Active mode shift to AV+PT: bike (%)	49.47	50.09	50.19	→

When comparing solutions in the optimal solution space of fare multiplier 1.0, Table 6.7 shows that fleet size of 225 has by far the highest average vehicle occupancy at 1.28, 24% higher than the next highest and 41% higher than the lowest. This solution has the lowest service rate and highest wait time at 95.18% and 391.08 seconds respectively. The solution with the highest objective function is fleet size of 300 at 13206. This solution has an average vehicle occupancy, service rate, and wait time of 1.03, 99.95%, 358.31 seconds. The solution with fleet size of 325 has the best wait time, 8 seconds lower as compared to the next best – a small increment. Similar to fare multiplier of 0.5, detour factor and active mode shift remains constant among these 3 solutions with active mode shift remaining at an uncomfortably high level.

When considering service contracting, some agencies may focus more on providing the best service to users while others may focus on reducing cars on the road and congestion. we would recommend fleet size of 300 for those that wish to provide the best service to customers. This solution has the highest possible service rate as well as only an 8-second increase in waiting time from fleet size 325. It also has the highest objective function. For those that wish to focus on reducing the number of cars on the road, I would recommend a fleet size of 225. This fleet size has a 5% lower service rate as well as a 33 second increase in average wait time but has the highest average vehicle occupancy of 1.28.

The above represent our recommendations for fleet size at fare multiplier of 0.5 as well as 1.0. In the end, we would consider the fare multiplier of 1.0 to be the more feasible option as a multiplier of 0.5 may be politically difficult. This showcases how service contracting decisions regarding fleet size and fare can be made using the proposed simulation-based design module.

Section 7

7.0 Conclusion

7.1 Summary of Results and Considerations

This thesis offers a systematic approach to the design, simulation and evaluation of AV+PT systems and demonstrates specific AV+PT service designs. The system design and modeling framework reflect the transit-oriented considerations that are important for high service availability, seamless connections, and equity. Using demand-supply interaction, we represent the choices of both travelers and operators. Results show the tradeoff between improving level of service and traveler experience, and the cost of larger fleet size and low occupancy. We observe that encouraging ride-sharing, allowing in-advance requests, and combining fare with transit are tools to enable service integration and sustainable travel.

This thesis, as well, used simulation-based design to showcase how real-life AV+PT service characteristics can be determined using the proposed simulation-based design module. Moreover, it has outlined how various important considerations to key stakeholders can be quantified. The ones tackled in this thesis are:

- Benefit derived from increased mobility opportunities through AV+PT
- Operational profit (or subsidy if required)
- Decongestion benefit (private vehicle use reduction)
- Health impact from active travel mode share decrease
- Environmental footprint (AV's)
    - Global warming cost
    - Morbidity and mortality
- Lost bus revenue

Through service contracting, this thesis was able to show how decisions regarding fleet size and fare can be made using the proposed simulation-based design module. The results show the tradeoffs for each of the above considerations as fare and fleet size are simultaneously changed, and also a sample decision making process to choose the optimal combination.

The approaches developed in this work are generalizable and can be adapted for other transportation networks and data sources. For those agencies interested in the potential impacts that AVs might have on cities' transportation, agent-based simulation presents an opportunity for these agencies to explore how these changes might occur.

Moreover, in the short term, many transit agencies are currently engaging AV related tests on their streets. This presents an opportunity where simulation can be used prior to actual tests to:

- understand the test's impact on the existing transportation system
- rapidly explore different configuration of the potential AV trial (AV+PT integration scenarios may be of particular interest)
- make operational decisions by observing different configurations' performance in simulation (e.g. optimal fleet size, optimal routes/geography for tests)

Finally, there are two important limitations to this work. The first is we used our best judgement of people's preference for autonomous vehicles, something that is typical of AV related simulations. The literature on this area is inconclusive at best and also people's opinions are very susceptible to change based on information given. There is a strong likelihood that people's opinions of this technology will be significantly altered when the vehicles actually come to market and impact the day-to-day life of people. The second is that this work and its conclusions were drawn based on a very specific case study area. Our case study area has some very specific characteristics that does not represent all transportation network conditions that are typical of a city. First, it is a spread-out residential area where there are currently not a lot of congestion issues. Second, it is centered around a commuter rail station with frequent and high-speed train service to downtown. Finally, the bus service in this area is infrequent and not economically efficient as a result of the low residential density.

7.2 Future Research Needs and Final Thoughts

We point to the future research needs in three broad areas:

The first is to examine how the integrated AV+PT system will impact latent demand. Harb [79] shows an over 80% vehicle mile traveled (VMT) increase in a naturalistic experiment with chauffeur drivers. This thesis makes a strong assumption of fixed total travel demand, but it is critical for the future research to examine the latent demand.

The second is to investigate the AV fleet sizing and management strategies, and the impact on and the re-purposing of the bus services. In our simulated scenarios, the intra-zonal bus demand dropped by 14%, it is important to examine how bus service needs to be re-optimized. More broadly, the simulation model should to be expanded to include bus service so that we can consider the AV fleet and bus fleet management jointly. Furthermore, the impact of variation in demand throughout the days (especially peak vs. off-peak) as well as different days on the week will result in different optimal fleet sizes throughout these time periods. This work can be extended (through a deeper analysis of whole day or whole week demand) to determine the fleet size that maximize overall benefits for whole day or week. As well, it can be extended to analyze to determine how to best utilize idle fleet (package delivery, etc.).

The third is to explore a range of AV+PT fare products and their impact on service. The success of an AV+PT service depends on how much it costs and how attractive it is to the travelers. Although in section 6.2.4 the issue of different fare magnitudes has been tackled, we can expand the study to how different fare products such as monthly pass, early-bird discounts, and concession fares will change consumer behavior in order to design and price the services based on the needs of different stakeholders.

Other future work includes:

1. Incorporating service reliability as a measure of performance. Developing a distribution for waiting times and in-vehicle times instead of using the average values.
2. Better understanding the cost of operating and maintaining the AV fleet.
3. AV's impact on congestion.
4. Quantify other considerations important to AV service stakeholders such as noise.

References:

[1] Fagnant, D. J. and K. Kockelman (2015a) Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations, Transportation Research Part A: Policy and Practice, 77, 167–181.

[2] Erick Guerra (2015), "Planning for Cars That Drive Themselves: Metropolitan Planning Organizations, Regional Transportation Plans, and Autonomous Vehicles," Journal of Planning Education and Research, pp. 1–15

[3] D. J. Fagnant, K. M. Kockelman, The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios, Transportation Research Part C: Emerging Technologies 40, 1-13, 2014.

[4] D. J. Fagnant, K. M. Kockelman, Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles, in: Transportation Research Board 94th Annual Meeting, 15-1962, 2015.

[5] K. A. Marczuk, H. S. S. Hong, C. M. L. Azevedo, M. Adnan, S. D. Pendleton, E. Frazzoli, et al., Autonomous mobility on demand in simmobility: Case study of the central business district in singapore, in: Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), 2015 IEEE 7th International Conference on, IEEE, 2015, pp. 167-172.

[6] Martinez, L.M. and Viegas, J.M. Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. International Journal of Transportation Science and Technology, Vol. 6, No. 1, 2017, pp. 13-27

[7] B. Kloostra, M. J. Roorda, Fully Autonomous Vehicles: Analyzing Transportation Network Performance and Operating Scenarios in the Greater Toronto Area, Canada, Technical Report, 2017.

[8] S. Zhu, A. L. Kornhauser, The Interplay Between Fleet Size, Level-of-Service and Empty Vehicle Repositioning Strategies in Large-Scale, Shared-Ride Autonomous Taxi Mobility-on-Demand Scenarios, Technical Report, 2017.

[9] Almeida Correia GH, van Arem B (2016) Solving the user optimum privately owned automated vehicles assignment problem (UO-POAVAP): a model to explore the impacts of self-driving vehicles on urban mobility. *Transp Res Part B Methodological* **87**:64–88.

[10] Joschka Bischoff and Michal Maciejewski. Simulation of city-wide replacement of private cars with autonomous taxis in Berlin. The 7th International Conference on Ambient Systems, Networks and Technologies, 2016.

[11] Boesch, P., Ciari, F., Axhausen, K.. Required autonomous vehicle fleet sizes to serve different levels of demand. Tech. Rep.; Transport Research Board; 2016

[12] X. Liang, G. H. de Almeida Correia, B. Van Arem, Optimizing the service area and trip selection of an electric automated taxi system used for the last mile of train trips, Transportation Research Part E: Logistics and Transportation Review 93 (2016) 115-129.

[13] A. Vakayil, W. Gruel, S. Samaranayake, Integrating Shared-Vehicle Mobility-on-Demand Systems with Public Transit, Technical Report, 2017.

[14] Y. Shen, H. Zhang, J. Zhao, Integrating shared autonomous vehicle in public transit system: An example of the first-mile problem, 2017. Under review at Transportation Research Part A.

[15] Jian Wen. amod-abm. https://github.com/wenjian0202/amod-abm, 2017.

[16] K. Spieser, K. Treleaven, R. Zhang, E. Frazzoli, D. Morton, M. Pavone, Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in Singapore, in: Road Vehicle Automation, Springer, 2014, pp. 229-245.

[17] Jie Yang, Jing Dong, and Wei Wang. A simulation model for performance analysis of electric autonomous taxi systems. Technical report, 2017.

[18] Jaeyoung Jung, R Jayakrishnan, and Ji Young Park. Dynamic shared-taxi dispatch algorithm with hybrid-simulated annealing. Computer-Aided Civil and Infrastructure Engineering, 31(4):275–291, 2016.

[19] Javier Alonso-Mora, Samitha Samaranayake, Alex Wallar, Emilio Frazzoli, and Daniela Rus. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proceedings of the National Academy of Sciences, page 201611675, 2017.

[20] Luis M Martinez and José Manuel Viegas. Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. International Journal of Transportation Science and Technology, 6(1): 13–27, 2017.

[21] M. W. Levin, s. D. Boyles, Effects of autonomous vehicle ownership on trip, mode, and route choice, Transportation Research Record: Journal of the Transportation Research Board (2015) 29-38.

[22] S. Childress, B. Nichols, B. Charlton, S. Coe, using an activity-based model to explore the potential impacts of automated vehicles, Transportation Research Record: Journal of the Transportation Research Board (2015) 99-106.

[23] Azevedo, C.L., Marczuk, K., Raveau, S., Soh, H., Adnan, M., Basak, K., Loganathan, H., Deshmunkh, N., Lee, D.H., Frazzoli, E. and Ben-Akiva, M., 2016. Microsimulation of demand and supply of autonomous mobility on demand. Transportation Research Record: Journal of the Transportation Research Board, (2564), pp.21-30.

[24] T. D. Chen, K. M. Kockelman, Management of a shared autonomous electric vehicle eet: Implications of pricing schemes, Transportation Research Record: Journal of the Transportation Research Board (2016) 37-46.

[25] H. Qiu, R. Li, J. Zhao, Dynamic pricing in shared mobility on demand service and its social impacts, 2017. Manuscript submitted for publication.

[26] B. Lenz, E. Fraedrich, New mobility concepts and autonomous driving: the potential for change, in: Autonomous Driving, Springer, 2016, pp. 173-191.

[27] Zachariah, J., Gao, J., Kornhauser, A., Mufti, T., 2014, Uncongested Mobility for All: A Proposal for an Area Wide Autonomous Taxi System in New Jersey. In: Proceedings of the Transportation Research Board 93rd Annual Meeting.

[28] Boesch, P., Ciari, F., Axhausen, K.. Required autonomous vehicle fleet sizes to serve different levels of demand. Tech. Rep.; Transport Research Board; 2016.

[29] Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015). Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. Sustainable Cities and Society, 19, 34–45.

[30] Fagnant, D. J., & Kockelman, K. M. (2015). Dynamic Ride-Sharing and Optimal Fleet Sizing for a System of Shared Autonomous Vehicles. Transportation Research, 20.

[31] Spieser, K., et al. Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in Singapore. In Road Vehicle Automation, Springer, 2014, pp. 229-245.

[32] Wang, B. Medina, S.A.O. Fourie, P. "Simulation of Autonomous Transit On Demand for Fleet Size and Deployment Strategy Optimization" Procedia Computer Science, 2018, pp. 797-802.

[33] Bösch, P. M., F. Ciari and K. W. Axhausen (2017) Transport policy optimization with avs, Arbeitsberichte Verkehrs-und Raumplanung, 1269.

[34] Castiglione, J., Freedman, J., Davidson, W., 2003. Application of a tour-based microsimulation model to a major transit investment. San Francisco County Transportation Authority and PBConsult, San Francisco.

[35] EXPEDITE Consortium, 2002. EXPEDITE Final Publishable Report. Report for European Commission, DGTREN, RAND Europe, Leiden.

[36] Odeck, J., Rekdal, J., Hamre, T.N., 2003. The socio-economic benefits of moving from cordon toll to congestion pricing: the case of Oslo. Paper Presented at TRB Annual Meeting.

[37] Koenig, J.G., 1980. Indicators of urban accessibility: theory and application. Transportation 9 (2), 145–172

[38] Bhat, C., Govindarajan, A., Pulugurta, V., 1998. Disaggregate attraction-end choice modeling: formulation and empirical analysis. Transport. Res. Rec. J. Transport. Res. Board 1645 (1), 60–68

[39] Bhat, C.R., Carini, J.P., Misra, R., 1999. Modeling the generation and organization of household activity stops. Transport. Res. Rec. J. Transport. Res. Board 1676 (1), 153–161

[40] Chen, A., Yang, C., Kongsomsaksakul, S., Lee, M., 2007. Network-based accessibility measures for vulnerability analysis of degradable transportation networks. Networks Spatial Econ. 7 (3), 241–256.

[41] Gulhan, G., Ceylan, H., Özuysal, M., Ceylan, H., 2013. Impact of utility-based accessibility measures on urban public transportation planning: a case study of Denizli, Turkey. Cities 32, 102–112

[42] Nassir, N., Ziebarth, J., Sall, E. and Zorn, L., 2014. Choice set generation algorithm suitable for measuring route choice accessibility. Transportation Research Record: Journal of the Transportation Research Board, (2430), pp.170-181.

[43] Nassir, N., Hickman, M., Malekzadeh, A., Irannezhad, E., 2016. A utility-based travel impedance measure for public transit network accessibility. Transp. Res. A Policy Pract. 88, 26–39

[44] McFadden, D. (1978) Modelling the choice of residential location. In: Karlqvist, A., Lundqvist, L., Snickars, F. and Weibull, J. (eds) Spatial Interaction Theory and Residential Location. North-Holland, Amsterdam.

[45] Koppelman, F.S. and Bhat, C., 2006. A self instructing course in mode choice modeling: multinomial and nested logit models.

[46] Kohli, Serbjeet, and Andrew Daly. "The use of logsums in welfare estimation: application in PRISM." *Proceedings of the European Transport Conference, Strasbourg, France*. 2006.

[47] Howard, D., & Dai, D. (2014). Public perceptions of self-driving cars: The case of Berkeley, California. In *Transportation Research Board 93rd Annual Meeting* (Vol. 14, No. 4502).

[48] Choi, J. K., & Ji, Y. G. (2015). Investigating the importance of trust on adopting an autonomous vehicle. *International Journal of Human-Computer Interaction, 31*(10), 692-702.

[49] Schoettle, B., & Sivak, M. (2014). A survey of public opinion about autonomous and self-driving vehicles in the US, the UK, and Australia.

[50] Alessandrini, A., Campagna, A., Delle Site, P., Filippi, F., & Persia, L. (2015). Automated vehicles and the rethinking of mobility and cities. *Transportation Research Procedia*, *5*, 145-160.

[51] Bansal, P. and K. M. Kockelman (2016) Forecasting Americans' Long-Term Adoption of Connected and Autonomous Vehicle Technologies, paper presented at the 95th Annual Meeting of the Transportation Research Board.

[52] Zmud, J., I. N. Sener and J. Wagner (2016) Consumer Acceptance and Travel Behavior Impacts of Automated Vehicles, Technical Report, Austin.

[53] Silberg, G., M. Manassa, K. Everhart, D. Subramanian, M. Corley, H. Fraser, V. Sinha and 29 A. W. Ready (2013) Self-Driving Cars: Are we Ready?, Technical Report, KPMG.

[54] Becker, Felix, and Kay W. Axhausen. Literature Review on Surveys Investigating the Acceptance of Autonomous Vehicles. No. 17-06736. 2017.

[55] Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies*, *67*, 1-14.

[56] Kyriakidis, M., Happee, R., & de Winter, J. C. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation research part F: traffic psychology and behaviour*, *32*, 127-140.

[57] Yap, M.D., Correia, G. and van Arem, B., 2016. Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. Transportation Research Part A: Policy and Practice, 94, pp.1-16.

[58] Dong, Xiaoxia, Matthew DiScenna, and Erick Guerra. Transit User Perception of Driverless Buses. No. 17-04370. 2017.

[59] Y. Freemark, J. Zhao, An urban agenda for autonomous vehicles: Embedding planning principles into technological deployment, 2017. Manuscript submitted for publication.

[60] A. Stuntz, J. Attanucci, F. P. Salvucci, A Process for Transit Fare Structure and Fare Level Analysis: Case Study at the Massachusetts Bay Transportation Authority, Technical Report, 2017.

[61] Y. Sheffi, W. B. Powell, An algorithm for the equilibrium assignment problem with random link times, Networks 12 (1982) 191-207.

[62] Niels Agatz, Alan Erera, Martin Savelsbergh, and Xing Wang. Optimization for dynamic ride-sharing: A review. European Journal of Operational Research, 223(2):295–303, 2012.

[63] Wen Jian. Value of Information in Dispatching Shared Autonomous Mobility-on-Demand Systems: A Simulation Framework: A thesis in Transportation Science (master's thesis), Massachusetts Institute of Technology, 2017.

[64] Dennis Luxen and Christian Vetter. Real-time routing with openstreetmap data. In Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, GIS '11, pages 513–516, New York, NY, USA, 2011. ACM. ISBN 978-1-4503-1031-4. doi: 10.1145/2093973.2094062. URL http://doi.acm.org/10.1145/2093973.2094062.

[65] https://tfl.gov.uk/modes/taxis-and-minicabs/taxi-fares

[66] M. Bierlaire, PythonBiogeme: a short introduction, Technical Report, 2016.

[67] Nassir, N., Hickman, M. and Ma, Z.L., 2018. A strategy-based recursive path choice model for public transit smart card data. Transportation Research Part B: Methodological. https://doi.org/10.1016/j.trb.2018.01.002

[68] Zipcar, Zipcar, 2017. Https://drive.uber.com/ukmarketplace/partner/zipcar/.

[69] L. Cheer, Uber to hike its cut of fares to 25 per cent - and drivers warn the 'greedy' money-grab will lead to fewer cars on the road, in worse shape, and higher prices, 2016. Http://www.dailymail.co.uk/news/article-3538933/Uber-looks-hike-drivers-fee-25-cent-lead-price-surge.html.

[70] The Telegraph, Proof that uber costs less than black cabs, 2015. Http://www.telegraph.co.uk/technology/uber/11902613/Proof-that-Uber-costs-less-than-black-cabs.html.

[71] J. Wen, Y.X. Chen, N. Nassir, J. Zhao, Transit-Oriented Autonomous Vehicle Operation with Integrated Demand-Supply Interaction. Manuscript submitted for publication.

[72] B. Gilles, J. Zhao, Rules of the Road, 2018. Manuscript submitted for publication.

[73] AAA Association Communication. (2016.) YOUR DRIVING COSTS How much are you really paying to drive? [Brochure]. Printed in USA.

[74] Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167-181.

[75] Fagnant, D. J., & Kockelman, K. (2013). Preparing a Nation for Autonomous Vehicles Eno Center for Transportation. *Washington, DC.*

[76] Abrantes, P. A. (2015). The economic value of bus subsidy. *Transportation Research Procedia*, *8*, 247-258.

[77] World Health Organization. 2014. Health Economic Assessment Tool. Retrieved from http://www.heatwalkingcycling.org

[78] Lemp, J. D., & Kockelman, K. M. (2008). Quantifying the external costs of vehicle use: Evidence from America's top-selling light-duty models. *Transportation research part D: transport and environment, 13*(8), 491-504.

[79] C. M. W. Harb, Xiao, Projecting travelers into a world of self-driving vehicles: Estimating travel behavior implications via a naturalistic experiment, Transportation Research Board 97th Annual Meeting

Appendix A: Heat Tool Assumptions

Assumptions:

1) The year 2011 was considered as the base year
2) Single case option was use (exercise was compared a base case where there is no exercise)
3) 10 years over which the impacts are calculated
4) 47898 total population considered in an average year, this is based on the expanded population of trips used in simulations
5) Considered only "physical activity" health benefits
6) assume 10 hours of similar demand level service a day, thus monetary value of life was divided by 365 days and also 10 hours for a per hour value
7) Parameter used were for the default CSA city values provided by the tool
    a. The parameters for walking are:
        i. Average walking speed is 5.3 km/h
        ii. Discount rate is 5%
        iii. Value of statistical life is 4036471 euros/death
        iv. All-cause mortality rates by country and age group for walk in reference case 389.36 deaths/inhab
    b. The parameters for biking are:
        i. Average cycling speed is 14 km/h
        ii. Discount rate is 5%
        iii. Value of statistical life is 4036471 euros/death
        iv. All-cause mortality rates by country and age group for walk in reference case 238.26.36 deaths/inhab

Appendix B: Google API Routing Travel Time

To generate the link travel times, we sought to identify the all link origins and destinations used by the OSRM engine. This was done through recording the route's leg's origins and destinations in large amounts of simulation. Using these ODs, we were able to generate link travel times for legs of trips – creating the lookup table. When a new route is determined in the simulation, we will try to match the legs of trips with the values in the lookup table. Consistently about 90% links used by vehicles of any given simulation are found in the lookup table. When links are not found, the travel time is approximated using Euclidian distance with constant vehicle speed.