Dynamic Interaction between Shared Autonomous Vehicles and Public Transit: A Competitive Perspective

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Abstract

The emerging autonomous vehicles (AV) can either supplement the public transportation (PT) system or be a competitor with it. This paper focuses on this competition in a hypothetical scenario—“if both AV and PT operators are profit-oriented,” and uses an agent-based model to quantitatively evaluate the system performance in this competition from the perspectives of four stakeholders—AV service operator, PT operator, passengers, and public authority. In our model, AV operator updates its supply by changing fleet sizes while PT by adjusting headways, and both use heuristic approaches to update supply in order to increase profits. We implement the model in the first-mile scenario in Tampines, Singapore. In four regulation scenarios—two by two combinations regarding whether AV and PT are allowed to change supplies—we find that since AV can release the bus operator from low-demand routes, the competition can lead to higher profits of both, and higher system efficiency, simultaneously, rather than a one-sided loss-gain result. For PT, after supply updates, spatially the services are concentrated to short feeder routes directly to the subway station, and temporally concentrated to peak hours. For passengers, the competition reduces their travel time but increases their travel costs. Nonetheless, the generalized travel cost is still reduced when counting the value of time. For system efficiency and sustainability, bus supply adjustment can increase the bus average load and reduce total passenger car equivalent (PCE), while the AV supply adjustment shows the opposite effect.

For policy implications, the paper suggests that PT should be allowed to optimize its supply strategies under specific operation goals constraints, and AV operation should be regulated to relieve its externality on the system, including limiting the number of licenses, operation time, and service areas, which makes AV operated like a complementary mode to PT. Besides, compensation/price incentives may be targeted passengers who suffer from higher travel costs and longer travel time due to AV and PT supply adjustment.

Keywords: shared mobility-on-demand system; autonomous vehicles; public transportation; agent-based simulation; market Competition

1. Introduction

The emergence of autonomous vehicles (AV) as a new transportation mode is anticipated to extensively influence the future urban transportation system in different aspects, including traffic flow stability and throughput rates (Talebpour and Mahmassani 2016), network congestion levels (Fagnant and Kockelman 2015), land use patterns (Koh and Wich 2012), and road safety (Zhang et al. 2016). As a critical component of urban transportation, public transportation (PT) systems cannot avoid the impact of AV. Due to the uncertainty of how the AV system may evolve, many possible scenarios of AV–PT interaction have been proposed (Lazarus et al. 2018). Some researchers argue that AVs will be competitors to the PT systems (Levin and Boyles 2015; Chen and Kockelman 2016) or even replace them (Mendes et al. 2017), while some are optimistic to the AV–PT integration, stating that they could be complementary (Lu et al. 2017).

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AV–PT integration has been widely studied under various operation and regulation scenarios. For example, [Salazar et al. (2018)] proposed a tolling scheme for an AV–PT intermodal system, which shows significant reduction of travel time, costs, and emissions compared to an AV-only scenario. [Wen et al. (2018)] designed a transit-oriented autonomous mobility-on-demand (AMoD) system, revealing the trade-off between level of service and operation cost. They found encouraging ride-sharing, allowing in-advance requests, and combining fare with transit help to stimulate sustainable travel.

Conversely, for AV–PT competition, a comprehensive analysis is still lacking. Most prior research only evaluated the effect of AV based on aggregate models, but did not specify the competition mechanisms between AV and PT ([Levin and Boyles, 2015] [Childress et al., 2015]). Recently, agent-based models (ABM) have been used to investigate the AV–PT competition. For example, both [Liu et al. (2017)] and [Mendes et al. (2017)] argued that traditional PT services may not survive once the shared AV services become available. Nonetheless, prior research using ABM all considered the AV–PT interaction to be static or a single-shot game—how PT systems will evolve when AV is introduced—rather than a repeated game with AV and PT competing by adjusting supplies.

This paper aims to extend the ABM approach to simulate the repeated games between AV and PT, and to evaluate the performance of both systems, such as level of service, operators’ financial viability, and transport efficiency. We assume that both AV and PT can be profit-oriented competitors with dynamic adjustable supply strategies under certain policy constraints.

Competition per se is neither good or bad. In classic economics, in ideal situation market competition can lead to optimal resource allocation. However, due to the possibility of market failure, regulations are often imposed on competition, or even mandate certain cooperation. In this paper, we envision four regulation scenarios, corresponding to four regulation levels, as listed in Table 1.

The four scenarios are differentiated by the regulations of the supplies of PT and AV—either be fixed or adjustable. A “fixed” scenario is one in which the operators of either AV or PT are NOT allowed to change their supply. An “adjustable” scenario is one in which operators can adjust their supply based on profit-oriented strategies. An overview of the four scenarios is given below.

- The “status quo” scenario corresponds to a fully-regulated transportation market without competition ([Shen et al., 2018]). The fare structure, route network, service areas are all set by transport authorities. The operators in this scenario are only responsible for the operation, management, and fleet maintenance.

- The “AV-only” scenario corresponds to TNC-regulated organization structure ([Shen et al., 2018]), where the AV operation can be licensed or regulated by public authorities, while the services are still provided by the private operators and operated independent from transit agencies (e.g., in New York City, London, and Singapore).

- The “PT-only” scenario corresponds to the “Scandinavian” organization structure ([Costa, 1996] [van de Velde, 1999]), where the transport authority sets service goals and then contracts out transit services to private operators. PT operators make operational decisions to maximize their profits while ensuring service standards.

- The “AV–PT” scenario is close to the U.K.-deregulation structure ([Wilson, 1991]), where PT and AV operators are profit-oriented competitors but both are also regulated by the public authority.

### Table 1: Regulation scenarios assumed in this paper

| Scenarios   | PT supply          | AV supply |
|-------------|--------------------|-----------|
|             | Fixed             | Adjustable| AV only | AV–PT |
| Status quo  |                   |           |          |
| PT-only     |                   |           |          |

According to [Lesh, 2013], the first/last mile connection to subway station shows the highest potential for market competition between AV and PT. Thus, we select the first-mile trip market in Tampines, Singapore as a focus area, with only buses comprising of the PT system.
As for operation strategies, for simplicity of discussion, we assume AV can only adjust the fleet size and PT can only adjust the headway. Service fare and bus routes typically are regulated by governments, and thus are assumed fixed throughout the paper.

We evaluate the AV–PT competition system from the perspectives of 1) AV and PT operators, based on their financial viability, 2) passengers, based on the level of service of both systems, and 3) transport authority, based on efficiency and sustainability. The details of performance metrics are given in later sections.

The contributions of this paper are twofold. First, the paper for the first time in literature simulates the dynamic reciprocal supply strategies between profit-oriented AV and PT systems; Second, we analyze the impact of four different regulation scenarios on the competition;

This paper is organized as follows. Section 2 presents a literature review and identifies the research gaps. Section 3 presents the specification of the ABM used in this paper. Section 3.3 explains the performance metrics in this paper. Section 4 discusses the results, and Section 5 concludes the paper.

2. Literature Review

AV is expected to reshape the future transportation system from different perspectives. Many advantages of AV, such as absolute compliance, expanded service hours, reduced labor forces and human errors make it an efficient mode of urban transportation, which enables the reduction of operation cost and serves travel demand smaller fewer fleet sizes (Fernández L. et al., 2008; Alonso-Mora et al., 2017; Spieser et al., 2014).

Given the promising application of AV, many recent studies have examined the impact of AV in different aspects, such as traffic flows (Talebpour and Mahmassani, 2016), road congestion (Fagnant et al., 2015), land use (Koh and Wich, 2012), and road safety (Zhang et al., 2016). Talebpour and Mahmassani (2016) used a micro-simulation model to evaluate the impact of connected and autonomous vehicles on traffic flows, which showed that AV can improve string stability and help to prevent shockwave formation and propagation. Azevedo et al. (2016) applied an integrated agent-based micro-simulation model to design and evaluate the impact of AV on people’s travel behavior. They found that the new AV technology can change people’s travel patterns, specifically in terms of mode shares, route choices and activity destinations. Fagnant and Kockelman (2014) found that each shared AV can replace around 11 conventional vehicles, but adds up to 10% more travel distance than comparable non-shared AV trips. There are also empirical studies in Lisbon (Martinez and Viegas, 2017), Toronto (Kloostra and Roorda, 2019) and New Jersey (Zhu and Kornhauser, 2017), which reveals AV technology can reduce travelled vehicle kilometres and emissions (Martinez and Viegas, 2017), decrease average travel time (Kloostra and Roorda, 2019), and reduce the number of vehicles on roads (Martinez and Viegas, 2017).

However, despite the large volume of recent research the impact of AV, research focusing on the AV–PT interaction is still lacking. Two major relationships between AV and PT have been discussed in the literature.

First, AV and PT can be complementary and integrated. AV and PT can be cooperative in a way that AV is integrated as a part of PT system for social welfare. In line with this assumption, Ruch et al. (2018) used a simulation model to analyze whether AV can substitute the rural PT lines. It was shown that such a service can operate at a lower cost and with a higher service level when the PT lines are short and are underutilized. Similarly, Shen et al. (2018) designed an AV–PT integration system with AMoD as an alternative to low-demand bus routes, which showed that the integrated system has the potential of enhancing service quality, occupying fewer road resources and being financially sustainable. Another cooperative scenario is the multi-modality between AV and PT. For example, Yap et al. (2016) conducted a stated preference survey to analyze the use of automated vehicles as egress of train trips. They found that AV is a good alternative to the first-class train passengers. Liang et al. (2016) used an integer programming model to study AV as a last-mile connection to train trips, which showed that using automated taxis can reduce the pick-up cost and improve profit. Vakayil et al. (2017) proposed a hybrid transit system where AMoD serves as the first- and last-mile feeder for the subway. The results show that an integrated system can provide up to a 50% reduction in total vehicle miles traveled. These studies provide sufficient analysis toward the AV–PT integration relationship. Also, the co-operation strategies for AV and PT are also designed (Salazar et al., 2018).

Second, AV can be competitive with traditional PT when AV is operated privately, and competes for market shares and profit. The analysis of this scenario is very limited. Based on a multiclass four-step model, Levin and Boyles (2015) found that the transit ridership will decrease when AV is introduced. Similarly, Childress
et al. (2015) used an activity-based model to evaluate the impact of AV, which revealed a reduction of PT’s mode share. Liu et al. (2017) simulated the impact of shared AV based on the case study of Austin, Texas, with results showing that conventional PT services may not survive once the shared AV services become available. Mendes et al. (2017) developed an event-based simulation model to compare the shared AV services with the proposed light rail services in New York City, which found that AV is more cost-efficient in providing the same level of service. Basu et al. (2018) applied an activity-driven agent-based simulation approach to test the impact of AV on mass transit and found that AMoD indirectly acts as a replacement to mass transit.

Understanding how AV competes with PT is critical for managing future PT services and developing sound intervention on the private transportation market. However, the existing studies addressing AV–PT competition focused on the static interaction process, i.e., only looking at what will happen when AV is introduced as a one-shot game. However, as competitors, it is highly likely that AV and PT will dynamically adjust the operation strategies in the market as repeated games. These interactive dynamics have not been considered in the literature. Moreover, most existing studies only evaluate the AV’s impact on the mode share of PT, without a comprehensive assessment of the cost and benefit of different stakeholders in the system, including operators, passengers, and transport authorities.

In this paper, we use an agent-based model to simulate the competition between AV and PT as a repetitive game, with both parties trying to increase their profits. We also comprehensively evaluate the system from different stakeholders’ perspectives, including the financial conditions, level of services, sustainability and transport efficiency, which aims to fill the research gap in the literature.

3. System Design

We use the Tampines Planning Area in Singapore as the study area to illustrate our AV–PT competition model, and the focus on the first-mile trips heading to the Tampines Mass Rapid Transit (MRT) station from surrounding residential blocks.

In Singapore, walking and buses are currently the dominant modes for first-mile trips (Mo et al., 2018). Bus service in Singapore is highly regulated by the Land Transport Authority (LTA), which is responsible for its fare structure and route design. The LTA contracts out bus services to different bus operators on a five-year basis.

3.1. Basic Assumptions

Based on the characteristics and operational structures of the Singapore transport system, we make the following assumptions for the AV–PT competition model.

(a) System level

- Travel mode: Before AV entering the market, walking, bus and ride-hailing are the only travel modes available for the first-mile trips. After AV emerges, ride-hailing will be replaced by the AMoD. This assumption is corresponding to the Singapore autonomous vehicle initiative policies (Land Transport Authority, 2017).
- Traffic condition: We focus on the mesoscopic simulation, the microscopic features such as road capacity, signal system, and driving behaviors are not considered in this study.
- Demand and supply: The spatial and temporal distributions of travel demand are assumed to be fixed for all simulation days. The supply of AV and PT can be adjusted for competition.
- Information: The AMoD and PT’s supply information is complete and in real time for passengers’ mode choice decisions.

(b) Agent level

- Ownership: PT and AMoD are both operated by private enterprises, but under government regulation, i.e., they are in a constrained competition.
- Objective: PT and AMoD are able to adjust their supply to improve their profits.
- Fare: PT and AMoD’s fare structures are fixed by the government and cannot be changed.
• Operation cost and subsidy: PT and AMoD’s operation cost are proportional to their fleet size and driving distance. There is no operation subsidy for PT based on the current Singapore policy (Gopinath and Kuang, 2018).
• Constraints: PT has a lower bound and an upper bound for the bus headway.
• Dynamic intraday supply: AMoD and PT’s supply can be different in different time periods in a day.
• Supply updating frequency: AMoD can update the next day’s supply strategy at the end of each day. PT can only update its supply strategy after a sufficiently long time (30 days in this paper; more discussion in Section 3.5).

To summarize, AMoD updates supply daily by adjusting the vehicle fleet size in each time interval of the next day, and PT adjusts its supply by changing the headway for each bus route in different time intervals monthly.

Price adjustment is also a common practice to increase profit in market competition. However, to isolate the impact of supply change, we only focus on supply in this paper, assuming prices to be fixed for both PT and AMoD. Moreover, given the price regulation history of LTA, it is very likely that the AMoD will be regulated on the fare structure to avoid price wars (Singapore Public Transport Council, 2019). Future research can explore on a combined model incorporating supply change and pricing.

3.2. Study Area
Tampines is a 6.86-km$^2$ mixed residential and working area located in the east of Singapore (Figure 1). It is centered around the Tampines MRT station, which is one of the busiest MRT stations in Singapore (Housing & Development Board, 2015). 51 bus stops serve Tampines, with 26 bus routes connecting to the MRT station. Three of them are dedicated feeder routes to the subway. The other 23 are passing-by routes. All 26 routes are included in the simulation model. We choose Tampines as a case to illustrate our model because 1) it possesses a significant first-mile demand to the MRT station, and 2) it embraces a large volume of bus supply, which provides a non-trivial testbed for competition analysis.

The first-mile travel demand is obtained from the transit smart card data. The dataset covers all PT trips in August 2014. A normal workday in August 2014 is selected as the study date. Since the smart card data in
Singapore includes both tap-ins and tap-outs, the accurate date and time of every entry and exit activity are recorded, as well as the boarding and alighting stops/stations, which allows us to extract first-mile trips by filtering the bus trips with a connecting subway trip. The temporal distribution of first-mile travel demand in study day is shown in Figure 2. There are a total of 51,850 passengers entering the Tampines MRT station during the study date.

![Figure 2: Time-of-day Distribution of First-mile Demand to Tampines MRT Station](image)

3.3. Stakeholders and System Evaluation

We evaluate the interests of multiple stakeholders in the AV–PT competition. Table 2 identifies four key stakeholders (passengers, AMoD operators, PT operators and transport authority) their evaluation indicators.

For passengers, the main interests are level-of-service and modal choice. The level-of-service indicators include travel cost, total travel time, waiting time and generalized travel cost—calculated as the sum of walking time, waiting time and riding time multiplied by the corresponding value of time (VOT). It is a comprehensive value that incorporates both travel time and travel costs. The VOTs are derived from the estimated choice model in Table B.1. In terms of modal choice, the number of travelers choosing walking, bus and AV are recorded, respectively.

For AMoD and PT operators, based on our profit-orientation assumption, their interests are financial viability and supply. The financial viability indicators include operation cost, revenue, profit, and market share, while the supply indicates the number of AV/bus supplied.

For the transport authority, efficiency and sustainability are considered. The average load per vehicle is one of the indicators for transport efficiency, which is calculated by total passenger travel distance divided by total vehicle travel distance. As for sustainability, we consider the vehicle kilometers traveled (VKT) and total passenger car equivalent (PCE). The unit PCE for a bus is set as 3.5 in this study (Ahuja, 2007).

These indicators are recorded in the simulation process, which shows the whole changing profile during the competition between AV and PT. The time of day distribution of some indicators is also recorded.

3.4. Agent Behaviors

The overall simulation system is composed of three main types of agents: buses, AMoD vehicles and passengers. The PT system is derived from Shen et al. (2018)’s study, which has been calibrated and validated with real-world data. Here we give an overview of the behaviors of the agents, with detailed formulation given in Appendix A.

- Passengers’ mode choices are based on mixed logit models, and use trip-specific variables, including waiting time, in-vehicle time, monetary cost, etc., and individual-specific variables, such as household income; If a passenger chooses bus, we assume he/she walking to the closest bus stop; If there is no bus available at the trip start time, and at the same time there is a shortage of AMoD, the agent walks to the MRT station directly.
Table 2: Evaluated Indicators of Stakeholders

| Stakeholder     | Interests       | Indicators                                      |
|-----------------|-----------------|------------------------------------------------|
| Passengers      | Level of service| Travel cost                                     |
|                 |                 | Total travel time                               |
|                 |                 | Waiting time                                    |
|                 |                 | Generalized travel cost                         |
|                 | Mode choice     | Walking demand                                  |
|                 |                 | Bus demand                                      |
|                 |                 | AV demand                                       |
| AMoD Operators  | Financial viability | Operation cost                                     |
|                 |                 | Revenue                                         |
|                 |                 | Profit                                          |
|                 | Supply          | Market share                                    |
|                 | Average number  | of AV provided per hour                         |
| PT Operators    | Financial viability | Operation cost                                     |
|                 |                 | Revenue                                         |
|                 |                 | Profit                                          |
|                 | Supply          | Market share                                    |
|                 | Number of bus   | dispatched per day                              |
| Transport Authority | Transport efficiency | AV average load per vehicle                       |
|                 | Sustainability  | Bus average load per vehicle                      |
|                 |                 | AV VKT                                          |
|                 |                 | Bus VKT                                         |
|                 |                 | Total PCE (AV and PT)                           |

- AMoD dispatching is based on the first-come-first-serve principle upon passengers’ requests. The vehicles follow the shortest paths from pick-up locations to the MRT station. When there is no empty vehicle available, the dispatching center will then look for vehicles with passengers who agree to share their trips. The AMoD operator updates the fleet size of each time period of a day, daily to increase its profit.

- Buses follow existing routes given by the LTA. The operator for each bus route independently optimizes its profit by changing the headway of each time period of a day, monthly.

3.5. Simulation Platform

We implemented the model on AnyLogic 8.1. The simulation is executed for \( T = 365 \) days to make sure that the competition process converges. There are four sets of input variables/parameters: simulation setting parameters \( \theta \), initial supply strategies of bus \( S_B^{(0)} \), initial supply strategies of AMoD \( S_A^{(0)} \), and the first-mile demand \( D \). The detailed notations and values used are given in Table 3. The values of many constants are chosen based on Singapore context, where details can be found in Appendix A.

The supply, profit, and supply changing unit are all time-specific for AV, which means that for different days and different time periods they may have different values. For buses, these variables are time- and route-specific. The pseudo-code for simulation is shown in Algorithm 1.

As shown in Algorithm 1, the overall framework aims to simulate the interaction between AV and PT over time period \( T \). ONE-DAY-Sim is a pseudo function of running the simulation for a single day given the supply, demand and \( \theta \), which can be seen as the engine of the simulation model. In this function, each agent will follow the behaviors mentioned in Appendix A.

The profits of AMoD and PT can be obtained after running this function. The profit, supply and supply change unit are then used as the input of function SUPPLYUPDATE (shown in Algorithm 2), deriving the updated supply strategies and new supply change unit for AV and PT. It is worth noting that since we assume the AV supply updating frequency to be daily, this function is executed for AV everyday, while for PT, this function is executed every \( N_B \) days considering the inflexibility of PT.

In reality, the schedule of PT should not be adjusted frequently considering people’s expectation for its reliability. A reasonable changing frequency should be more than 6 months, which allows the transit operator to notice the public, and gives people enough time to be prepared for the new schedule. However, using \( N_B = 6 \) month will lead to a high computational load. Based on our numerical test, given a specific bus schedule, the system will become stable in one or two weeks when only AMoD updates its supply. Thence,
Table 3: Notations and Values of System Parameters

| Categories                     | Parameters/Variables                                                                 | Value                  |
|-------------------------------|--------------------------------------------------------------------------------------|------------------------|
| Simulation setting parameters | Duration of simulation \((T)\)                                                      | 365 days               |
| \(\theta\)                   | Supply changing unit reduced factor \(\gamma\)                                       | 0.5                    |
|                               | Passenger choice lag factor \(\alpha\)                                              | 0.5                    |
|                               | Passenger mode choice parameters \(\beta\)                                          | See Table B.1          |
|                               | Passenger maximum \(AV\) waiting time                                              | 10 min                 |
|                               | Passenger bus waiting time                                                          | 30 min                 |
|                               | Passenger ride-sharing-agreement rate                                               | 50%                    |
|                               | \(AV\) supply time interval \((i_A)\)                                               | 1 hour                 |
|                               | \(AV\) supply updating frequency \((N_A)\)                                         | 1 day                  |
|                               | \(AV\) fixed operation cost                                                        | 4 SGD/hour-veh         |
|                               | \(AV\) variable operation cost                                                     | 0.12 SGD/km            |
|                               | \(AV\) base distance of fare \((d_b)\)                                              | 1 km                   |
|                               | \(AV\) base fare \((f_b)\)                                                         | 3.4 SGD                |
| Dual                          | \(AV\) distance-based fare \((f)\)                                                  | 0.22 SGD/400 m         |
|                               | \(AV\) detour discount rate of fare \((\lambda)\)                                 | 2                      |
|                               | \(AV\) supply lower bound \((S^L_A)\)                                              | 0                      |
|                               | \(AV\) supply upper bound \((S^U_A)\)                                              | \(+\infty\)            |
|                               | \(AV\) initial supply changing unit \((C_{A}^{ini})\)                             | 10 vehicles            |
|                               | Bus supply time interval \((i_B)\)                                                  | 2 hour                 |
|                               | Bus supply updating frequency \((N_B)\)                                             | 30 days                |
|                               | Bus operation cost                                                                 | 2.71 SGD/km            |
|                               | Bus dwell time                                                                     | 30 sec                 |
|                               | Bus fare                                                                           | 0.77 SGD/trip          |
|                               | Bus headway upper bound \((S^U_B)\)                                                | 2100 sec               |
|                               | Bus headway lower bound \((S^L_B)\)                                                | 210 sec                |
|                               | Bus initial headway changing unit \((C_{B}^{ini})\)                               | 3 min                  |
| Bus supply \(S_B\)            | Bus headway of route \(l\) in time interval \(t\) on day \(d\) \((S^{l,t,d}_B)\)| Intermediate |
|                               | Bus headway arrangement on day \(d\) \((S^{d}_B) = [S^{l,t,d}_B]_{l,t}\)          | Intermediate           |
|                               | Bus initial headway changing unit \((C^{B^{ini}})\)                               | Intermediate           |
| Av supply \(S_A\)             | Number of \(AV\) supplied in time interval \(t\) on day \(d\) \((S^{d}_A)\)      | Intermediate           |
|                               | Av supply strategies on day \(d\) \((S^{d}_A) = [S^{t,d}_A]_{l,t}\)               | Intermediate           |
|                               | \(AV\) initial supply strategies \((S^{0}_A)\)                                   | See Appendix A.2       |
| Demand \(D\)                 | Demand of first-mile trips \(D\)                                                   | See Figure 2           |
| Supporting variables          | \(AV\) supply changing unit in time interval \(t\) for day \(d\) \((C^{t,d}_A)\)| Intermediate |
|                               | \(AV\) supply changing unit on day \(d\) \((C^{d}_A) = [C^{t,d}_A]_{l,t}\)        | Intermediate           |
|                               | Bus profit of route \(l\) in time interval \(t\) on day \(d\) \((P^{d}_A)\)      | Intermediate           |
|                               | Bus profit vector day \(d\) \((P^{d}_A) = [P^{l,t,d}_A]_{l,t}\)                  | Intermediate           |
|                               | Bus headway changing unit of route \(l\) in time interval \(t\) for day \(d\) \((C^{l,t,d}_B)\)| Intermediate |
|                               | Bus headway changing unit vector on day \(d\) \((C^{d}_B) = [C^{l,t,d}_B]_{l,t}\)| | Intermediate           |
|                               | Bus headway changing unit vector on day \(d\) \((P^{d}_B) = [P^{l,t,d}_B]_{l,t}\)| | Intermediate           |

* Values “Intermediate” means the intermediate variables in the model.
Algorithm 1 Agent-based Simulation

1: procedure SIMULATION($\theta$, $S_B^{(0)}$, $S_A^{(0)}$, $D$)
2:   initialize $p_A^{(0)} = 0$, $p_B^{(0)} = 0$, $S_A^{(0)}$, $S_B^{(1)} = S_B^{(0)}$
3:   initialize $C_A^{(1)} = C_A^{ini}$, $C_B^{(1)} = C_B^{ini}$
4:   let day counter $d = 0$
5:   while $d < T$ do
6:      $d = d + 1$
7:      $p_A^{(d)}$, $p_B^{(d)} = \text{ONE-DAY-SIM}(S_B^{(d)}$, $S_A^{(d)}$, $D | \theta$)
8:      $S_A^{(d+1)}$, $C_A^{(d+1)} = \text{SUPPLYUPDATE}(p_A^{(d)}$, $p_A^{(d-1)}$, $S_A^{(d)}$, $C_A^{(d)}$
9:      if $d \mod N_B = 0$ then
10:         $S_B^{(d+1)}$, $C_B^{(d+1)} = \text{SUPPLYUPDATE}(p_B^{(d)}$, $p_B^{(d-N_B)}$, $S_B^{(d)}$, $C_B^{(d)}$
11:      else
12:         initialize $C_A^{(d)} = C_A^{ini}$
13:      $S_B^{(d+1)} = S_B^{(d)}$
14:      $C_B^{(d+1)} = C_B^{(d)}$
15:   return the system evaluation indicators (Table 2)

any value of $N_B$ that is greater than two weeks is equivalent to 6 months because the system state will not change after 2 weeks. $N_B = 30$ days is used in this study, which is able to simulate the long-period updating frequency of the bus. The system evaluation indicators (Table 2) are recorded during the simulation process and returned at the end of the model.

In terms of supply updating, we propose a heuristic algorithm, which applied to both AmoD and PT. Since we have assumed that the spatial and temporal demand to be fixed, the profits across different time periods and routes are independent. In other words, we assume people are not changing their departure times if they observe fewer cars or buses in a time period, and profits then should be only functions of supply.

For example, $p^{l,t,d}_B$, the profit of bus route $l$ in time interval $t$ on day $d$ only depends on the headway of route $l$ in time interval $t$ on day $d$. Then, we can adjust the supply of $l$ in the same time period $S^{l,t,d}_B$ to improve the corresponding profit as a single-variable optimization problem. Similarly for AmoD, if the profit $p^{l,d}_B$ is greater than $p^{l,d-1}_A$, we know that the last change of supply $C^{l,d-1}$ led to the profit increase. Thereupon, we can continue the increase of the fleet size of the same time period in the next day.

If the change of profits between two supply strategies becomes sufficiently small (in this paper we set the threshold to be 5%), we reduce the size of changing unit by $\gamma$ (i.e., $C^{l,d+1} = \gamma \cdot C^{l,d+1}$). This setting ensures the convergence of results.

We acknowledge that the heuristic algorithm is a simplification for the profit maximization problem because the profits of different time periods and routes are unlikely to be independent, especially when the routes have overlapping stations. Nonetheless, we apply this simplified algorithm for the following reasons: 1) The concept of this algorithm is in line with the reality, where information is incomplete and every adjustment is a trial of a new supply strategy based on previous experience; 2) Capturing the dependency may lead to a complicated optimization problem, which is beyond the scope of this paper; 3) Based on the numerical test, this heuristic algorithm can yield a continually improving profit. So it reaches the purpose of mimicking agents’ competition for profit improvement, which is enough for this research.

4. Result Analysis

There is a rich space for all the value combinations of $\theta$, as shown in Table 3. Each value combination represents a distinct setting of competition markets —some are realistic and some are not. While it is not the focus of this paper to systematically explore all possible scenarios, in this paper we only focus on four specific combinations, labeled as four regulation scenarios introduced earlier (Table 1).

In the following subsections, we will show how the indicators of different stakeholders change during the competition process.
Algorithm 2 Supply Updating

1: procedure SupplyUpdate($p(d), p(d-N), S(d), C(d)$)
2: let the index of elements in $p(d)$, $p(d-N)$, $S(d)$ and $C(d)$ correspond with each other. (i.e., the $k$th element of $p(d)$, $p(d-N)$, $S(d)$ and $C(d)$ represents the information of same time interval and same route.)
3: initialize $k = 0$
4: while $k < (\text{length of } p(d))$ do
5: $k = k + 1$
6: let $p_{k,d}$, $p_{k,d-N}$, $S_{k,d}$ and $C_{k,d}$ be the $k$th element in $p(d)$, $p(d-N)$, $S(d)$ and $C(d)$, respectively.
7: if $p_{k,d} > p_{k,d-N}$ then
8: $C_{k,d} = C_{k,d} + 1$
9: else
10: $S_{k,d} = S_{k,d} + C_{k,d} + 1$
11: if $S_{k,d}$ violates the upper or lower bound constraints then
12: set $S_{k,d} = C_{k,d} = 0$
13: if the difference between $p_{k,d}$ and $p_{k,d-N}$ is small enough then:
14: $C_{k,d} = \gamma \cdot C_{k,d} + 1$
15: let $S(d+1) = [S_{k,d+1}]_k$ and $C(d+1) = [C_{k,d+1}]_k$
16: return $S(d+1), C(d+1)$

4.1. PT Perspective

The revenue, operation cost and profit of the PT operator are shown in Figure 3. Each point represents the average value of the corresponding month (same for all following graphs).

Since PT does not change supply in AV-only and the status quo scenarios, the curves for these two scenarios are relatively stable. The patterns for PT-only and AV–PT scenarios are similar: the profit of PT first increases and then stabilizes, which proves the effectiveness of the proposed supply updating algorithm.

![Figure 3: PT Finance over the Simulation Process](image)

The final PT profit of the PT-only scenario is higher than those in all others’, which is intuitive because there is no AV competition in that scenario. The final PT profit of the AV-only scenario is lower than that in the status quo, which shows that the competition of AV reduces the profit of PT.

Observing the revenue and operation cost of PT, we find that they both decrease over the simulation period, where the operation cost shows a sharper reduction. This implies that the strategy for the bus in the competition is to reduce the quantity of supply to reduce the operation cost.

In terms of bus supply and market share (Figure 4), we find the similar phenomenon. The number of buses dispatched per day (i.e., bus supply) keeps decreasing and PT’s market share shows the similar declining trend. Since bus will not change supply in PT-only and status quo scenarios, the supply curve for
these two situations are flat lines. Comparing different scenarios, we find that bus will decrease to the lowest service frequency with AV’s competition. Correspondingly, the market share for AV–PT scenario is also the lowest.

![Figure 4: PT Supply and Market Share over the Simulation Process](image)

The operation cost of AV–PT and PT-only scenarios are similar though their final supplies (Figure 4a) are different. This is because most of the bus routes are not pure feeder routes and only crossing the study area. These routes still need to serve the non-first-mile trips (see details in Appendix A.3), thus the corresponding decrease of operation cost is very limited.

Another interesting phenomenon is that the additive effect of supply adjustment of both bus and AV. Take the bus market share as an example. The curve of PT-only scenario roughly represents how much unprofitable market share is gradually “given up” by the PT operator. The AV-only curve shows how much market share the bus is grabbed by AV (impact from AV supply adjustment). The curve of AV–PT scenario thus shows the additive effect of two, which is nearly the sum of the above two reductions.

![Figure 5: Distribution Change of PT Supply](image)
In addition to the total supply, we also zoom in to the change of temporal and spatial distributions of supply before and after adjustment (Figure 5). Note that in the AV-only and in the status quo scenarios bus supplies are not adjustable, so they are not plotted. The bus supplies of the first month are the same for the PT-only and the AV–PT scenarios so only one curve of "initial" is shown.

From the temporal distribution, we found that after the supply adjustment, the numbers of dispatched buses for most time periods except for the morning peak (6:00–10:00) are reduced. For the PT-only scenario, the bus supply of the evening peak does not change, either. The implication is that the PT operator concentrates supplies to morning peak and evening peak, which have larger demands and are more profitable.

As for spatial distribution, some routes (e.g., 29_1, 28_2) are allocated with higher frequencies, while some routes (e.g., 291_2, 292_1) are adjusted to a lower service rate. The routes with increased and reduced supplies are shown in Figure 6. Generally, the increased-supply routes are short and cost-efficient ones, which cross the residential areas and go directly to the MRT station. The routes with decreased supply are long and sinuous ones. Greater reduction in operation cost can be achieved by decreasing the supply of these routes. Therefore, the spatial distribution change is related to an implicit coordination within the bus routes (even if our algorithm does not consider the inter-routes coordination). To summarize, the PT operator will reduce the supply for higher-cost routes, thus transfer the demand to the lower-cost routes, resulting in a more profitable operation scheme.
4.2. AMoD Perspective

Figure 7 shows the AMoD revenue, operation cost and profit of AMoD over the simulation period. Since there are big changes of AMoD's supply in the first several days, the curves showing the supply of different days in the first month are also shown with the red line, labeled on the upper x-axis. Note that the first-month curve for the AV-only and AV–PT scenarios are the same because the bus supplies stay the same, and AV does not change in the other two scenarios. Therefore, only one curve is shown for the first month.

From the figures, we find that the AMoD’s revenue, operation cost and profit all increase rapidly at the beginning, and then converge, which suggests that the AMoD operator will provide more services to improve its profit in the competition. The trends of AMoD’s supply and market share also validate this point. As shown in Figure 7, the AMoD’s supply and market share keep increasing during the first several months and then become stable. The major change of AMoD’s supply from the status quo happened in the first month.

Comparing different scenarios, we find that the AV–PT scenario can achieve the highest AV profit and the highest market share, though the AV supply for this scenario is only the second-highest (AV-only is the highest), which implies that the bus supply adjustment can not only improve the profit of bus but also benefit that of AV. This is because the initial bus service is over-supplied for the first-mile market. When the bus operator is allowed to adjust its supply, the yielded unprofitable travel demand is then served by AV. This observation corresponds to the previous research of AV–PT integration system (Shen et al., 2018). Therefore, we may infer that, when the PT is oversupplied, despite that we assume AV and PT compete with each other, they still implicitly show some extent of cooperative attributes, resulting in higher profits of both. However, we must notice that the cooperative attributes are only manifested in the change of bus supply. In terms of AV supply adjustment, as discussed above, it is only unilaterally beneficial to itself.

Another interesting finding is on AMoD’s operation cost, where the values in the AV–PT scenario and in the AV-only scenario are very close in spite of different supplies. This can be explained by the VKT figures
in Section 4.4. Though the AV–PT scenario has lower AV supply, it can produce more VKT (more distance-based cost) than the AV-only scenario, which implies that the AV utilization rate in the AV–PT scenario is higher. We can also observe the additive effect of supply adjustment on AV. Different from the effect on bus, the two changes both benefit AV. Thus, the AV–PT scenario has higher profit and market share than both AV-only and PT-only scenarios.

Similar to our analysis for PT, we also plot the time-of-day distribution of the AMoD supply before and after adjustment. As shown in Figure 9, the final supply patterns of AV–PT and AV-only scenarios are similar. After 12 months of adjustment, the supply has been re-distributed across time. More supply will be provided in the morning and evening peak hours, which is considered more profitable. And the supply in off-peak hours (e.g., 11:00–13:00) stays the same or becomes even lower. These temporal changes are corresponding to the demand distribution in Figure 2.

4.3. Passenger Perspective

As for the passengers’ perspective, we are interested in the level of service and their mode choice. The changes of level-of-service indicators throughout the competition are shown in Figure 10.

During the study period, passengers’ travel cost shows different patterns in different scenarios. It decreases in the PT-only scenario, and increases in the AV–PT and in the AV-only scenario, though the magnitude of change is relatively small (around ± 0.03 SGD per person). The direction of change is reasonable because AV is more expensive than PT. When AV starts to compete and serve more demand, the average travel cost will increase. When there are only buses adjusting supply, a greater number of people will change to walk and only a small proportion of people convert to AV (as shown in Figure 11) – the average travel cost decreases.

In terms of total travel time, we find that all scenarios show decreasing trends. This indicates that in the PT-only scenario, passengers’ travel time and travel cost will both decrease after the adjustment of bus supply, which implies absolute benefits to passengers. Conversely, in the AV–PT and AV-only scenarios, the directions of the changes in travel time and cost differ. To capture the combined effect of travel time and travel cost, we calculated the generalized travel cost, and use it to indicate the change of level of service. The calculation method is shown in Section 3.3.

As shown in Figure 10d, passenger’s generalized travel cost decreases in all scenarios, among which the AV–PT scenario shows the largest decline. This implies that the supply adjustment of buses and AV not only benefits the operators but also improves the level of service for passengers. The major contributing factor in the change of generalized travel cost is the decrease in travel time.

Another important indicator for the passenger is waiting time. As shown in Figure 10c, in the PT-only scenario, passenger’s waiting time keeps increasing, which is a direct consequence of the reduction of bus supply. In the AV-only scenario, passenger’s waiting time keeps decreasing, which can be explained by the increase of AV supply. Moreover, in the AV–PT scenario, we can observe a combined effect of the two above. The gap between the first month and status quo is caused by the increase of AV supply in the first month. Starting from the first month, passenger’s waiting time gradually increases, since the effect of bus supply reduction starts to manifest. Nonetheless, due to the opposite effect from the AV side, the increase in waiting
time is not as pronounced as in the PT-only scenario. Finally, the converged waiting time is still shorter compared with the status quo.

The passenger mode choice splits for the first-mile trips are shown in Figure 11. Overall, the demand for AV increases, while the demand for bus decreases. The demand for walking varies across different scenarios. In the AV–PT and PT-only scenarios, more people turn to walk due to the bus supply reduction. While in the AV-only scenario, fewer people walk because of the increased supply of AV.

In addition to the aggregated change of mode choices, we are also interested in, among the people, who change their behaviors. For illustration, we only show the analysis for the AV–PT scenario. Two attributes of passengers are explored—household income, and distance from home to MRT station. We aim to answer what types of people will change their mode choice (from bus to AV/walking). People who originally choose buses are set as the control group. People who change their travel modes from bus to AV or walking are set as the experiment groups. Our purpose is to test whether there is a statistically significant difference between the control groups and the experiment groups in their household income and distance to MRT station. The two-sample Kolmogorov-Smirnov (KS) test is applied to test this hypothesis.

Table 4 summarizes the results of the KS test. For household income, we found that people who change their mode choice from bus to AV are significantly different from the control group. The average income for this group is 5,222.8 SGD, while the average household income of the control group is 4,780.9 SGD. This implies that higher-income people tend to change from bus to AV after a decline in bus supply. However, as for people now walking, the household income does NOT show a significant difference, which suggests people changing to walk are NOT in the low-income group, implying the competition between AV and PT does NOT deteriorate the condition of the poverty.

In terms of the distance to MRT station, both experiment groups show a significant difference from the control group. By comparing the average value, we found that people who live near MRT stations tend to
convert to walk more, while people who live far from MRT stations tend to convert to AV. This implies that the interaction of AV and PT may polarize people’s travel mode choices, and increase the car dependence of people living far from subway stations.

![Figure 11: Change of Passenger Mode Choices](image)

**Table 4: KS Test Results for the AV–PT Scenario**

| Attributes                  | Groups                      | Mean (Std.)      | KS Statistics | p-values |
|-----------------------------|-----------------------------|------------------|---------------|----------|
| Household Income (SGD)      | Baseline                    | 4780.9 (3669.7)  | N.A.          | N.A.     |
|                             | Experiment (Bus to AV)      | 5222.8 (3734.4)  | 0.061         | 0.000*   |
|                             | Experiment (Bus to Walk)    | 4773.0 (3635.6)  | 0.007         | 0.963    |
| Distance to MRT Station (m) | Baseline                    | 1065.0 (334.2)   | N.A.          | N.A.     |
|                             | Experiment (Bus to AV)      | 1130.2 (313.7)   | 0.087         | 0.000*   |
|                             | Experiment (Bus to Walk)    | 924.5 (311.6)    | 0.177         | 0.000*   |

* control groups are set as reference, so they do not have KS statistics and p-value.
* The larger the KS Statistics, the greater the difference between the two groups.
* *: Significant at 99% confidence level.

4.4. **Transport Authority Perspective**

Transport authority cares about efficiency and sustainability of transportation, which are shown in Figure 12 and Figure 13 respectively.

![Figure 12: Change of Transport Efficiency Indicators](image)

In Figure 12 we found that the average load of AV slightly increases in the PT-only scenario. However, in the AV–PT and AV-only scenarios, the AV load decreases a lot in the first month (the gap between the status quo and the first month) and then stabilizes. This suggests that to maximize profit, ride-sharing behavior is inhibited in the model. This may be because, in the first-mile scenarios, travel distance is usually short.
Hardly can ride-sharing happens or generates higher profits for the operator. On the other hand, considering the price structures of AMoD we proposed, serving two passengers with two vehicles separately may yield more profit. Therefore, after competition, though the AMoD operator earns more profit, the AVs transport efficiency is worse.

Observing the average load curve for buses, different from AV, we find the bus average load increases for the AV–PT and PT-only scenarios, which means that after the competition, the bus is operated more efficiently, with not only higher profit, but also higher average load.

In terms of sustainability, we measured VKT and PCE for buses and AV, as shown in Figure 13. Overall, the VKT of AV increases, while the VKT of buses decreases, which is consistent with the change of supply. For total PCE, since the unit PCE for the bus is large, the shape of total PCE is similar to that of bus VKT. The system total PCE decreases in the AV–PT and PT-only scenarios, which means that the deregulation of bus operation has the potential to reduce environmental impact. When the bus is not allowed to change its supply, the total PCE increases due to the increase of the VKT of AV.

![Figure 13: Change of Transport Sustainability Indicators](image)

4.5. Summary

To better illustrate the change of the interests of different stakeholders, a summary is given in Figure 14. The “triggers” are highlighted by red color, and the arrows represent the causal relations. The increase and decrease of different indicators are shown by “+” and “−”, respectively, compared to the status quo. We found that the AV-only scenario is beneficial to AV (profit+) and passengers (generalized travel cost−), but may not be welcomed by PT (profit−) and transport authorities (PCE+). The PT-only and the AV–PT scenarios are both beneficial to all stakeholders, and the AV–PT scenario shows larger benefits.

5. Conclusion and Discussion

This paper proposed, simulated and evaluated the interaction between AV and PT from a competition perspective—assuming that both AV and PT are profit-oriented, and improve their own profit by supply adjustment. The first-mile market in Tampines, Singapore is selected for a case study. Four scenarios with specific policy implications are evaluated. The main findings are summarized below.

- Overall, allowing profit-oriented bus and AMoD services to compete by adjusting supply can improve profits for both while still benefiting the public and the transport authority. Such competition forces bus operators to reduce the frequency of inefficient routes, and allow AVs to fill in the gaps of bus coverage.

- During the competition, both AV and bus redistribute their supplies spatially and temporally. For buses, the supply of long-distance sinuous routes is reduced. The supply-increased routes are typically short ones crossing the residential areas and connecting directly to the subway station. In the temporal dimension, both AV and bus concentrate their supplies in the morning and evening peak hours and reduce the supplies in off-peak hours.
Figure 14: Summary of the Change of Indicators (Red: Triggers, Purple: Increase, Green: Decrease)
The competition between AV and PT can decrease passengers’ travel time but increase their travel cost. The generalized travel cost is still reduced when counting the value of time.

The competition can polarize people’s mode choices: Bus demand decreases while AV and walk demands increase. People who live near MRT stations convert to walk, and people who live far from MRT stations turn to AV. Higher-income people tend to change their choices from bus to AV, but there is no evidence showing low-income people are forced to walk.

The bus supply adjustment can increase the average bus load and reduce total PCE, which improves both efficiency and sustainability. The AV supply adjustment shows the opposite effect.

Comparing different scenarios, AV-only scenario is beneficial to AV and passengers, but will not be welcomed by PT and transport authorities. PT-only and AV–PT scenarios are both beneficial to all stakeholders, but AV–PT scenario shows higher degree of benefits.

5.1. Policy implications

The comparison of the four scenarios indicates that competition does not necessarily lead to a loss–gain result. A win–win outcome is also possible under certain policy regulations. Our findings can help authorities design future AV–PT marketing policies when the two modes are operated by private companies.

Since the PT supply adjustment can benefit transport efficiency and sustainability, the government should consider allowing PT operators to optimize their supply strategies. However, as passengers’ waiting time and travel cost will increase due to PT’s supply adjustment, the government need to further discuss how much freedom should be given to PT operators to balance efficiency, sustainability, and passenger convenience. One possible solution is to set specific constraints or operation goals to private PT operators while allowing them to optimize supply, such as bounds for headway, waiting time, ridership, and passenger satisfaction scores.

AV’s supply adjustment can reduce passengers’ travel time, but also reduce transport efficiency and sustainability. Policies targeting AV operators should focus on its negative impact on the system. The government can directly regulate AV’s operation by limiting the number of licenses, operation time, vacancy rate, and service areas. The regulation policy should take into consideration the supply adjustment of PT. For example, government can limit AV to serve in low PT frequency areas and time periods, which makes AV more like a complementary mode to PT, especially when PT decreases its supply in some low-profit areas. Besides direct regulation, subsidies to incentivize AV to serve specific passengers can also be implemented.

For passengers, the increase of the proportion of people who walk to MRT stations implies that some people will be “sacrificed” due to AV–PT competition. Authorities may compensate people who suffer from higher travel costs or longer travel time, such as discounts of using AV and PT, or providing other feeder modes (e.g., bike share and E-scooter share). Transport authorities can also tax AV and PT operators to cover the expenses on providing alternative travel modes.

5.2. Limitations and future research

The paper can be improved in the following aspects. 1) The results presented in this paper are based on the assumptions and settings in Singapore. Thus, they may not be representative of other countries or cities. This is a typical problem in many simulation-based works [Liu et al., 2017; Loeb and Kockelman, 2019]. However, this paper is not intended for a forecast of a specific city but is to provide a general framework of analysis, which are extendable to other cities. Future research can systematically explore the impact of scenario settings and assumptions on results.

2) Methodologically, several technical components of the paper can be improved in the future. First, the heuristic supply updating algorithm may not converge to the maximum-profit points for AV and PT. Future research can apply more advanced algorithms (e.g., reinforcement learning) to replace it. Moreover, the supply updating process can be implemented as a multi-agent learning process, which allows more flexibility for operators’ competing behaviors. Second, we assume the total demand of passengers, and its spatial and temporal distribution to be fixed in this paper, which is a simplification. Future research can introduce a supply-demand interaction module [Wen et al., 2018] to relax this assumption.
3) Further, AV–PT competition is not only limited to the first-mile market but may exist for all trip purposes and in all spatial contexts. However, since our current method needs to simulate all agents’ behaviors for a sufficiently long time to get converging results (one year in this paper), it would be computationally difficult to incorporate the whole urban network. Future research could explore the proposed AV–PT competition framework in a larger urban network and broader trip purposes by implementing a more computationally efficient method.

Beyond this paper, future research can also be done in broader areas. The first is to evaluate the impact of pricing, either from the operators’ perspective or from the authorities’ perspective. For example, a multi-variable optimization algorithm may be developed to allow operators to adjust fare and supply at the same time. This is an extension of the current framework but relaxing the fixed-fare constraints.

From authorities’ perspectives, future research could target at 1) the impact of different tax incentives and subsidies in the competition. Operators and passengers will respond to different pricing incentives, leading to different system performance. We can study how the government can better design the competition mechanism to improve service quality and social welfare; 2) Evaluating the impact of technology and technical competence. Generally, AV is more flexible than PT in terms of supply strategies adjustment. We can study the impact of different technical competence of PT on its competitiveness. This can help PT agencies to better understand the trade-offs between service stability and flexibility; 3) The comparative study of different AV PT organizational structures. Given many possible relationships of the two in the future (Shen et al. [2018]), it is necessary to identify which relationship is better based on the interests of different stakeholders. Prior studies on AV–PT interaction are based on specific contexts of certain cities. A generalizable and mechanism-oriented model would be valuable to extend our understanding of this competition between AV and PT to come.

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Appendices

Appendix A. Agent Behaviors

Appendix A.1. Passenger Behavior

Passengers are assumed to enter the system every minute during the simulation day. To mimic the AV and PT competition process, the simulation needs to be run for a sufficiently long time period (one year in this paper).

As discussed, in this study we assume the passenger demand to be fixed (Figure 2). A Voronoi diagram based on the location of bus stops is used to assign aggregate travel demand to the building level.

Passengers’ mode choice is modeled based on the result of a mixed logit model (Shen et al., 2019). The trip-specific variables (travel cost, waiting time, on-vehicle time, walking time, etc.) and sociodemographic variables (e.g., income) are considered. This demand model is estimated from an AV preference survey in Singapore, which is well-matched with this study. Besides, the mixed logit model allows us to capture the preference heterogeneity among people. Each individual is assigned a set of choice coefficients drawn from the pre-determined distributions. The detailed model coefficients are shown in Appendix B.

When a passenger is generated, we will first calculate the corresponding trip-specific variables based on his/her location. Since routing is not the focus of this study, we assume that passengers only choose the closest bus stop. The corresponding walking time, waiting time, and in-vehicle time are then calculated. Note that the waiting time for AMoD is inversely proportional to the AMoD supply, while the expected waiting time for PT is half of the headway. When the passenger departure time is not within a bus route’s operating time, the bus mode will be set as unavailable.

Passengers’ incomes are drawn from the distribution derived from Singapore household travel survey data (Land Transport Authority, 2012). The mixed logit model is used to calculate the probability of choosing different modes. During the simulation process, people’s mode choice will change with the change of AV and PT’s supply. Considering the imperfect information transfer, a lag effect is added to people’s behavior. Denote the model-derived probability of passenger n choosing mode i in day d is $P_{d,n,i}$. The actual probability used for simulation is calculated in Eq. A.1.

$$P_{d,n,i} = \alpha P_{d-1,n,i} + (1 - \alpha) \hat{P}_{d,n,i},$$

where \(\alpha\) is the lag factor, which represents how much people’s behavior will be lagged by the previous day. After calculating the choice probability, passengers will be assigned a specific travel mode accordingly.

When walking is chosen as the travel mode, the passengers will walk directly to the MRT station along the footpath. When AV is chosen as the travel mode, the passengers will start to call for the ride repeatedly until the system has successfully booked a car for him/her. Once a vehicle is assigned, he/she then moves to the pick-up location to wait for the AV. As the density of bus stops in Singapore is very high, the pick-up location is set as the closest bus stop from the passenger. To prevent a passenger from waiting too long when no AV is available, maximum waiting time is set to 10 min in this study, beyond which he/she will forgo the AV request and travel by bus if available, otherwise, he/she will travel by walking.

When buses are chosen, the passenger will walk directly to the bus stop to wait for the next bus. Since we assume that the bus agent can update its headway to maximize its profit, people may wait for a long time. Therefore, we set a maximum waiting time (30 min) for the bus as well. People will switch to AV or walking based on the choice probability when the waiting time is beyond the threshold.

Appendix A.2. AMoD Behavior

The concept of the mobility-on-demand system was proposed and demonstrated in the 1970s, and was called Dial-a-Ride Transit (DART) [Wilson et al., 1976]. In this study, the AMoD service with ride-sharing resembles a carpooling system (Galland et al., 2014; Martinez et al., 2015), for which in this study only the first-mile service is provided, and is restricted to the service area, Tampines. This arrangement is consistent with the proposed usage of the AV prototype in Singapore (Chong et al., 2011).

We assume the routing behaviors of all AVs to be identical, following the shortest path without considering the traffic. AVs are assumed to fully comply with the central controller and never reject the service requests from customers. Each AV allows a maximum of four passengers to share the ride. AV’s initial supply is...
approximated using Singapore Taxi data. Since there is no first-mile demand during the MRT close hours, we adjusted the initial $AV$ supply to zero during that time period. New $AV$s are generated from several car clubs (see Figure 1). When an $AV$ is called to stop the service by the control center, it will return to the nearest car club and be removed from the simulation. $AV$s will stay idle without moving when there is no request.

The operation cost of $AMoD$ agent consists of two parts: fixed cost and variable cost, both are calculated per hour, the temporal resolution in this paper, for $AV$. The fixed cost is the cost of operating one $AV$ during this hour, such as depreciation cost and parking cost. We use the lowest car renting fare in Singapore (4 SGD/hour-veh) to approximate the fixed cost. The variable cost is calculated based on vehicle travel distance and gasoline fare. It is set as 0.12 SGD/km in this study.

Ride-sharing only happens under specific conditions. Given the heterogeneous ride-sharing preference among the population (Nazari et al., 2018), we define a ride-sharing-agreement ratio (50% in this study). That is, only half of the people are willing to share trips with others. For the short-distance first-mile trips, sharing with others is not a good choice given the potential increase in detour distance and travel time (Schreieck et al., 2016). Therefore, we assume that all passengers prefer to ride alone if possible, even for those who agree to share the ride. Thus, when a passenger calls for a ride, the system first scans all empty $AV$s. If there are empty $AV$s, the system assigns the closest available $AV$ to pick up the passenger. Once the $AV$ and the passenger are matched, a notice is sent to the passenger to request a meet-up at the pick-up point. If there are no empty $AV$s, the system searches for all occupied $AV$s. Passengers who have agreed to share the ride will be considered to take a shared ride. An $AV$ is shareable only if 1) it has available seats, and 2) the incremental travel time to on-vehicle passengers due to picking up new passengers will not exceed a pre-determined threshold. Detailed calculation methods can be found in Shen et al. (2018). We share the same parameters setting in the ride-sharing module.

The fare structure of $AMoD$ is identical to that of the taxi service in Singapore, with a base fare within first $d_b$ km and a distance-based fare beyond $d_b$ km. The difference is that we add a ride-sharing discount for $AMoD$ service. The total travel fare for passenger $i$, $F_i$ is formulated in Eq. A.2

$$F_i = \begin{cases} f_b \cdot (1 - r^i) & \text{if } d_i \leq d_b \\ [f_b + f \cdot (d_i - d_b)] \cdot (1 - r^i) & \text{otherwise} \end{cases}$$

(A.2)

where $d_b$ is the base distance, which equals to 1 km in this study; $f_b$ is the base fare within $d_b$; $f$ is the distance-based fare per km after $d_b$; $d_i$ is the direct travel distance of passenger $i$ in km; $D_i$ is the detoured actual travel distance in km; $r = \frac{D_i}{d_i} - 1$ is the detour ratio; $\lambda$ is the discount degree offered due to the detour.

In terms of competition, the $AMoD$ enterprise could update the hourly supply to improve its profit. Given the complex interaction between agents, it is very difficult to propose an algorithm that ensures every adjustment is optimal for the $AMoD$ enterprise. Also, such an algorithm is beyond the scope of this research. In this study, we propose a heuristic supply updating algorithm for $AMoD$. Instead of finding the optimal adjustment, we assume a fixed step size of each updating. The sign of the updating (i.e., increase or reduction) is determined by supply and profit in the previous steps, which aims to make the profit higher. This concept is also in line with the reality, in which information is incomplete and every adjustment is based on previous experience. A detailed description of the algorithm can be found in Section 3.5.

**Appendix A.3. PT behavior**

Buses services are schedule-based, which are operated based on the given routes and time tables. The bus routes and initial schedules information are provided by the LTA. Once a bus is dispatched, it will follow the route at a constant speed, passing through a sequence of stops. The spatial distribution of bus stops can be found in Figure 1. Upon arrival at a bus stop, each bus dwells for a certain amount of time to pick up passengers. The dwelling time is set as 30 seconds in this study.

The operation cost of the bus agent is purely distance-based, which is 2.71 SGD/km. This calculated from the annual financial reports of two major bus companies in Singapore (SBS Transit, 2017; SMRT Corporation Ltd., 2017), which involves the labor cost, depreciation cost, fuel cost, maintenance costs, etc.. We assume all the operation cost is proportional to the distance traveled. The bus fare structure is set based on the real-world scenario. All passengers are charged a fixed fee of 0.77 SGD per trip.
To compete with AMoD, the bus operator is allowed to adjust its supply strategies—the headways—to increase its profits as well. The adjusting algorithm is similar to AMoD’s, while the difference is that the adjusting frequency is lower than that of AMoD.

To ensure the basic service of PT, we set an upper bound for the adjusted headway. Every step of headway adjustment cannot exceed the upper bound, otherwise, passengers will have to wait too long. On the other hand, to avoid the bus dispatching rate to be too high, a headway lower bound is also introduced.

Since we calculate the revenue and cost based on the first-mile demand, it is important to ensure the supply adjustment does not affect the market outside the first-mile market. There are two types of bus routes in this study: MRT feeder buses, for which the supply adjustment only applies to the first-mile market; and bus routes that pass through the study region (passing-by routes). If we directly adjust the headway of the second type routes, it will not only affect the demand for first-mile trips but also affect other passengers who are just passing the study region. Thus, we need to redefine the supply adjustment for these routes. Here, we assume the supply reduction (i.e., increase of headway) for the passing-by routes to be equivalent as if some buses of these routes will not stop in the study region. Instead, they directly drive through the region along the shortest path. For example, as shown in Figure A.15, after supply decrease, some of the buses of Route 21 will be rerouted to the shorter green path and not stop in the study area. The corresponding reduction in the operation cost is calculated by the decreased travel distance. Note that the decreased operation cost may be small under this setting.

In terms of supply increase (i.e., decrease in headway) for the passing-by bus routes, we assume that this is equivalent to adding new MRT feeder bus routes with the same stations in the study region. The corresponding increase in operating cost is calculated as the cost of running this new route. This way, we can isolate the first-mile market, where the supply adjustment for all bus routes will not affect the outside areas.

![Figure A.15: Rerouting example of Route 21](image)

**Appendix B. Mixed Logit Model for Passenger Mode Choice**

The mixed logit model is conducted based on an AV preference survey in Singapore (Shen et al., 2019). The deterministic part of the utility function $V_{njt}$ for individual $n$ choosing alternative $j$ in choice situation $t$ is
given as

\[ V_{njt} = \alpha_{nj} + \beta'_{nj} T_{njt} + \delta'_{nj} X_n, \]  

(B.1)

where \( T_{njt} \) is the vector of trip specific attributes of mode \( j \) for individual \( n \) in situation \( t \); \( X_n \) is the vector of sociodemographic variables of individual \( n \); \( \alpha_{nj} \) is the alternative specific constant to estimate the inherent preference of individual \( n \) on mode \( j \); \( \beta'_{nj} \) and \( \delta'_{nj} \) are the corresponding coefficients to be estimated. The situation \( t \) is introduced because the survey contains panel questions.

The results for the mixed logit model is shown in Table B.1 where for each parameter, we estimate both the mean and the standard deviation.
Table B.1: Estimation Results of Mixed Logit Model

| Variables                                      | Parameters | value  | t-test |
|-----------------------------------------------|------------|--------|--------|
| Alternative Specific Constant                 |            |        |        |
| Walk                                          | Mean       | fixed at 0 |        |        |
| Std.                                          | fixed at 0 |        |        |
| Bus                                           | Mean       | -0.569 | -2.11  ** |
| Std.                                          | 0.818      | 1.89   *  |
| On-demand AV                                  | Mean       | -0.568 | -2.56  ** |
| Std.                                          | 0.758      | 3.72   ***|
| Generalized travel cost                       |            |        |        |
| Walk: Walking time (min)                      | Mean       | -0.363 | -28.20 *** |
| Std.                                          | 0.171      | 22.26  ***|
| Bus: Travel cost (SGD)                        | Mean       | -1.14  | -8.86  *** |
| Std.                                          | 0.436      | 0.16   |
| Bus: In-vehicle time (min)                    | Mean       | -0.212 | -12.10 *** |
| Std.                                          | 0.174      | 9.16   ***|
| Bus: Waiting time (min)                       | Mean       | -0.271 | -10.27 *** |
| Std.                                          | 0.223      | 5.31   ***|
| Bus: Walking time to bus stop (min)           | Mean       | -0.214 | -10.61 *** |
| Std.                                          | 0.140      | 4.14   ***|
| On-demand AV: Travel cost (SGD)               | Mean       | -0.984 | -18.56 *** |
| Std.                                          | 0.465      | 13.54  ***|
| On-demand AV: In-vehicle time (min)           | Mean       | -0.195 | -11.0  *** |
| Std.                                          | 0.0288     | 1.16   |
| On-demand AV: Waiting time (min)              | Mean       | -0.222 | -8.50  *** |
| Std.                                          | 0.0310     | 0.58   |
| Sociodemographic variables                    |            |        |        |
| On-demand AV: household monthly income lower than SGD 4,000 | Mean | -0.497 | -2.81  *** |
| Std.                                          | 0.300      | 0.62   |
| Statistical summary                           |            |        |        |
| Number of individuals                         | 1,242      |        |        |
| Number of observations                        | 8,689      |        |        |
| Number of random draws                        | 5,000      |        |        |
| Initial log-likelihood at zero                | -10832.448 |       |        |
| Final log-likelihood                          | -6581.302  |        |        |
| Adjusted McFadden $\rho^2$                    | 0.390      |        |        |

*: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Std.: standard deviation.