IMPROVING THE SUSTAINABILITY OF PASSENGER TRANSPORTATION SYSTEMS: A SPATIAL AGENT-BASED APPROACH

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Improving the Sustainability of Passenger Transportation Systems: A Spatial Agent-Based Approach

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CERTIFICATE OF ORIGINALITY

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LU MIAOJIA (Name of student)

DEDICATION

To my son, may you keep an optimistic and open mind

for all of life’s possibilities.

ABSTRACT

To alleviate fossil fuel use, mitigate traffic congestion, and reduce air emissions, it is necessary to find sustainable mobility alternatives and better adapt existing transportation modes to move people in a more environmentally sound and economically feasible way. In recent years, sustainable mobility systems have begun to emerge, encompassing a range of novel technologies and solutions such as high-speed railway, autonomous vehicles, and bike sharing. The current literature on the sustainability implications of transportation systems often neglect the interactions between these emerging mobility systems and existing transportation modes and the heterogeneous individual travel patterns that affect transportation sustainability. Therefore, to better understand these emerging transportation systems and inform decision making, an interdisciplinary approach tightly linking life-cycle analysis, agent-based modeling, and geographic information system are used to generate the behavioral rules of passengers choosing different transport modes, simulate the vehicles traveling in real-world road networks, and evaluate the economic, social, and environmental impacts of the multimodal transportation system. Three case studies focusing on three emerging mobility systems—high-speed railway, autonomous taxis, and bike sharing—are proposed to demonstrate the benefits of using this hybrid method.

The high-speed railway study evaluates the life-cycle environmental performance of the existing multi-modal transportation system with the newly-built high-speed railway. Geographic information and psychology

theory are integrated to construct the real-world intercity transportation maps and produce the passengers' mode choice behaviors influenced in part by passengers' social networks. Results from the high-speed railway study show that the occupancy rate of the high-speed rail should be maintained at 80% or more to lower the overall environmental impacts. The through train may need to be gradually shut down to mitigate the system environmental impacts by up to 30%.

The autonomous taxi study evaluates the travel costs and environmental implications of substituting conventional personal vehicle travel with autonomous taxi travel. A spatial agent-based model is developed to simulate how commuters travel by autonomous taxi in real-world road networks. The autonomous taxi study demonstrates that to meet daily commute demand with wait times less than 3 minutes, the optimized autonomous taxi fleet size is only 20% of the conventional solo-commuting personal car fleet. The commuting cost decreases by 38%, but the environmental performance of autonomous taxis system is not positive, mainly due to the unoccupied vehicle travels and low ride sharing.

Lastly, the bike sharing study simulates the environmental and human health impacts of bike sharing on travelers' usage of other transport modes in a multi-modal transportation system, considering their interactions through the modeling of the modal split based on the heterogeneous mode choice behaviors of travelers. Two scenarios are proposed for the development of a bike-sharing system: bike infrastructure extensions, and bike-sharing incentives. Two scenarios are evaluated along with the corresponding environmental and social impacts. The simulation results indicate that free use of bike-sharing to solve the first/last mile problem of the transit system can be most sustainable with 1.5 million US dollars in transportation damage cost saved per year, and 22 premature deaths further prevented per year due to mode shift to cycling and walking.

In summary, these spatial agent-based life-cycle analysis models can be powerful tools to help policy-makers improve the environmental, economic, and social performances of multi-modal transportation systems.

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ABM	agent-based modeling
aTaxi	autonomous taxi
BAU	business as usual
BR	bounded rationality
CAHSR	California High-Speed Railway
ESRI	Environmental Systems Research Institute
EV	electric vehicle
FFBS	free-floating bike sharing system
GHG	Greenhouse Gas
GIS	geographic information system
GPS	Global Positioning System
GWP	global warming potential
HEAT	Health Economic Assessment Tool
HKIA	Hong Kong International Airport
HIS	Household Interview Survey
HSR	high-speed rail
ICE	internal combustion engine
LCA	life-cycle analysis
LCI	Life Cycle Inventory
mph	miles per hour
MTR	mass transit railway
NHTS	National Household Travel Survey
NTD	New Taiwan Dollar

PC	personal car
PKT	passenger kilometer traveled
PR	perfect rationality
RUM	random utility maximization
SAV	shared autonomous vehicle
SAEVs	shared autonomous electric vehicles
SBBS	station-based bike sharing
TAZ	traffic analysis zone
VMT	vehicle miles traveled
VKT	vehicle kilometer traveled
VOT	value of time

Chapter 1 Introduction

1.1 Overview

Transport is an activity that immensely affects humans and the natural environment. Well-designed transport systems can yield comfortable, time-saving convenience for users. On the other hand, the transportation sector has also introduced various problems that need great attention, such as global warming, air pollution, and noise pollution. In order to solve these transportation problems, new sustainable mobility alternatives have begun to emerge with novel technologies and solutions such as high-speed rail, autonomous vehicle, and bike sharing. Understanding the sustainability of a whole transportation system modified by the introduction of these new mobility systems is the major motivation of this work.

The current literature on assessing the sustainability of these emerging systems often neglects the interactions between the new mobility systems with the existing transportation modes and are limited to using aggregate data to represent personal mobility dynamics, such as the average vehicle-miles-traveled. But the sustainability performance of the transportation system is highly related to individual travel patterns. Take high-speed rail as an example—its environmental performance on a passenger-kilometer basis can be improved with a high occupancy rate. The occupancy rate of high-speed rail is related to its mode share in a multi-modal transportation system. Thus, passengers' mode choice behaviors can affect the environmental performance of the transportation modes. Or consider autonomous taxis—personal travel behaviors (e.g. how many vehicle miles traveled in a commute trip, and the starting and end points of the commute trips) can determine the environmental and economic performance of autonomous taxis and conventional vehicles, which can be better characterized based on a real road network rather than a hypothetical city.

Therefore, it is necessary to integrate the personal mobility dynamics at the individual level into assessments of these sustainable mobility systems. In the present study, an interdisciplinary approach tightly linking life-cycle analysis, agent-based modeling and geographic information systems is used to form the behavioral rules of passengers choosing different transport modes and simulate the vehicles traveling in real-world road networks. A multi-criteria assessment model is embedded in this hybrid method, which was designed to cover the three dimensions of transportation sustainability: environmental, economic, and social.

The contribution of this thesis is twofold. First, a hybrid method integrating individual travel patterns into sustainability assessment is developed. Second, each case study in this thesis also has its real-world policy implications.

1.2 Research questions

This thesis includes three case studies focusing on three emerging transportation systems: high-speed rail (HSR), autonomous taxi (aTaxi), and bike sharing. These systems were chosen because they present promising opportunities to improve transportation sustainability and have received increasing attention and policy support in many countries. The scope and specific research questions for each case are summarized below.

Case 1: Environmental impacts of the newly introduced high-speed railway (Chapter Two)

This case investigates how the life cycle environmental performances of existing transport systems are affected by the introduction of HSR. Compared to the previous studies which only consider the life-cycle environmental impacts of HSR and fail to account for the influences of other transport modes in a dynamic transportation market (Chester & Horvath, 2010b, 2012; Grossrieder, 2011; Yue et al., 2015), this case not only evaluates the environmental performances of HSR in a multi-modal transportation system, but also takes into consideration passengers' individual travel patterns. Specifically, I address the following research questions:

1) With the introduction of high-speed rail, how do mode shares change in a multi-modal transportation system?
2) Can the environmental performance of a multi-modal transportation system be improved with the newly-built high-speed rail?

Case 2: Environmental and economic implications of using autonomous taxis for commute travel (Chapter Three)

This case examines the environmental and economic benefits of using autonomous taxis to replace conventional personal vehicles in commute travel. The Current literature on autonomous vehicle simulations is based on highly developed grids or hypothetical cities with constant travel speeds and uniform travel patterns (Chen et al., 2016; Fagnant & Kockelman, 2014b; Levin et al., 2017; Liang et al., 2016; Martínez et al., 2016; Zhang et al., 2017). This case study addresses both gaps by integrating a real-world road network and individual travel behaviors to better represent autonomous taxi travel. The specific research questions include:

1) What is the optimized fleet size of autonomous taxis to meet the daily commute demand?

2) How many vehicle-miles-traveled can be reduced by implementing autonomous taxis?

3) How much can air emissions be reduced by implementing autonomous taxis?

4) How much can commuting costs be reduced by implementing autonomous taxis?

5) How does road occupancy change when using autonomous taxis for commute travel?

Case 3: Environmental and social benefits of bike sharing (Chapter Four)

The environmental and social impacts of bike sharing on travelers' usage of other transport modes in a multi-modal transportation system have not yet been quantified. Bike-sharing research focusing on Asian urban areas is also limited (Pai & Pai, 2015). This case evaluates the environmental and social benefits of bike sharing in Taipei City. Some bike sharing operation strategies are proposed to improve the environmental and social performances of the integrated transportation system with bike sharing. The specific research questions include:

1) How does bike-sharing change the travel behaviors of users in Asian cities?

2) Are the environmental benefits of bike-sharing overstated when taking into consideration the whole passenger transportation system?

3) Can bike-sharing can contribute to improving human-health even in a polluted air environment?

4) What bike-sharing operation strategy can yield the largest environmental and social benefits?

1.3 Research methodology

The methodology of this thesis is depicted in **Figure 1-1**. A spatial agent-based life-cycle analysis approach is used in all cases. But the three methods, i.e., agent-based modeling (ABM), geographic information system (GIS), and life-cycle analysis (LCA), have a different degree of emphasis across the following case studies. Each method was improved and optimized to fit the respective research topic as the studies progressed.

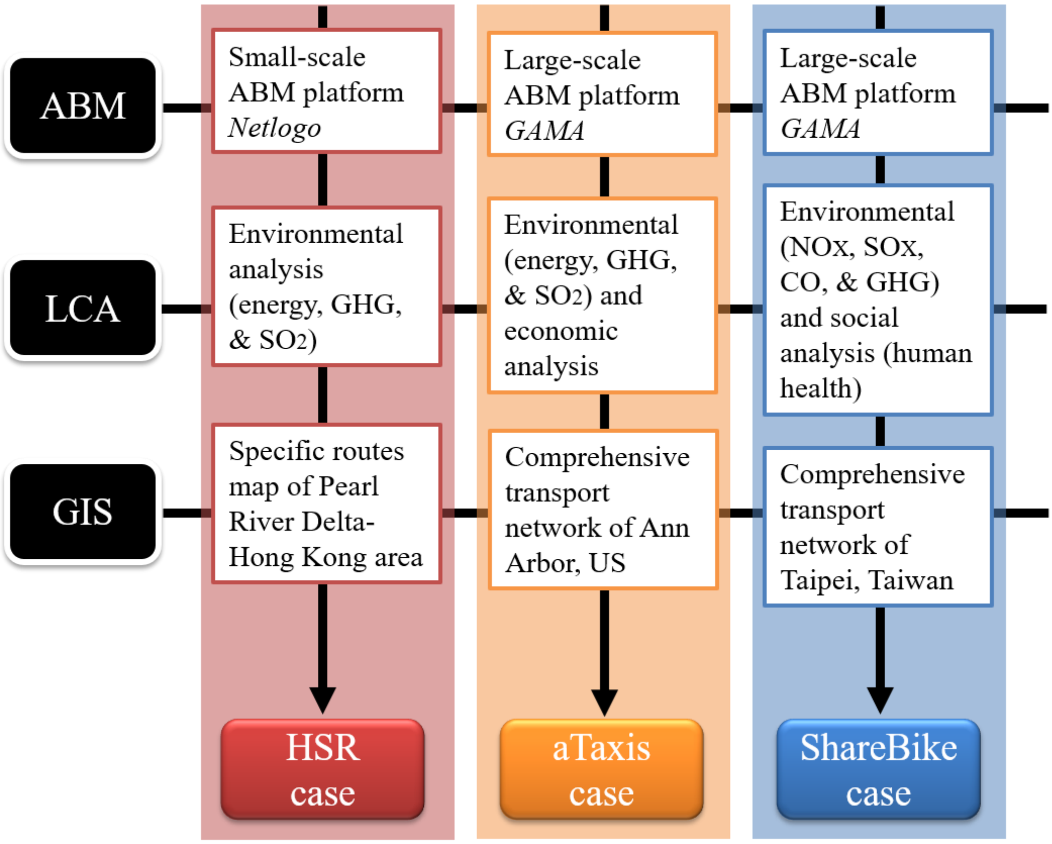

Figure 1-1. Methodology of the thesis

In the case of high-speed rail, an ABM platform named Netlogo is used (Wilensky 1999), NetLogo has an intuitive language with a comprehensive library, which is very user-friendly to the programming beginner. The built-in GIS extension supported by NetLogo provides the ability to load Pearl River Delta-Hong Kong spatial data into the model. The specific routes including the airline, HSR link, train rail link, and highway are represented in the model. 1,000 passenger agents and 5 cross-boundary transport modes interact with each other in this transportation world. The mode choice behavior is the main focus in the HSR case, with the small world theory applied to construct passengers' social network, which can partly influence the passenger's mode choice behavior. The logit model is enhanced with this psychology theory to define the mode choice behavior. The life cycle environmental performances of the transport modes are estimated by adjusting the emission factors of reference modes from the literature.

In the case of autonomous taxis, the real-world transportation application is emphasized. GAMA (GAMA, 2016), a large-scale ABM platform is applied in this case, which aims at building spatially grounded multi-agent simulations. The transportation map is made up of the real-world road network with different types of buildings (such as residential and office buildings) rather than a highly-developed grid city with traffic zones. The vehicles and passengers travel on this road network with heterogeneous behaviors. The vehicles travel at different speeds based on the road capacity. The passenger chooses different modes (here refers to the autonomous taxi or private car) based on his/her waiting time limit and expected time of autonomous taxi arrival. Passenger's car sharing behavior depends on his/her willingness to share and the vehicle sharing algorithm. 20,000 passenger agents, 6,194 road agents, and more than 2,000 vehicle agents interact with each other in this transportation system. The travel costs and environmental impacts of the transport modes are considered in this case, with the emission factor of conventional gasoline sedans used as a reference.

The case of bike sharing is also developed based on the GAMA platform (GAMA, 2016). The Taipei city, specifically with the city's roads, buildings, and district areas are loaded to realistically represent the real-world transportation system. Two kinds of behavior theories, namely random utility maximization and bounded rationality, are applied to construct passengers' mode choice behaviors. Not only the environmental damage costs but also the human health benefits from engaging in physical activity including cycling and walking are calculated. In addition, recommendations for healthy cycling and walking durations in an air pollution region are presented.

1.4 Structure of the dissertation

The remainder of the dissertation is organized as follows. Chapters two to four present three cases of applying a spatial agent-based life-cycle analysis approach to evaluate the economic, social, and environmental performances of the multi-modal transportation system. The last chapter concludes with key insights drawn from the findings and directions that can be pursued in future research.

Chapter two evaluates the environmental impacts of the multi-modal transportation system with a newly-built HSR. There are two kinds of agents in this transportation world: transportation modes and passengers. Passengers' mode choice behaviors can change the market shares of the transport modes, and the operational and life-cycle environmental performances of this transportation "world" also will be influenced accordingly. Several scenarios at the operation stage are simulated to minimize the environmental impacts based on predicted mode shares. The simulation results suggest that the occupancy rate of the HSR should be maintained—more than 80% to lower the overall environmental impacts. The through train may need to be shut down to mitigate the system environmental impacts by up to 30%. The HSR case study has been published in *ASCE Journal of Urban Planning and Development (Vol. 143, Issue 4)* (Lu & Hsu, 2017).

Chapter three simulates the economic and environmental implications of substituting conventional personal vehicle travel with autonomous taxi travel. All the vehicles travel in real-world road networks at varying speeds, and all the travelers have their own trip routes and specific travel behaviors. The simulation results indicate that a personal car fleet can be replaced with an autonomous taxi fleet 20% its size to meet the daily commute demand with a wait time of less than 3 minutes. But the environmental impacts of autonomous taxis do not show significant improvement over private cars. The autonomous taxi case study has been published in *ASCE Journal of Urban Planning and Development (Vol. 144, Issue 4) (Lu et al., 2018b).*

Chapter four investigates the environmental and social benefits of bike sharing in a multi-modal transportation system. Two operation scenarios are proposed for the development of a bike-sharing system: bike infrastructure extensions, and bike-sharing incentives. The simulation results indicate that free use of bike sharing to connect the first/last mile trips of transit can be most sustainable with 1.5 million US dollars in transportation damage costs saved per year, and 22 premature deaths further prevented per year due to the mode shift to cycling and walking. The bike-sharing case study has been published in *Sustainable Cities and Society (Vol. 41)*(Lu et al., 2018a).

Chapter 2 Spatial Agent-Based Model for Environmental Assessment of Passenger Transportation

2.1 Introduction

In recent years, high-speed railway (HSR) has become a popular transport option with its fast, comfortable, and environmentally friendly features. High-speed rail networks have spread in France, Germany, Spain, Italy, Switzerland, Belgium, China, Japan, and South Korea. As HSR is powered by electricity, it offers potential environmental advantages (e.g. fewer carbon emissions) over what can be provided by other transport modes that are mostly powered by gasoline or diesel. However, the whole life cycle of the HSR system should not only include the operation of HSR but also consider vehicle manufacturing, infrastructure construction, and so on. In addition, after the opening of an HSR link, passengers may shift from other transportation modes (such as plane and bus) to the HSR, and their mobility habits may change (Feliu, 2012). For example, for trips shorter than 300 miles or 3.5-4 hours, the market share of railway could go up to 50% (Chester & Ryerson, 2014). Different levels of passenger occupancy can easily change the relative environmental performances of the various modes (Chester & Horvath, 2009b). To date, no study has yet taken into account the interactions between existing transport modes and a newly-built HSR, nor of the changes to the whole system's environmental performances with the introduction of HSR.

The motivation of this study is to investigate how the life cycle environmental performances of existing transport systems will be affected by the introduction of HSR. To accomplish this task, we present here a spatial agent-based model for environmental assessment of dynamic transport system (ALENT). ALENT combines **A**gent-based modeling and **L**ife-cycle analysis to explore the **EN**vironment impacts of an existing passenger **T**ransportation system with a newly introduced HSR. There are two innovations in this study: First, a logit model combined with the small-world theory is applied to simulate the passengers' mode choice behaviors. Second, a hybrid agent-based modeling (ABM)/life-cycle analysis (LCA) model, ALENT, was built to simulate the operational and life-cycle environmental performances of HSR and other competing modes with the influences of dynamic market behaviors incorporated, an addition beyond traditional life cycle thinking. Consequently, some environmental strategies can be proposed based on the comparative environmental performances of the transport modes. These environmental strategies for transport modes involve many factors, such as physical (fuel consumption, emissions controls, occupancy rates), geographic (electricity mixes with varying shares of coal-fired power, hydropower, nuclear power, and wind power), and temporal (vehicle age) factors. At this stage, only the occupancy rate is discussed as a core factor in ALENT, as it is more related to market behaviors.

This study will first provide some background on the value of linking LCA and ABM in the context of transportation. Then a hybrid model for environmental assessment is proposed. Following this, a real-world case study is presented, describing an application of the frameworks outlined here. We conclude with a summary of the work and discuss further avenues of research.

2.2 Literature review

A great deal of research has focused on the transportation environmental impacts of HSR. Chester and Horvath (2010a) conducted a life cycle environmental assessment of HSR and other alternative modes (automobile, bus, commuter rail, and aircraft) and compared both the direct and indirect effects of fuel, infrastructure, and vehicle stage. It was found that the California High-Speed Railway (CAHSR) had the potential to be the lowest energy consumer and Greenhouse Gas (GHG) emitter at high occupancy rates, though it produced much larger SO_2 emissions than the other modes. Chester and Horvath (2012) also found that HSR could achieve larger amount of environmental benefits than other transportation modes with advanced vehicles with high ridership and using renewable energy. In Europe, although a proposed Swedish HSR track could increase GHG emissions due to new railway construction and maintenance, Åkerman (2011) found significant GHG emission reduction potential due to transportation modes shifting to HSR. Grossrieder (2011) also examined the life cycle environmental performance of Norwegian HSR and analyzed the infrastructure, rolling stock, and operation parts. It was found that the environmental impacts could be reduced by 50% in a likely future 2050 scenario by improving the production technology of the materials for the infrastructure and by having more passengers. Yue et al. (2015) studied the life-cycle assessment of HSR in China with a case study of the high-speed rail that links Beijing and Shanghai, and found the life cycle environmental impacts of China’s HSR may not be as desirable as the HSR systems in the developed countries because of the considerable number of bridges needed and reliance on fossil fuel-based electricity.

However, when used alone, LCA fails to account for the local variability in dynamic systems. Although in LCA several scenarios are developed to explore the effects of changes in HSR infrastructure planning, passenger occupancy, and fuel production, LCA cannot lead to comprehensive strategies that encompass the dynamic nature of the transportation market. The transportation market, like other systems in the real world, is not static and simple. Especially with the introduction of a new transportation mode like high-speed railway, the market share of the existing modes will be affected. It has been estimated that for trips shorter than 300 miles or 3.5-4 hours, the market share of the railway could go up to 50% (Chester & Ryerson, 2014). Ranges in mode share can easily change the environmental performance of the affected transport modes. Thus, the assessment of life-cycle environmental performances of transport modes needs to integrate market behavior considerations. How to optimize the transportation mode shares based on such integrated analysis is a critical issue addressed in the following study.

McFadden (1972) proposed a logit model based on utility theory, which has been widely used in previous discrete choice research. Consumers' choice among alternatives is also based on the utility theory of products (Anderson et al., 1992). A representative passenger is assumed to choose the traveling mode which yields the highest utility or satisfaction (Liu & Li, 2012). The utility depends on the various characteristics of the alternative modes, such as travel time, ticket fare, and service quality. As Forinash and Koppelman

(1993) argued, the logit model was suitable for travel choice modeling. Levinson et al. (1997) apportioned the trips between high-speed rail, aircraft, and highway based on a multinomial logit mode choice model, with the key factors of travel time, fare cost, and service frequency considered. Liu and Li (2012) presented a nested logit/simultaneous choice model to improve the demand forecast for high-speed railway and confirmed that travel costs had a significant impact on both mode choice and trip generation. Khan (2007) employed various nested logit models to simulate the traveling mode choice behaviors in a multi-modal environment. Adler et al. (2010) used a nested multinomial logit model for predicting the likelihood of success of high-speed rail in the face of competition from airlines. Yamaguchi and Yamasaki (2009) constructed simulation analysis with a dynamic spatial nested logit model to analyze the competition of the Maglev/Shinkansen system, though only price factors were considered as a function parameter.

In logit models, every agent is treated as an independent research object, whose social connections are ignored, and the impacts of the previous choice on current choice are also not considered. Omitting these dimensions in making mode choice forecasts can lead to less reliable results since these factors affect consumers' choice to a certain extent. Thus, mode choice for an entirely new transportation system cannot be forecasted accurately using an unadjusted logit model, which could compromise the quality of corresponding policy-making decisions. Although there are a variety of alternative models for policy making, Creedy (2001) argued that direct policy advice requires the construction of large-scale simulation models composed of "low-level" units such as consumers or operators. A key principle of ABM is that from simple interactions and learning among individual entities can emerge large-scale outcomes (Wilensky & Rand, 2015). ABM appears to be perfectly tailored to investigate the complex dynamics in coupled human-natural systems such as a transportation system (Müller et al., 2014). As ABM is usually used for scenario exploration (Kelly et al., 2013), it is very useful for assisting stakeholders in weighing different options.

This study combines utility theory and psychology theory in an ABM model to simulate consumer choice behaviors to more accurately reflect real-world choices. In order to supplement the limitations of the logit model, namely the lack of consideration of connections between consumers, social networks among consumers are formalized as a Watts-Strogatz model (Watts & Strogatz, 1998), which describes the small-world and clustering characteristics of networks. The small-world effect refers to a circle of agents where each agent has close contact with one another, like neighbors, and the clustering characteristic refers to the existence of clusters in social networks, represented as some random non-neighbor agents. Here we use “friends” to represent social networks, implemented in line with the Watts-Strogatz model. The psychological research has found that an individual’s utility from a product depends not only on the product itself, but also on how popular the product is in individual’s large social setting (Duesenberry, 1949). Elias and Jephcott (1978) discussed this socialization effect in exploring the evolution of preferences on the civilization process. Hayakawa and Venieris (1977) empirically validated this argument with findings showing that people with equal or higher status have an effect on others’ consumption behavior. The impact of fashion trends on the clothing market strongly demonstrate the "role-models" effects.

The remainder of this study focuses on how LCA and ABM can be combined to investigate the environmental impacts caused by the introduction of HSR. Specifically, we focus on the case of the Hong Kong-mainland China cross-boundary transportation market.

2.3 Materials and methods

Figure 2-1 shows the research framework of ALENT. ALENT comprises two kinds of entities: modes and passengers. Modes refer to the main intercity transport modes, including HSR, train, bus, and airplane. As the life cycle impacts of transportation modes can be as large as 20 times that of the vehicle operational stage (North et al., 2010), the infrastructure and fuel stages should also be considered in the life cycle assessment of a passenger transportation system (Chester & Horvath, 2009b). Life-cycle environmental assessment of these intercity modes is conducted taking into account resources used, fuel production, vehicle manufacturing, infrastructure construction, and operation. The disposal stage of each transport mode is not considered in this study due to the lack of data as well as their limited life cycle environmental impacts according to other HSR LCA studies. Passengers embedded in this transportation "world" have some "friends" who can influence their mode choices. Passengers' mode choice behaviors can change the mode shares of the transport modes, and the operational and life-cycle environmental performances of this transportation "world" also will be influenced accordingly. Several scenarios at the operation stage are simulated to minimize the environmental impacts based on predicted mode shares.

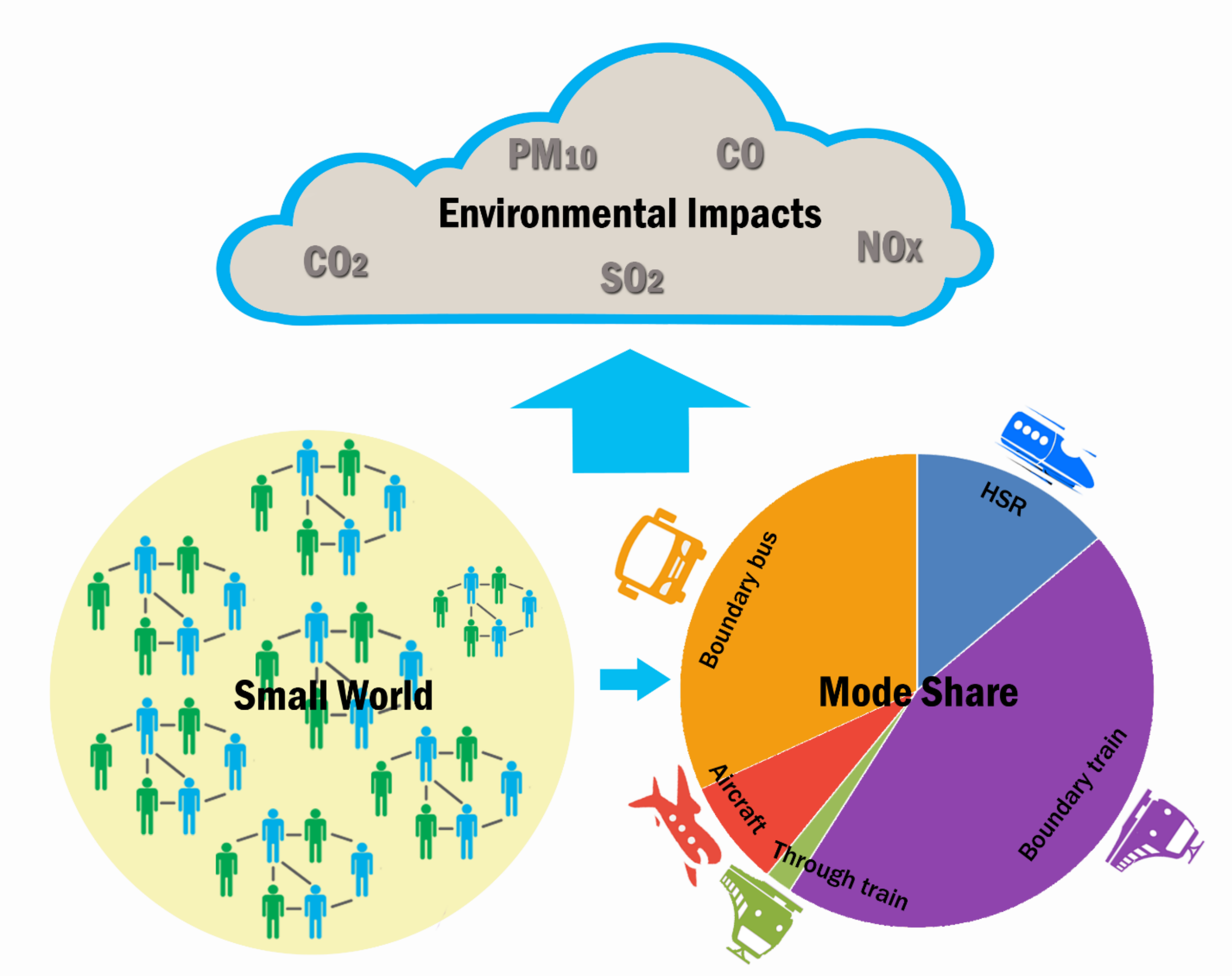

Figure 2-1. Research framework of ALENT

2.3.1 Hybrid logit and ABM model

As indicated previously, the motivation of this study is to highlight how LCA and ABM can be combined to investigate the environmental impacts of a transportation system. To demonstrate this, first, we create a hybrid logit and ABM model that simulates individuals making mode choices in the transportation system. **Figure 2-2** shows the hybrid model design. The notation used to formulate the model is shown in the following:

Sets:

$\boldsymbol{U_{ij}}$	The actual utility of the product *j* selected by agent *i* last time
$\boldsymbol{Un_{ij}}$	The actual uncertainty of the product *j* selected by agent *i* last time
$\boldsymbol{EU_{ij}}$	The expected utility of agent *i* choosing product *j*
$\boldsymbol{EUn_{ij}}$	The expected uncertainty of agent *i* choosing product *j*
$\boldsymbol{U_{min}}$	The minimum satisfaction of agent *i* in product selection
$\boldsymbol{Un_{max}}$	The maximum uncertainty of agent *i* in product selection
β_i	The social need weighting of agent *i*
x_i	The fraction of the "friends" of agent *i* who choose or evaluate product *j*

In the following equations (Eqs. (1) to (10)), we denote i for agent/passenger, and $i \ni N^*$, and we define j for product/transport mode, and $j \ni N^*$. Compared to other discrete choice models, the utility of using a product in ALENT is that it not only considers the individual parts C1 related to alternative modes' characteristics, but it also includes a social effect part C2. The following equations (Eqs.(1) to (9)) related to passengers' mode choice behaviors are adjusted appropriately based on the consumer behavior equations in Janssen and Jager (2003). We constructed the C1 individual satisfaction in Eq. (3) based on the key dimensions of ticket fare, travel cost, service quality, and accessibility of the transport mode, and these dimensions are given different weightings based on passengers' preferences.

The total utility of passenger *i* choosing product *j* is equal to U_{ij} and the uncertainty of passenger *i* choosing product *j* is equal to Un_{ij}. The more that "friends" in the consumer's social network choose other modes, the more uncertain that consumer is. U_{ij} and Un_{ij} are expressed in Eqs. (1) and (2):

$$U_{ij} = (1 - \beta_i) \times C_1 + \beta_i \times C_2 \; for \; i \ni \; N^* \text{ and } j \ni \; N^* \tag{1}$$

$$Un_{ij} = \beta_i \times (1 - C_2) \tag{2}$$

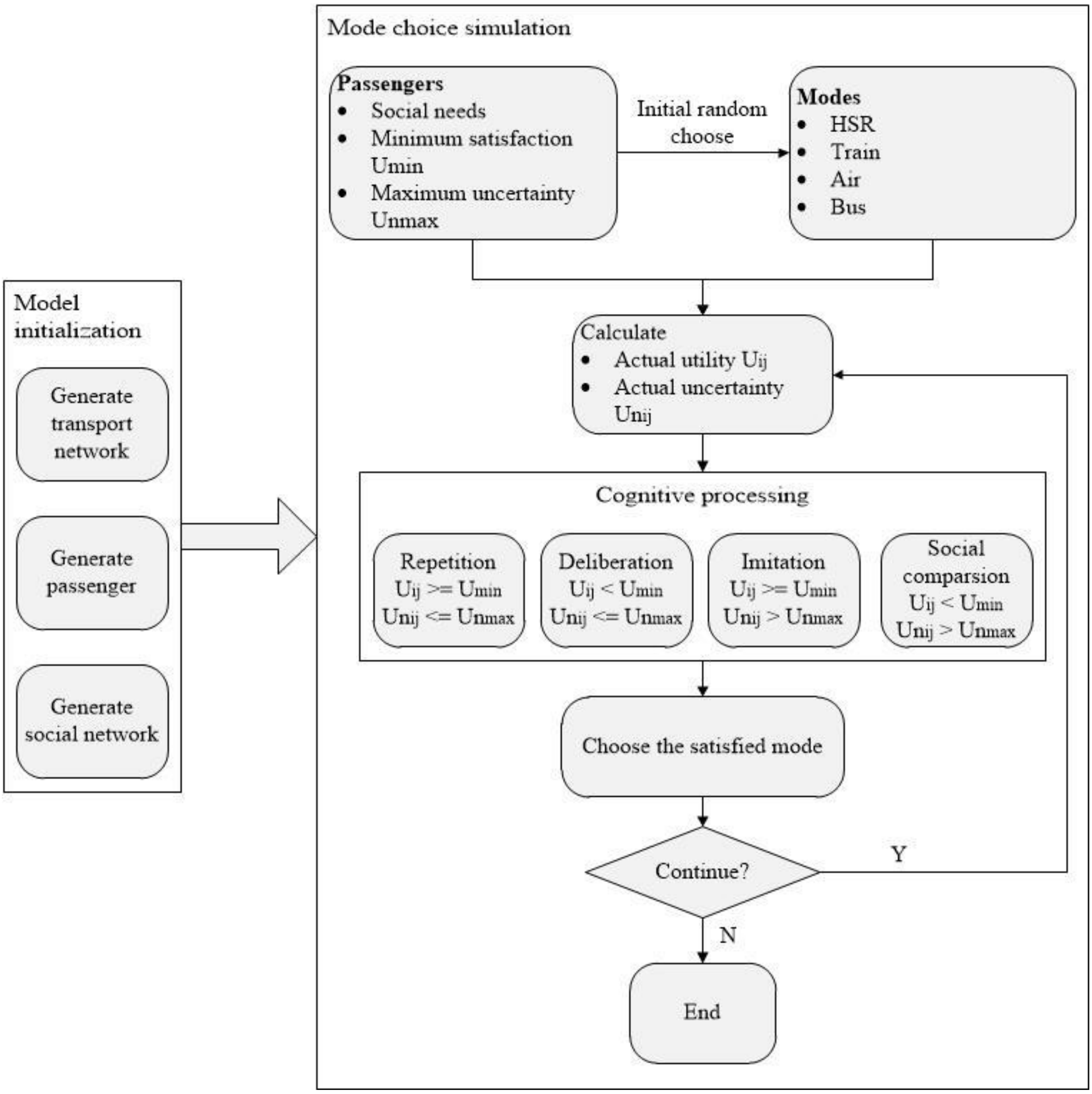

Figure 2-2. Model design

The following parameters C_1 and C_2 are utilized to quantify the choice probability of a passenger choosing a specific mode. C_1 represents individual satisfaction, and C_2 denotes social satisfaction. C_1 and C_2 are independent of each other in the mode utility equation. C_1 denotes the individual satisfaction of consumer *i*, expressing the difference between the personal preferences of a consumer for a specific product and the product's characteristics. Thus, C_1 is defined in Eqs. (3) and (4) as:

$$C_1 = 1 - |P_i - d_i| \tag{3}$$

$$= 1 - \sqrt{w_t \times (p_t - d_{i,t})^2 + w_f \times (p_f - d_{i,f})^2 + w_c \times (p_c - d_{i,c})^2 + w_a \times (p_a - d_{i,a})^2}$$

$$w_t + w_f + w_s + w_a = 1 \tag{4}$$

In Eqs.(3) and (4), w_t, w_f, w_s, and w_a are the weights of travel time, ticket fare, service quality, and accessibility level, respectively; p_t, p_f, p_s and p_a are the dimensions of travel time, ticket fare, service quality, and accessibility level of the transport mode chosen by the passenger *i*; $d_{i,t}$, $d_{i,f}$, $d_{i,s}$ and $d_{i,a}$ are the preferred characteristics for travel time, ticket fare, service quality, and accessibility level, respectively, of passenger *i*. p_i is normalized by the mode's travel time, ticket fare, service quality, and accessibility level from real operation data. d_i obeys normal distribution and is dimensionless, normalized between 0 and 1.

In this study, the key factors that influence passenger agents in determining a satisfying mode include: ticket fares (De Palma & Rochat, 2000; Levinson et al., 1997; Liu & Li, 2012; Yamaguchi & Yamasaki, 2009), travel time (De Palma & Rochat, 2000; Levinson et al., 1997), accessibility level (Chester & Horvath, 2010a), and service quality (De Palma & Rochat, 2000; Levinson et al., 1997). Ticket fare is the non-discounted fare of one transport mode. Travel time includes walking time, waiting time, onboard time and interchange time. Accessibility level represents a locational characteristic that permits a station or airport to be reached through the effort of those at other places using various shuttle services. It depends on the mode station's geographical location (e.g., distance to urban center) and the conditions of road networks. Service quality is composed of car cleanness, neat appearance of employees, employee service attitude, the comfort of air conditioning, on-time performance, frequency rate, and the convenience of making reservations and ticketing. C_2 depends on how popular the chosen mode is in the consumer's social network and is represented as x_i in Eq. (5).

$$C_2 = x_i = \frac{n_1}{n_f} \tag{5}$$

where n_1 is the number of friends with the same choice made as consumer *i*, n_f is the number of friends in consumer *i*'s social network. Consumer *i*'s social satisfaction increases when more friends consume the same product as consumer i. This social effect involves Veblen effects (Veblen, 2007) and bandwagons (Granovetter & Soong, 1986).

We can calculate the actual utility and actual uncertainty based on the Eq (1) to Eq (5). The expected utility and expected uncertainty of an agent

(Eqs. (6) and (7)) are expressed as the same calculation equations with actual utility U_{ij} and actual uncertainty Un_{ij}, which reflects the expected value of agent *i* choosing product *j*. The only difference between them is that *EU* is an expected value while *U* is the experienced value at the last time step.

$$EU_{ij} = (1 - \beta_i) \times \left(1 - \left|p_i - d_{ij}\right|\right) + \beta_i \times x_i \tag{6}$$

$$EUn_{ij} = \beta_i \times (1 - x_i) \tag{7}$$

Given the actual utility U_{ij} and actual uncertainty Un_{ij}, agents may engage in different cognitive processes during subsequent selection processes when making comparisons with their own U_{min}-minimum satisfaction and Un_{max}-maximum uncertainty (or uncertainty tolerance level). These four types of cognitive processes defined by Janssen and Jager (2003) include:

Repetition (satisfied and certain:$U_{ij} \geq U_{min}, Un_{ij} \leq Un_{max}$), the agent *i* habitually chooses the product that has been chosen in the previous time step. In actuality, the majority of agents will engage in repetition behaviors when the market is relatively stable. Such a market resembles the daily shopping of most people, such as when buying coffee and milk, which are often purchased in a habitual manner.

Deliberation (unsatisfied and certain:$U_{ij} < U_{min}, Un_{ij} \leq Un_{max}$), the agent *i* evaluates the expected utility EU_{ij} of each product and uses a logit function to solve the discrete problem. Agents are assumed to have perfect information of each product's characteristics. So the probability P_{ij} of agent *i* choosing product *j* is expressed as Eq. (8):

$$P_{ij} = \frac{e^{EU_{ij}}}{\sum_{j \in I} e^{EU_{ij}}} \tag{8}$$

Finally, the product with the highest P_{dij} is chosen by agent i. This appears to capture the durable goods market (such as computer and television), and financial services (such as insurance and loans). People in this market want to make full use of their money, and they are less likely influenced by their friends' choices.

Imitation (satisfied and uncertain: $U_{ij} \geq U_{min}, Un_{ij} > Un_{max}$), the agent i evaluates the respective product share of product i among its social networks, or in other words, the agent i calculates the x_i of each product and selects the product that has the highest P_{ij}. A logit function to describe this discrete choice is as follows:

$$P_{ij} = \frac{e^{x_i}}{\sum_{j \in I} e^{x_i}} \tag{9}$$

Because certain agents imitate their friends' choice, a lot of agents will choose the same product. Their actual utility U_i will consequently be higher and actual uncertainty Un_i lower. Thus most of the agents will engage in repetition behaviors in the later stages, and a lock-in market ultimately emerges. These lock-in markets often occur in the local domains of certain products, where the selection is more likely influenced by their social networks.

Social comparison (unsatisfied and uncertain: $U_{ij} < U_{min}, Un_{ij} > Un_{max}$), social comparison behavior is the most complicated consumer behavior encompassed in this study. In essence, the deliberative behavior occurs in agent *i*'s social network rather than in the overall market. The agent *i* first chooses the product *j* which has the highest x_{ij} in its social network, and the product's expected utility EU_{ij} should not be lower than the actual utility U_{ij} at the last time step. If it is lower, then the agent *i* will choose the product that has the highest EU_{ij} in its social network. This type of market typically resembles fashion markets, in which products such as Christmas decorations and hair styles more rapidly change over time compared to other consumer products. For example, young people often care more about their dress style and think it is important in their daily life, but they are often uncertain about their choices. Thus, they engage in social comparison behaviors in their friend circle to seek guidance.

After one-cycle mode choice, the passenger's actual utility and actual uncertainty will be updated. The updates reflect changes that occur in passenger preferences and the social environment during the cycle, which will affect the selection in succeeding time steps if the passenger chooses to continue to travel in this transportation system.

2.3.2 Environmental impact simulation

The second stage of implementing ALENT is the calculation of the environmental performances of HSR and its competing modes at the operational stage and life-cycle stage. In order to reflect the modes' environmental performances with dynamic mode shares, the function unit of environmental data imported into ALENT is set as per vehicle-kilometer traveled (VKT). The operational and life-cycle energy consumption, GHG emissions, and criteria air pollutant emissions of the passenger transportation modes—HSR, train, midsize aircraft, and urban bus—are derived from several studies (Chester & Horvath, 2008, 2010a, 2010b; Chester & Horvath, 2009b; Chester et al., 2010; Grossrieder, 2011; Yue et al., 2015) with the function unit of VKT. The environmental impacts from the above studies show that energy consumption, GHG emission, and criteria air pollutant emissions are within the reported literature ranges.

Table 2-1 and **Table 2-2** show the operational and life-cycle environmental impacts of the transport modes for reference. The detailed parameters for these referenced modes are explained in the **supplementary material**. These environmental impacts with function unit—per vehicle-kilometer are converted as per passenger-kilometer based on occupancy rates from the simulation results of ALENT.

Table 2-1. Operational environmental impacts of referenced modes

Modes	Energy (MJ/VKT)	GHG (gCO2e/VKT)	SO_2 (g/VKT)	CO (g/VKT)	NO_X (g/VKT)	PM10 (g/VKT)	VOC (g/VKT)
HSR	428	31,750	188	22	18	2.5	5
Train	170	9,300	52	5.2	3	0.57	1.4
Aircraft	263	17,800	5.8	23	59	0.37	2.2
Urban bus	32	2,400	0.022	4.5	18	0.71	1.4

Table 2-2. Life-cycle environmental impacts of referenced modes

Modes	Energy (MJ/VKT)	GHG (gCO2e/VKT)	SO_2 (g/VKT)	CO (g/VKT)	NO_X (g/VKT)	PM10 (g/VKT)	VOC (g/VKT)
HSR	660	43,100	225	175	90	7.6	45
Train	310	18,000	85	63	35	7.4	25
Aircraft	312	22,000	17	60	70	2.2	7.0
Urban bus	43	3,300	1.9	11	22	1.4	3.8

2.4 Case study of the Hong Kong-Pearl River Delta area

2.4.1 The cross-boundary transportation

China has built the world's largest High-Speed Rail (HSR) network (Yue et al. 2015). The 26-km long Hong Kong section of HSR running between West Kowloon and Shenzhen Boundary will connect with the 16,000-km National high-speed railway network in 2018. Upon the opening of the Express Rail Link, the journey times between Hong Kong and the Mainland by train will be greatly shortened. The concept of a one-hour living circle within the Pearl River Delta area may materialize, and cultural and academic exchange will also be promoted (MTR Corporation Limited, 2009). However, with the introduction of HSR, the mode shares of existing modes between Hong Kong and mainland China, including boundary train, aircraft, through train, and boundary bus, will be influenced. As the mode share of private automobiles occupies less than 5% in the Hong Kong-mainland China cross-boundary transportation market (Planning Department, 2015), it will not be considered in this study. Detailed descriptions of these studied modes are explained in the **supplementary material**. Here a cross-boundary passenger trip is defined as a one-way direct movement of a person as a passenger between Hong Kong and the Mainland in either direction. In order to simplified model simulation, the interchange of transport modes is not considered in this study. The parameters of this case (such as weightings of key drivers) are drawn from a cross-boundary mode choice behavior survey. The survey was conducted as a computer-assisted personal interview and included a mode choice experiment and a key driver rating experiment. 498 potential passengers were investigated, whose basic information and key driver weightings are listed in **supplementary material**.

Evaluating cities within the life-cycle framework can illustrate the interdependent environmental impacts of a particular travel choice and the consequences and benefits of the travel behavior (Chester et al., 2010). In this study, the environmental performances of the Guangzhou-Shenzhen-Hong Kong HSR, boundary train, through train, aircraft, and boundary bus are evaluated based on passengers' different mode choices.

Figure 2-3 shows a screenshot of ALENT. ALENT was built with Netlogo, an ABM software platform (Wilensky, 1999). Using functions provided through the NetLogo-Geographic Information Systems (GIS) extension, the spatial map of Pearl River Delta, Hong Kong, and their main stations, airports, and roadways, especially for the main roadways, including the airline, HSR link, train rail link, highway, and other general roads in the form of Environmental Systems Research Institute (ESRI) shapefiles were loaded and represented on the ALENT interface. The spatial analysis capability of GIS has helped to explore and measure the physical factors such as the accessibility of retail center and the walkability of the city (Southworth, 2005; Yin, 2013; Zhu, 2016). The accessibility level of the specific transport mode is also measured with this spatial map, which depends on Euclidian distances (Li & Liu, 2007) between the mode's station and urban centers. The modes' travel times and ticket fares are represented as *min per 100 Km* and *HKD per 100 Km*, respectively. Users can adjust the modes' key driver values according to corresponding operation strategies. Energy consumption, GHG emissions and SO_2 emission per passenger kilometer traveled (PKT) are used to represent environmental performances of HSR and its competing modes. The mode shares and environmental performances of the transportation system are simulated and different operation scenarios are tested for after the opening of HSR (the year 2018).

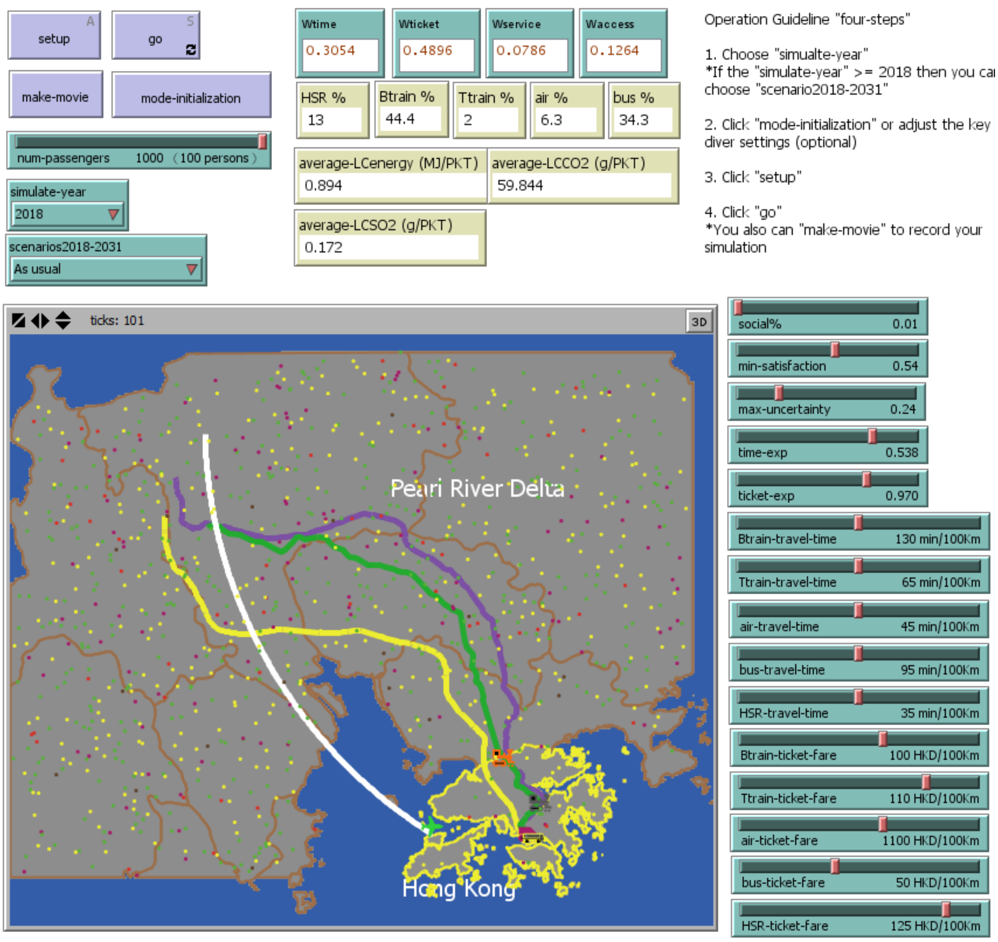

Figure 2-3. The screenshot of ALENT

In ALENT, the modes' key drivers are normalized with real operation data and are represented in **Table 2-3**. All key drivers are dimensionless, which are normalized between 0 and 1. HSR refers to Guangzhou-Shenzhen-Hong Kong HSR. Boundary train refers to passenger train service that starts at Hung Hom Station in Kowloon and terminates at Lo Wu or Lok Ma Chau stations, both of which are all boundary crossing points into Shenzhen. Aircraft refers to the passenger plane service between Hong Kong International Airport and the Mainland. Through train refers to passenger train service between Hong Kong and the Mainland, which terminates at Hung Hom station in Hong Kong. Boundary bus includes all types of bus and coach services between the Mainland and Hong Kong. Travel time and ticket fare are negative indicators, whose normalized values are negatively correlated with the real values. And accessibility level and service quality are positive indicators, whose normalized values are positively correlated with the real values. For example, the shorter the travel time, the larger the travel time dimension of the mode. The cheaper the ticket fare, the larger the ticket fare dimension of the mode. As the heterogeneous feature of ALENT, passengers' preferences for key drivers are different from each other and obey normal distribution. Passengers' different preferences can reflect their social demographic characteristics, for example, lower-income people prefer cheaper ticket fare, which means their preferences for ticket fare are lower than the average level.

Table 2-3. Modes' key driver dimensions

Transport modes	Travel time	Ticket fare	Service quality	Accessibility level
HSR*	0.78	0.92	0.85	0.70
Boundary train	0.18	0.93	0.75	0.80
Aircraft	0.72	0.26	0.85	0.65
Through train	0.59	0.93	0.80	0.75
Boundary bus	0.41	0.97	0.70	0.80

2.4.2 Calibration and validation

ABM has been widely applied in various fields. However, validation issues in ABM have been paid little attention (Fagiolo et al., 2007). Compared to traditional methods, ABM always involves a much higher degree of freedom to represent the complexity of real-world systems (Xu et al., 2009). When there are inherent complexity and diversity, ABM validation needs to be designed according to the characteristics of the specific model. In particular, historical transportation data is statistically analyzed in this study to measure the goodness of fit regarding both quantitative values and patterns.

The calibration experiment was conducted by varying the combinations of two kinds of unknown parameters, i.e., the standard deviation of passengers' preferences for key driver dimension σ, and average passengers' preferences for key driver dimensions μ, to find the best fitting degree with historical mode share data from the Cross-boundary Travel Survey 2003-2014 (Planning Department, 2015).

Table 2-4 shows the best parameter combinations which generate Monte-Carlo simulation outputs (100 runs) fitting the historical data best in terms of minimizing squared residuals. 100-runs are simply assumed to be enough for an accurate representation of the simulation results in our study. We ran the model with several runs, which is from 10-runs to 100-runs with 10-runs step. We first ran two sets (10-runs and 20-runs) and checked whether the output of the 20-runs was within 1% of the output of the 10-runs (it wasn't). We then ran a third set (30 runs) and compared the outputs of the 20-runs and 30-runs. We continued to run sets until the output in the new sets are were within 1% of the previous set. The output converged within 100-runs of the model. The explanation also can be applied to other Monte-Carlo simulations in the dissertation.

The calibration results with the best parameter combinations are shown in **Table 2-5**. The calibration experiment finds that passengers' average preferences for travel time and ticket fare improve linearly over the years (see **Table 2-4**), with an 0.027 and 0.003 annual increase for travel time and ticket fare, respectively. This means that passengers in the cross-boundary transport market have been pursuing transport modes with faster speed and lower price from 2003 to 2014. These preference trends for travel time and ticket fare are used to predict the future mode share with the introduction of HSR in 2018. Thus, the baseline settings of passengers' average preferences of travel time, ticket fare, service quality, and accessibility level dimension μ in 2018 are set as 0.538, 0.970, 0.750, and 0.800, respectively. The standard deviation of passengers' preference distribution in 2018 is set as 0.300.

Table 2-4. Best fitting-degree parameter combinations from 2003 to 2014

Years	2003	2006	2007	2009	2011	2014
Dtime μ	0.160	0.241	0.268	0.322	0.376	0.430
Dticket μ	0.940	0.949	0.952	0.958	0.964	0.970
Dservice μ	0.750	0.750	0.750	0.750	0.750	0.750
Daccess μ	0.800	0.800	0.800	0.800	0.800	0.800
SD σ	0.300	0.300	0.300	0.300	0.300	0.300

Note: Dtime, Dticket, Dservice and Daccess represent the travel time, ticket fare, service quality and accessibility level dimensions of passengers' average preferences. SD represents the standard deviation of passengers' preference distribution.

Table 2-5. Historical mode share and simulated mode share from 2003 to 2014

Mode share	2003	2006	2007	2009	2011	2013/14
Historical mode shares						
Boundary train	0.692	0.603	0.598	0.585	0.584	0.547
Aircraft	0.031	0.039	0.044	0.042	0.046	0.043
Through train	0.022	0.022	0.020	0.019	0.023	0.022
Boundary bus	0.255	0.336	0.338	0.354	0.347	0.388
Simulated mode shares						
Boundary train	0.678	0.639	0.618	0.587	0.561	0.529
Aircraft	0.038	0.037	0.044	0.045	0.047	0.044
Through train	0.021	0.017	0.022	0.019	0.016	0.021
Boundary bus	0.264	0.307	0.317	0.349	0.376	0.406
RSS	0.00033	0.00212	0.00084	0.00004	0.00138	0.00063

Note: RSS represents the residual sum of squares.

Passenger preferences change for service quality, and accessibility level is not discussed in this study due to the high heterogeneity of ALENT. These are tradeoffs between the decrease of the degree of freedom and the increase of the model's ability in representing real-world complexity (Xu et al., 2009). The simulation results for mode share in 2018 are consistent with official forecast data based on the above parameter combination(Transport Housing Bureau, 2009).

2.5 Analysis of results

Based on the calibrated configuration of the ALENT model, the future mode shares and environmental performances after the introduction of HSR can be estimated, and some operation strategies will be proposed with consideration of both mode shares and corresponding environment performances. The simulation results of the passengers' cognitive processes during mode choices are shown in the **supplementary material**.

2.5.1 Future mode shares and occupancy rates

If the existing modes maintain their usual current operation strategies, the shares of the transport modes before and after the opening of HSR are projected to be as shown in **Figure 2-4**. The mode share of Boundary train is reduced by 10%, and HSR gains 13% market share in the opening year.

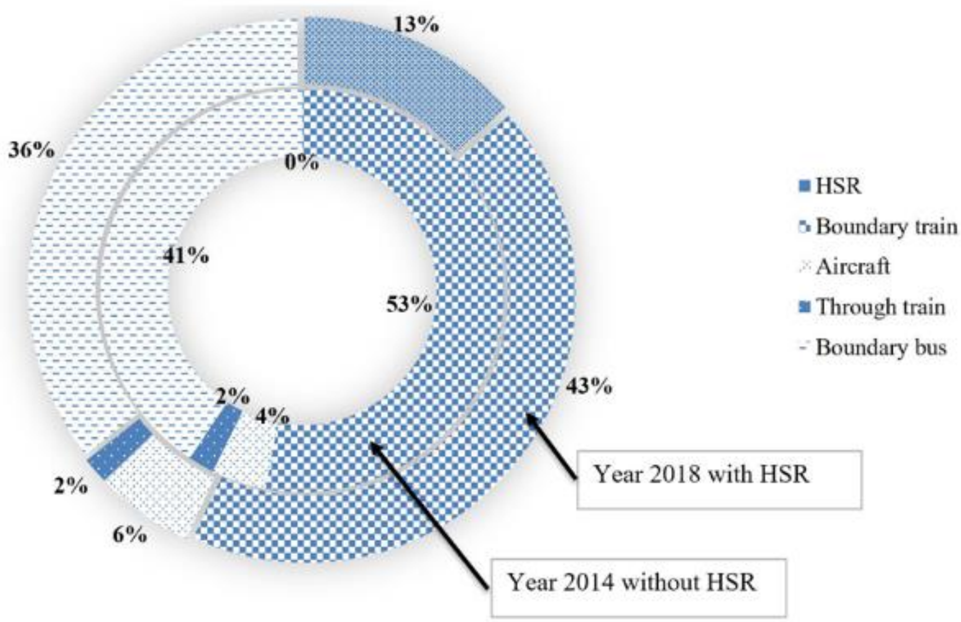

Figure 2-4. The mode shares of transport modes before and after HSR

Table 2-6 shows the simulation results of cross-boundary daily ridership by transport mode in 2014 and 2018. Here we assume the existing transport operators do not adjust their operation strategies in 2018, in other words, they keep the daily frequencies and number of seats the same as in 2014, and their corresponding occupancy rates are thus estimated. Then we use the simulation results to propose proactive operation strategies for the transportation system in 2018. Each mode's occupancy rate is calculated as Eq. (10):

$$\text{Occupancy rate}_j = \frac{mode\ share_j \times total\ trips}{daily\ frequency_j \times no.of\ seats_j} \quad (10)$$

Note: total number here refers to the daily average number of passenger trips between Hong Kong and the Mainland China. According to forecasts from the Hong Kong Transport and Housing Bureau Report (Legislative Council Panel on Transport 2009), the total number will grow 3.3% per year from 2016 to 2031.

As **Table 2-6** shows, the occupancy rates of the through train in 2018 is forecasted to be a bit less than in 2014, while the occupancy rate of the boundary train in 2018 remains the same as in 2014. The newly-introduced HSR's occupancy rate is projected to expand to around 78% during the first year of operation. The 2018 occupancy rates for the boundary bus and aircraft are estimated to be higher than in 2014, especially for aircraft flying between Hong Kong and mainland China, with an occupancy rate predicted to increase to 1.24 (if their daily flights and number of seats remain unchanged). Airlines may need to increase daily flights to meet higher demand in the future. These simulation results could serve to support future plans for expanding Hong Kong International Airport (HKIA) into a three-runway system (HKIA, 2015).

Table 2-6. Average cross-boundary daily ridership and occupancy rates by transport mode

Modes	2014		2018	
	Daily ridership	Occupancy rate	Daily ridership	Occupancy rate
HSR	0	0.00	91625	0.78
Boundary train	287830	0.94	288318	0.94
Aircraft	25965	0.82	39284	1.24
Through train	11290	0.67	11058	0.66
Boundary bus	215296	1.00	236617	1.11
Total number	540381	N/A	666902	N/A

2.5.2 Future environmental assessment

Nolte and Wurtenberger (2003) state that increasing a mode's occupancy has the biggest potential of any measure to reduce environmental impacts on a passenger-kilometer basis. Achieving high occupancy rates can be realized through market strategies such as adjusting the ticket fare, reducing the travel time, increasing service quality, and increasing the accessibility level (adding feeder buses between the urban center and other stations). These market strategies are proposed based on the simulation results of ALENT.

2.5.2.1 Baseline scenario-environmental performance in 2018

The environmental performances of cross-boundary modes are normalized per passenger kilometer traveled (PKT) by using converted Life Cycle Inventory (LCI) of environmental performances per–VKT and the occupancy rates as described in Eqs. (11) and (12). Energy consumption, greenhouse gas emissions, and SO_2 emissions are evaluated. Further details about the converted environmental performances of cross-boundary modes can be found in the **supplementary material**.

$$LCI\ result/_{PKT} = \frac{LCI\ result/_{VKT}}{\text{occupancy rate } \times \text{no. of seats}} \tag{11}$$

$$(0 < occupancy\ rate < 1.0)$$

$$LCI\ result/_{PKT} = \frac{LCI\ result/_{VKT}}{\text{no. of seats}} \quad (occupancy\ rate\ \geq\ 1.0) \tag{12}$$

In **Figure 2-5** the life-cycle energy consumption and GHG emissions of HSR are in second place, less than for aircraft. But the life-cycle SO_2

emission of HSR is much larger than other competing cross-boundary modes. Compared to other modes, the boundary train and boundary bus show better environmental performance. In

Table 2-7, except the through train, the environmental performances of other existing modes in 2018 are better than in 2014 as future daily ridership increases. But the average life-cycle energy consumptions, GHG emissions, and SO_2 emissions of the cross-boundary transportation system are increased by 17%, 16%, and 42%, respectively after the introduction of HSR. It should be acknowledged that the life-cycle environmental impacts of China’s HSR may not have the same distinguished environmental performances as the HSR systems in the developed countries such as Norway (Grossrieder 2011), Sweden (Åkerman, 2011), and Japan (Miyauchi et al., 1999). If HSR’s mode share grows continually from 2018, it may have the potential to lower its environmental performances as the occupancy rate increases. Thus, some operation scenarios related to HSR are simulated as follows.

Figure 2-5. Operational and life-cycle environmental impacts of cross-boundary transport modes in 2018

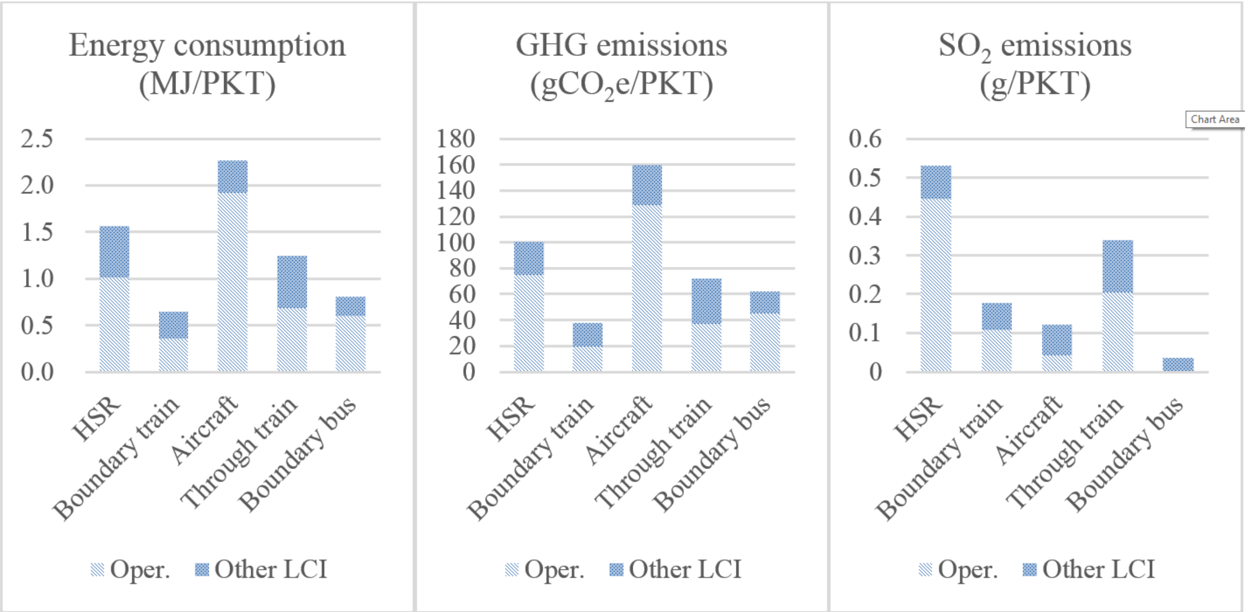

Table 2-7. The environmental performances of cross-boundary transportation system

Modes	Energy (MJ/PKT)		GHG emissions (gCO2e/PKT)		SO_2 emissions (g/PKT)	
	2014	2018	2014	2018	2014	2018
HSR	0.00	1.56	0.00	100.79	0.00	0.53
Boundary train	0.65	0.65	37.78	37.70	0.18	0.18
Aircraft	2.78	2.27	196.11	159.75	0.15	0.12
Through train	1.24	1.24	71.90	72.11	0.34	0.34
Boundary bus	0.73	0.73	55.79	55.79	0.03	0.03
Weighted average	0.78	0.91	52.18	60.43	0.12	0.17
Changes	—	+17%	—	+16%	—	+42%

Note: $Weighted\ average\ = \sum mode\ share_i \times LCI\ result/PKT_i$

2.5.2.2 HSR ticket fare scenario in 2018

As previously discussed, HSR can reduce its energy consumption, GHG emissions, and SO_2 emissions by maintaining a high occupancy rate. As HSR has the shortest travel time among the cross-boundary modes, better environmental performance can be realized by adjusting HSR's ticket fare. **Figure 2-6** represents the whole life-cycle environmental performances changing with the HSR ticket fare (the original ticket fare is 125HKD/100Km). All the other parameters were set to remain the same as the 2018 parameter settings. HSR's occupancy rate is highest—0.833—when its ticket fare is set as 60HKD/100Km, but the whole life-cycle environmental performance is worse than the baseline scenario because of the lower occupancy rate of aircraft. The best combination of occupancy rate and environmental performance emerges in the scenario of an HSR ticket fare of 85HKD/100Km, with a resulting occupancy rate of 0.808. This scenario leads to 1.60%, 1.50%, and 2.60% reduction of the average life-cycle energy consumptions, average life-cycle GHG emissions, and average life-cycle SO_2 emissions respectively compared with the baseline scenario (when ticket fare is 125HKD/100Km). Thus, it appears that adjusting the HSR ticket fare may not have a pronounced effect on the system's environmental performances.

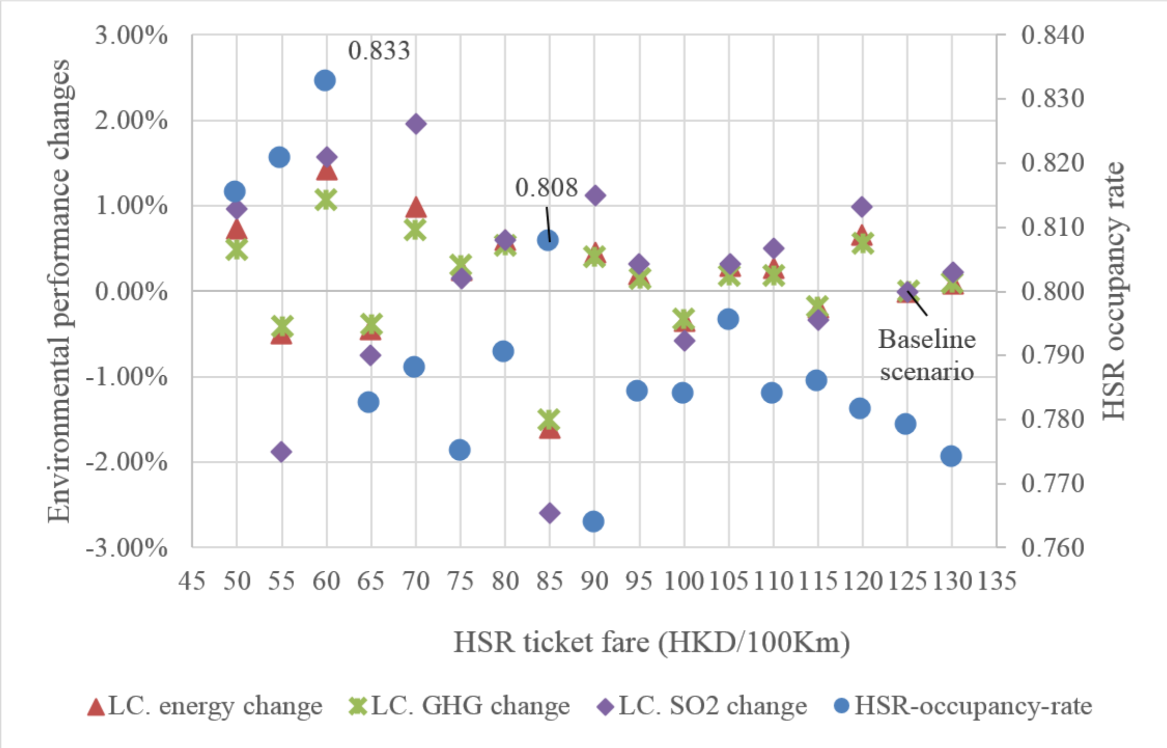

Figure 2-6. Changes of the average life-cycle environmental impacts of cross-boundary transport system

2.5.2.3 2018 scenario without the through train

As the through train shares the same line as the HSR shuttle service—both traveling between Hong Kong, Shenzhen, and Guangzhou—and has a ticket fare not cheaper than HSR while having a much longer travel time, it is assumed that the through train would be shut down in this scenario. **Table 2-8** shows the environmental performance of the baseline scenario and the without through train scenario in 2018. The individual environmental performances of HSR, boundary train, aircraft, and boundary bus are all better in the without through train scenario than in the baseline scenario. More specifically, the average life-cycle energy consumption, GHG emissions, and

SO_2 emissions are reduced by 25%, 25%, and 53%, respectively in the without through train scenario.

Table 2-8. Life cycle environmental performances of without through train scenario compared to the baseline scenario in 2018

Items	Energy consumption (MJ/PKT)		GHG emissions (gCO2e/PKT)		SO_2 emissions (g/PKT)	
	WTTS	BS	WTTS	BS	WTTS	BS
HSR	1.45	1.56	94.52	100.79	0.49	0.53
Boundary train	0.63	0.65	37.06	37.70	0.18	0.18
Aircraft	2.25	2.27	158.23	159.75	0.12	0.12
Through train	0.00	1.24	0.00	72.11	0.00	0.34
Boundary bus	0.72	0.73	55.00	55.79	0.03	0.03
Weighted average	0.72	0.90	48.52	60.43	0.11	0.17
Changes	-25%	—	-25%	—	-53%	—

Note: WTTS means without through train scenario, BS means baseline scenario.

2.6 Summary

ALENT is a hybrid model integrating agent-based modeling and life-cycle environmental assessment, capable of simulating relevant environmental performances of transport modes under different market scenarios. ALENT can serve as an ABM-enhanced LCA with two distinct advantages. First, ALENT evaluates modes' environmental performance by capturing market competition and passenger interactions according to specific scenarios. Second, ALENT implements a simulation strategy that integrates the dynamic interplay of the passengers, modes, and environment as a complete system, enabling it to more accurately reflect the outcomes of such interconnectivity in the real world compared to strategies that only target individual components.

Based on the ALENT simulations generated by this study, several recommendations are proposed to improve the life-cycle environmental performances of the cross-boundary system,. First, Guangzhou-Shenzhen-Hong Kong HSR needs to sustain a high occupancy rate—more than 80%—to lower its environmental impacts. Second, shutting down the through train, which provides the same service as HSR but with longer travel times, can mitigate system life-cycle environmental impacts by up to 30%. Third, the boundary train may need to cut its daily frequency as its mode share decreases after 2018. In contrast, airlines will need to increase their daily flight frequencies or capacity by 2018. ALENT is used to examine the Hong Kong-mainland cross-boundary transportation case here, but ALENT can be applied to other cities for environmental performance evaluation of transportation system development. Decision makers can use this modeling tool to determine appropriate actions within their particular jurisdictions.

Given data availability constraints, the LCI of cross-boundary modes is estimated by adjusting the LCI of referencing modes from the literature. In future research a hybrid life-cycle analysis method integrating process-based LCA and Economic input-output based LCA can be applied to more thoroughly evaluate the life-cycle environmental performances of these cross-boundary modes. Liu et al. (2016) found the feeder bus connections are significant for commute by rail. Thus future simulation scenarios could include other dimensions such as fuel production (different electricity mix), accessibility change (with or without feeder bus), market influences (passengers' sensitivity to ticket fare may be lower during holidays), and mode complementarities (HSR replacing short-haul airline as a transfer mode for an international airline).

Chapter 3 Multi-Agent Spatial Simulation of Autonomous Taxis for Urban Commute

3.1 Introduction

Since 1969, commuters in the U.S. have primarily traveled to work in personally-owned vehicles, representing 90% of all commuters during the past two decades (Santos et al., 2011). Consequently, heavy traffic congestion can easily occur during commute peak hours, which can generate hefty travel costs and considerable environmental impacts. For example, Los Angeles currently experiences the most severe traffic congestion in the U.S., with a typical half-hour commute taking 60% longer during the morning and 81% longer during the evening (Jonathan, 2016). Light-duty vehicles, including passenger cars and light-duty trucks, are responsible for 61% of transportation greenhouse gas (GHG) emissions in the U.S. (EPA, 2016). Every year over 2,200 premature deaths and at least $18 billion in health care costs in 83 of the U.S.'s largest urban areas can be partly attributed to air pollution from traffic (Larry, 2011). Meanwhile, personal cars remain unused for approximately 95% of the day (OECD, 2015). The 2009 National Household Travel Survey (NHTS) data show that the average vehicle ownership per licensed driver is 0.99 (Santos et al., 2011). There are far more cars in the U.S. than Americans need to reach their desired destinations according to current travel patterns in most locations (Fagnant & Kockelman, 2014b).

Fully autonomous vehicles are expected to become a commercial reality in the next decade. Given the higher capital cost of early adoption, they are likely to be introduced first in public fleets and by transportation corporations, such as Lyft, Uber, and Car2Go (Heard et al., 2018). Ride-sharing and car-sharing companies are teaming up with automakers to introduce fleets of driverless taxis, which they see as becoming ubiquitous in urban areas. Autonomous taxis (aTaxis) may provide a solution to the problems presented above. The trajectory of technological progress suggests aTaxis will eventually be able to travel anywhere a conventional vehicle can go. The use of aTaxis in car-sharing services may compete with conventional taxis or even shared taxi services because this new mode can bypass the costs associated with drivers (Liang et al., 2016; Zachariah et al., 2014). Specifically, aTaxi systems have the potential to reduce the average wait time and enhance ride-matching experiences for passengers compared with a conventional car-sharing program (such as Zipcar and Car2go) with fixed rental and return stations, and aTaxi also can reduce the operating costs and provide more affordable service for low-income populations compared with app-based car-sharing programs (such as Uber) (Shen & Lopes, 2015; Zhang et al., 2015a). Compared with personal vehicles, aTaxis can transform transportation from an owned asset into a subscription or pay-on-demand service, with vehicle ownership needs to be reduced accordingly (Fagnant & Kockelman, 2014b). Used in this way, aTaxis can enable consumers to make more spontaneous trips, be more productive and/or have more time to relax during travel, in addition to providing more predictable and shorter travel times while improving rider safety (Burns et al., 2013).

This study analyzes the potential of using aTaxis as a transport mode for commuting travel rather than as a full substitution of existing transportation networks. The objective of this study is to optimize the aTaxi fleet size to meet the commuting demand, keeping the wait times below an acceptable threshold while minimizing the system vehicle miles traveled (VMT). Then the corresponding environmental performance and total travel cost of this system are evaluated using an Agent-Based Modeling (ABM) method. The commute model simulates heterogeneous travel patterns to anticipate aTaxi system implications for various travelers, who previously commuted in personal vehicles. The research contributes to the understanding of the impact of autonomous vehicles in three areas. First, the simulation is based on a real road network; Second, the hidden travel costs related to the value of commuters' time are considered; And third, the environmental impacts of the internal combustion engine (ICE) aTaxis and electric aTaxis are both evaluated.

The study is organized as follows: first, the ABM literature on autonomous vehicles is reviewed to inform the development of our method for modeling the commute with aTaxis in an urban road network. The method is shown and explained in detail in the subsequent section. Then the application to Ann Arbor, MI in the U.S. is presented, followed by the main results of several scenarios. The conclusions drawn from the simulation results, and finally, potential directions for future research are offered.

3.2 Literature review

Several modeling efforts have addressed the potential impacts of autonomous vehicles on traffic networks. Fagnant and Kockelman (2014b) designed an agent-based model for autonomous vehicle-sharing throughout a *grid-based* urban area and concluded that one shared autonomous vehicle (SAV) could replace approximately eleven privately-owned vehicles, traveling 10% more distance than used for comparable non-shared trips, but also resulting in an improved environmental impact. Boesch and Ciari (2015) suggested agent-based transport models are suitable for modeling future transport scenarios that incorporate autonomous vehicles. They discussed some possible research questions on autonomous vehicles, such as potential future car fleet size, prospective demand patterns, and possible interactions between public transport and autonomous vehicles. Burns et al. (2013) applied a relatively simple analytical model to the case of Ann Arbor, Michigan and concluded that autonomous vehicle-sharing could enhance mobility at considerably lower cost than privately-owned vehicles. Zellner et al. (2016) used an agent-based approach to examine how interventions such as using autonomous shuttles and making streetscape enhancements for pedestrians and cyclists may mitigate the first/last mile problem of public transit, with consideration to other factors such as parking fees and fuel costs. Four Chicago neighborhoods with different densities and income levels were simulated, and the automated shuttle buses were assumed to have no capacity constraints. They concluded that a dedicated automated shuttle service could support significant mode shifts by increasing the utilization of public transit. Liang et al. (2016) simulated the use of electric automated taxis for the first/last mile of train trips with the objective of maximizing daily profits through optimizing service zone locations and which reservations were accepted. However, the model only considered trips are occurring in the service zone, thus ignoring inter-zonal trips. Additionally, it assumed all the origins and destinations of passengers' requests are coming or going to the center of the service zone. And the automated taxis were also treated as "flows" rather than as independent vehicles, which means that the battery recharging needs of specific vehicles were not represented.

Zhang et al. (2015a) used agent-based modeling to study the effect of shared autonomous vehicles (SAV) on urban parking demand by varying the fleet size and passenger wait time in a hypothetical city laid out in a *grid network*. Their simulation results indicated that with a low market penetration rate of 2%, SAV users reduced their parking demand by 90%. Fagnant and Kockelman (2015a) used an agent- and network-based simulation to deliver a benefit-cost analysis for fleet size optimization with dynamic ride-sharing based on a system of SAVs in Austin, Texas. The authors concluded that dynamic ride-sharing could reduce overall vehicle miles traveled, thus avoiding new congestion problems. Chen et al. (2016) simulated the operation of shared autonomous electric vehicles (SAEVs) under various vehicle range and charging infrastructure scenarios in a *gridded city* modeled roughly on Austin, Texas, and predicted that with each SEAV replacing 5-9 privately-owned vehicles, the unoccupied VMT could be reduced by 3-4%, with average wait times between 2 and 4 minutes. Martínez et al. (2016) developed an agent-based model to simulate a station-based one-way car sharing system by dividing the city of Lisbon into a homogeneous grid of 200m by 200m cells, where trips are generated between two grid-cells at each hour. Martínez et al. (2014) proposed an agent-based simulation model to assess the market performance of newly shared taxi service in Lisbon. A set of rules for space- and time-matching between the shared taxis and passengers was identified, but the interactions between passengers and vehicles (such as the waiting time limit of passengers) were ignored. Levin et al. (2017) used realistic flow models to make predictions about the benefits of replacing personal cars with SAVs and found that, without dynamic ride-sharing, the additional unoccupied repositioning trips made by SAVs increased congestion and travel times., However, the model is based on a downtown grid network, and intra-zonal trips are not considered. Zhang et al. (2017) examined the influence of SAVs on urban parking demand based on a real transportation network with calibrated link level travel speeds, but the trips always start and end at the Traffic Analysis Zone (TAZ) centroid and the intra-zonal travel time is ignored.

Most of the research done so far on this topic has been simulated on a highly developed grid or hypothetical city and is constrained by several assumptions, such as grid-based transportation network, constant travel speed across the network, and passengers with uniform travel behavior. Furthermore, the planning and operation of autonomous taxis on commuting travel have received less attention, and the present work seeks to fill these knowledge gaps.

3.3 Proposed multi-agent model

This study utilizes agent-based modeling to simulate the anticipated autonomous vehicles' effect on commute travel. Agent-Based Models (ABMs) are well suited for modeling and studying the impacts of traffic behavior (Lu & Hsu, 2017). Du and Wang (2012) suggested an ABM approach can explore explanations, testify assumptions, and predict changes or emergence of individual behaviors upon urban change. ABMs enable representation of highly heterogeneous and behaviorally complex populations of agents and modeling both spatially and temporally large-scale interactions between the agents for the study of dynamic but coherent system behaviors (Eppstein et al., 2011). One of the benefits of the agent-based computational process approach is that no complicated mathematical algorithms are required. The agents are driven by rational behaviors, and irrelevant aspects are ignored. These features of ABMs may explain their increasing popularity in studies of transportation logistics and traffic flow. Miller and Heard (2016) suggest that agent-based models can help define reasonable scenarios of technology deployment and evaluate designs that can lower transportation-related emissions.

The aTaxi model is implemented with GAMA, a software platform for constructing spatially explicit agent-based simulations (GAMA, 2016). Integrating a geographic information system (GIS) and traffic simulation leads to a more realistic representation of real-world transportation activities (Cai et al., 2012). **Figure 3-1** shows how the research is conducted according to the following steps:

Step 1: Collecting commute and spatial data of the study city, including road network, the geographic distribution of office, commercial, and residential buildings, commuting speed, and a number of commuting trips by trip start time.

Step 2: Using agent-based modeling to understand how a system of aTaxis will perform in meeting the daily commute demand.

Step 3: Optimizing the fleet size to ensure the wait times are below an acceptable threshold during peak hours while simultaneously minimizing total VMT.

Step 4: Once the fleet size is known, evaluating the available travel cost and environmental impacts of this commute system.

Step 5: Finally, comparing the travel cost and environmental performance of the aTaxi scenario with the personal car scenario.

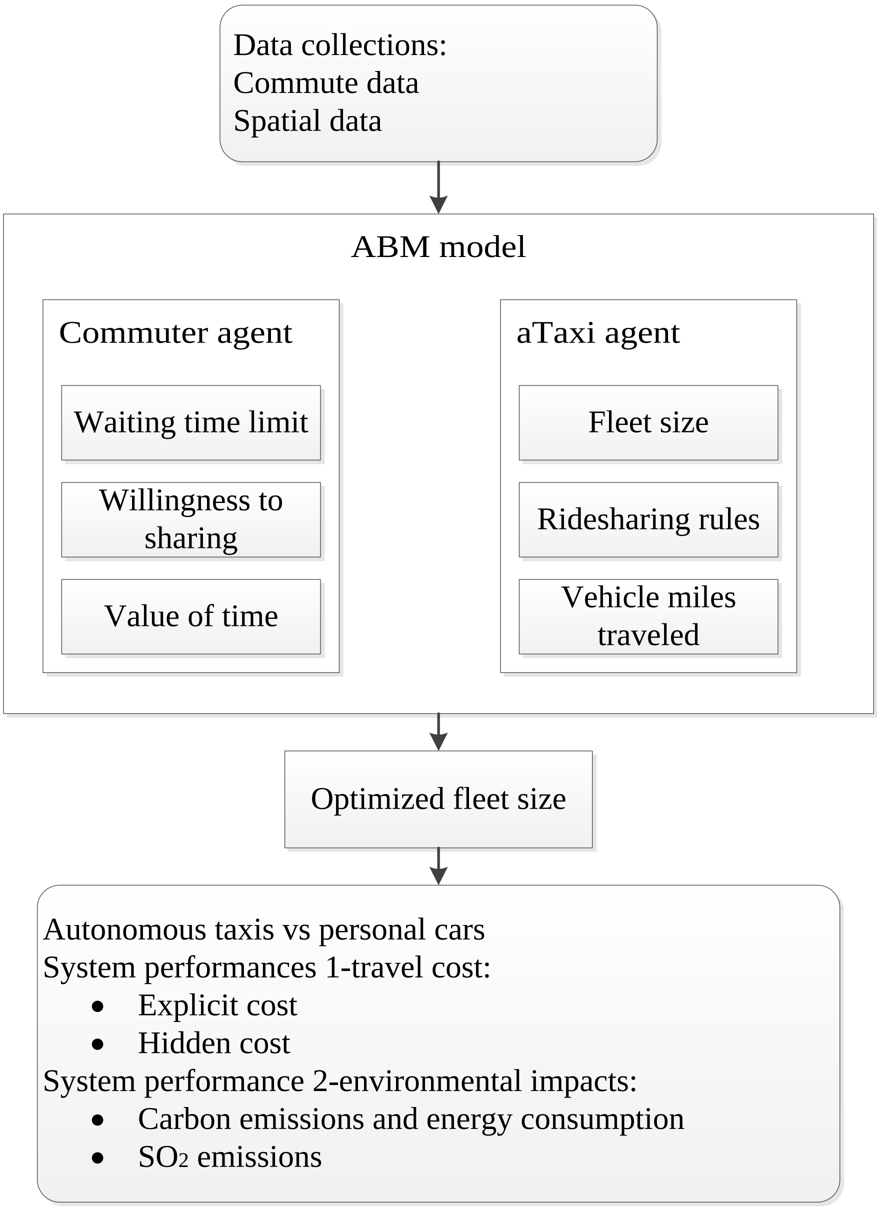

Figure 3-1. Research workflow of aTaxi model

3.3.1 Simulation environment and agents

Commuting demand is concentrated in two peak periods: 6:00–9:00 am and 4:00–6:00 pm. Given the first possible commuting, the trip begins at 12:00 am, and the last return commuting trip begins at 11:59 pm (Santos et al., 2011), 0:00:00–23:59:59 was chosen as the service period of the aTaxi.Twenty four hours of commute behaviors were simulated using a time step of 5 minutes, resulting in 288-time steps in the 24-hour service period. In the model, office and residential buildings are represented as the origin and destination of those commuting trips, and the real road networks are followed during the commute trips.

There are two types of agents in this model, commuter agents, and aTaxi agents. Commuters who place a request to an aTaxi, and the individual aTaxis that set their shortest route paths serving the commuters to their destinations behave according to the well-known Floyd–Warshall algorithm (Aini & Salehipour, 2012), which is one of the most efficient algorithms for finding the shortest path between any two nodes in a given network (Floyd, 1962; Warshall, 1962).

(a) The commuters

Every commuter has two spatial parameters: home (a residential building) and workplace (an office building). Population density is based on the spatial distribution of commuters' home locations at the beginning of the simulation. People commute between the home and workplace every weekday, with most starting their commute to work around 6:00–9:00 am and beginning their journeys home around 4:00–6:00 pm. Commuters' time leaving home and workplace obey the normal distribution. The 20,000 commuters have their choice of transportation: personal car or aTaxi. Krueger et al. (2016) showed that travel cost, travel time, and waiting time might be decisive factors that influence the adoption of SAVs and the acceptance of dynamic ride-sharing. In the model used here, commuters have different hourly incomes that obey a lognormal distribution. Commuters' waiting time limits are uniformly distributed and vary from 1 minute to 5 minutes. Commuters can decide whether or not to share vehicles with others. Commuters that choose not to share will bear a higher travel cost. Zhang et al. (2015b) showed that the average hourly income for ride-sharing commuters is 13% lower than the national average. Hence, commuters' willingness to share is negatively correlated to their hourly income in the model.

(b) The autonomous taxis (aTaxis)

Based on commuters' willingness to share, there are two types of aTaxis: one that can be simultaneously shared by multiple passengers; one that can pick up and drop off a single passenger. The second condition occurs when: 1) the passenger is not willing to share an aTaxi with others, or 2) an aTaxi does not show up before reaching the waiting time limit of the potential second passenger. Idle aTaxis are randomly distributed in the city at the beginning of the simulation. During the simulation, aTaxis park directly at the last passenger's destination if not assigned to the next trip. It picks commuters up from their homes then brings them to their workplace, or it picks them up from their workplaces then brings them home. The maximum capacity of aTaxis is set as four. Only passengers on the same trip starting hour have the potential to share a vehicle. The vehicles used in the model operate at different travel speeds by time of day. To realistically simulate traffic congestion during peak hours, vehicle travel speed depends on the number of vehicles on the road and the road capacity (see Eqs. (1) and (2)). The road capacity is calculated based on the maximum number of vehicles on the road during the peak hour. In Eq. (2), the free-flow speed is a theoretical distance per time unit that a vehicle could travel without the presence of other vehicles (Jeerangsuwan & Kandil, 2014), which is set at 33 miles per hour (mph) (Zhang et al., 2015a). The aTaxi can optimize its route to deliver all on-board commuters to their respective destinations. An optimized route means the shortest distance between the highest α_v (speed coefficient) to deliver all the commuters to their destinations. The aTaxis' schedule routes are first-come, first-served for commuters willing to share rides, as explained in detail in the next section.

$$\alpha_v = e^{\frac{-N_{road}}{RC}} \tag{1}$$

$$\alpha_v \in [0.10, 1.00]$$

$$v = \alpha_v \times v_{ff} \tag{2}$$

Where N_{road} is the number of vehicles on the road, RC is road capacity, v is vehicle speed, and v_{ff} is vehicle's free flow speed.

3.3.2 Interactions among agents

3.3.2.1 Ride-sharing

Ride-sharing appears to be essential for sustainable adoption of autonomous vehicle use to mitigate congestion and environmental consequences (Taiebat et al., 2018). Fagnant and Kockelman (2015a) showed that VMT might rise by over 8% if no ride-sharing is allowed in satisfying travel demand with autonomous taxis. Zhang et al. (2015b) also found that autonomous vehicle ride-sharing can offer superior service to a non-ridesharing autonomous vehicle system, through shorter trip delays, lower trip costs, less VMT generation, and, in the long run, better environmental outcomes. In this study, commuters can choose to participate in ride-sharing if they are willing.

There are four operational parameters in the model: *waiting time limit, occupancy, added distance, and in-vehicle time*. *Waiting time limit* is the maximum time passenger wait between when the passenger requests the vehicle and when the vehicle arrives for pick-up. If the passenger cannot get an aTaxi within the waiting time limit, he/she will use the personal car as usual. *Occupancy* is the number of passengers in the aTaxi, which varies from 0 to 4. Ride-sharing occurs when the occupancy is more than 1. According to Zachariah et al. (2014), to share a ride, an additional occupant cannot increase the distance of any direct trip by more than 20%. Thus, the *added distance* should be 20% less than the random original distances between passengers' homes and workplaces. For example, consider two potential passengers who want to travel from their workplaces to home. Passenger A is the first passenger and passenger B is the potential second passenger. Passenger A's home location and workplace location are set as A_h and A_w and passenger B's home location and workplace location are set as B_h and B_w. The following equations need to be satisfied for the ride-sharing to occur. $B_{request}$ means the aTaxi location when passenger B asks to share a ride. The added distance algorithm is defined in Eqs. (3), (4) and (5) as:

$$d_{B_{request}-Bw} \leq t_B \times v \quad (3)$$

$$d_{A_w-B_w-A_h-B_h} \leq 1.2 \times d_{A_w-A_h} \quad (4)$$

$$d_{A_w-B_w-A_h-B_h} \leq 1.2 \times d_{B_w-B_h} \quad (5)$$

Where d represents the distance, and t is waiting time limit.

The aTaxi first takes passenger A home because of the first-come, first-served rule. The aTaxi then stops to board additional passengers if the maximum capacity has not been reached. This study only considers ride-sharing in the SAV scenarios and assumes all commuters drive individually with their personal vehicles in the business as usual (BAU) scenario. In the SAV scenarios, one scenario has two kinds of mode choices—aTaxi and personal car (PC). The passengers choose different transport modes based on their waiting time limit and the waiting time for the closest aTaxi. In the BAU scenario, the *occupancy* and *added distance* are set to 1 and 0, respectively, and passengers' wait time is 0. *In-vehicle time* represents the time spent in the traveling vehicle, which is converted into cost in economic evaluations.

3.3.2.2 Travel cost

Travel cost is the primary concern for people choosing among different transport modes. One of the objectives of this study is to minimize the total travel cost in this commuting system based on the passengers' perspectives. Some studies used detailed cost categories to estimate the total cost for the operation of SAV system including vehicle costs (capital, running, and maintenance costs), infrastructure costs, and fleet management service costs based on various operational scenarios (Bösch et al., 2017; Chen &

Kockelman, 2016). This research only considers the service cost for commuters. The operational costs undoubtedly account for a large proportion of system's costs for Transportation Network Companies, but travel economics for commuters largely influences the decision for adoption and utilization of system from a consumer point of view. In this study, the explicit financial costs of the service for commuters are considered, as well as the hidden costs associated with the time invested in various mobility-related activities. This analysis has received less attention in the literature compared to the operational cost of the system.

(a) Explicit cost

The regular fare for UberX (non-surge periods) consists of a base fare of US$1 and a US$1.65 booking fee, plus US$1.30 per mile plus US$0.26 per minute. As aTaxis do not need drivers, operating costs are lower (Liang et al., 2016). With consideration of these costs reductions and other factors, Fagnant and Kockelman (2015a) set their simulated non-shared trip price to US$1.00 per mile (less than a third of average taxi cab rates in Austin, Texas). The simulation results of Burns et al. (2013) showed that the costs per trip-mile of personal cars and SAVs were US$ 0.75 and US$ 0.41, respectively, without considering the decreased parking costs and the value of time. Bauer et al. (2018) estimated that the lowest cost of service provided by shared automated electric vehicles fleet could be US$0.29- US$0.61 per revenue mile. Spieser et al. (2014) concluded that a mobility system featuring autonomous vehicles could be almost half as expensive as a system based on conventional human-driven cars. An average US$1 per trip mile fare for non-shared aTaxis was assumed here, and the personal car fee was assumed to be

US$1.4 per trip mile based on the price ratio of aTaxi and personal car mentioned above. In the case of sharing, the explicit cost after picking up the next passenger is shared by all the passengers, based on their trip distances.

(b) Hidden cost

Value of time (VOT) here is defined as "the monetary valuation of the total time invested in mobility-related activities" (Ellram, 1999; Spieser et al., 2014). The time spent requesting, waiting for, entering, and traveling is monetized with passengers' VOT based on the level of comfort. Less comfortable trips incur a higher cost (Spieser et al., 2014). For example, personal trips on local roads during free-flowing traffic are priced at 50% of the median wage (Manpower-Research, 2015), while the cost of traveling during heavy traffic is represented at 150% of the median wage (Institute, 2013). For aTaxis, commuters can experience a higher level of comfort, since they can use their travel time to perform other activities (reading, eating, talking, texting, sending an email or watching a movie). Zhang et al. (2015a) and Wadud (2017) also contend that the personal valuation of travel time may decline, as passengers reap productivity gains due to time free from driving. In contrast, Yap et al. (2016) showed that in-vehicle time in an autonomous vehicle is experienced more negatively than in-vehicle time in manually driven cars, the travelers' negative attitudes regarding trust and sustainability of autonomous vehicles are major influences. After considering the above research results, the personal trip time in aTaxis and personal cars was priced at 20% and 67% of the personal wage, respectively (Spieser et al., 2014). For example, when the wage is \$28.40 per hour (the median Ann Arbor wage), the corresponding VOT in aTaxis is approximately \$5.68/hour, which is one-third of that in personal cars, at $19.03/hour. **Table 3-1** summarizes the parameters for total travel cost evaluation.

Table 3-1. The components of the total travel cost

Travel cost	Personal car	aTaxi
Explicit cost	$1.40 per trip-mile for the non-shared trip	$1.00 per trip-mile for the non-shared trip
Hidden cost	$19.03 per hour with median wage level	$5.68 per hour with median wage level

3.3.2.3 Environmental impacts

According to Fagnant and Kockelman (2014a), even gasoline-powered SAVs could substantially reduce negative environmental impacts, consuming approximately 16% less energy and generating 48% less volatile organic compound emissions per person-trip compared to conventional vehicles. However, Miller and Heard (2016) argue that the GHG emissions of autonomous vehicles could decrease on a functional unit basis (i.e., per-passenger-mile), while overall transport-related GHG emissions increase as VMT increases (Brown et al., 2014; Morrow III et al., 2014). Added VMT may also amplify drawbacks associated with high automobile use, such as increased gasoline consumption and oil dependence, and higher obesity rates (Fagnant & Kockelman, 2015b). Zhang et al. (2015b) indicate that although SAV systems tend to generate more VMT, the vehicle life cycle GHG and air pollutant emissions and energy consumption can still be reduced due to fewer cold starts and reductions in parking infrastructure requirements. Fagnant and Kockelman (2014b) also acknowledge that compared to personal cars, the reduced parking needs of aTaxis could reduce emissions as well as traffic congestion.

GHG and pollutant emissions from conventional vehicles could be further ameliorated through the use of low-emission and energy-efficient drivetrain technologies (Taiebat et al., 2018). Fully electrically-powered fleets could eliminate all tank-to-wheel emissions from car travel (OECD, 2015). Chen et al. (2016) showed that SAVs and electric vehicle technology have natural synergies. Thus, electric aTaxis have been integrated into this commuting system. Hawkins et al. (2013) found that electric vehicles (EVs) powered by the present European electricity mix could decrease the global warming potential (GWP) 10% to 24% compared to conventional diesel or gasoline vehicles, assuming lifetimes of 150,000 km. The specific energy requirements to operate light-duty vehicles is around 0.30 - 0.46 kWh/mile (Kintner-Meyer et al., 2007), and the average emission rates of DTE Energy system serving Michigan electric customers are about 3.1 lbs/MWh for SO_2 and 1,950 lbs/MWh for CO_2 (Parks et al., 2007), so the SO_2 emissions and GHG emissions of electric aTaxis are straightforward to estimate.

The vehicle life cycle inventories from Chester and Horvath (2008, 2009a) are used, which include parking infrastructure. In our model, it is assumed that personal cars and aTaxis are all conventional gasoline sedans. Following the assumption of Fagnant and Kockelman (2015a), aTaxis are assumed to have a 250,000-mile service life, aligning with the expected 7-year service life of Canadian taxis, which typically log more than 248,000 miles over their lifetimes (Stevens & Marans, 2009), though SAVs may actually offer longer service due to their smoother automated driving profile.

Life-cycle environmental impacts of autonomous vehicles and light-duty vehicles (Fagnant & Kockelman, 2014b; Zhang et al., 2015b) were the basis for the environmental impacts of aTaxis and personal cars shown in **Table 3-2**. Only energy consumption, GHG emissions, and SO_2 emissions are considered.

Table 3-2. Potential environmental impacts of aTaxis and personal cars per vehicle-mile traveled

Environmental impacts	Personal cars	aTaxis	Electric aTaxis
Energy consumption (MJ/VMT)	4.96	4.35	3.48
GHG emissions (kg CO_{2eq}/VMT)	0.36	0.34	0.27
SO_2 emissions (g/VMT)	0.12	0.10	0.60

3.4 Case study of the city of Ann Arbor

3.4.1 Model experiment settings and initialization

In this section, a detailed view of a city's existing commuting patterns, topology, and other characteristics used to build a transportation model are presented to. Recently passed legislation in Michigan allows self-driving vehicles to operate on any Michigan roadway, which widens opportunities for autonomous vehicle development ("Senate Bill 0995," 2016). Ann Arbor is representative of small to medium-sized cities in the United States, based on the data from the 2009 NHTS. The city covers an area of 44 square miles with a population of 117,770 (City-data, 2013). Among the 39,095 people who live and work in Ann Arbor, 50% (around 20,000) drive single-passenger vehicles to work, 20% walk to work, 11% take the bus, and 5% bike to work, according to the Washtenaw Area Transportation Study's most recent transit profile conducted in 2009 (Biolchini, 2013). The analyses focus on the 20,000 people that drive alone in their commute travels, which is the BAU scenario in this study.

The model is based on an area of 6.97 miles × 6.29 miles containing Ann Arbor. Taking advantage of Ann Arbor Open Data, the spatial information for buildings, roads, and the city boundary are incorporated into the model (City-Services, 2017). In **Figure 3-2**, the residential and office buildings are represented by different colors (grey for residential and purple for office/commercial), which serve as the origins and destinations of commuter travels within Ann Arbor. The population density in the model is based on the spatial distribution of residential buildings. The vehicles are shown as red squares. For people shown as circles, different colors depict the different objectives, with blue denoting “working” people traveling from home to work, and yellow depicting “resting” people traveling from work to home. The median income of Ann Arbor residents is $56,835 per year, which translates into $28.4/hour (40 hours/week, 50 weeks/year). **Table 3-3** shows the basic parameters used in the Ann Arbor case study.

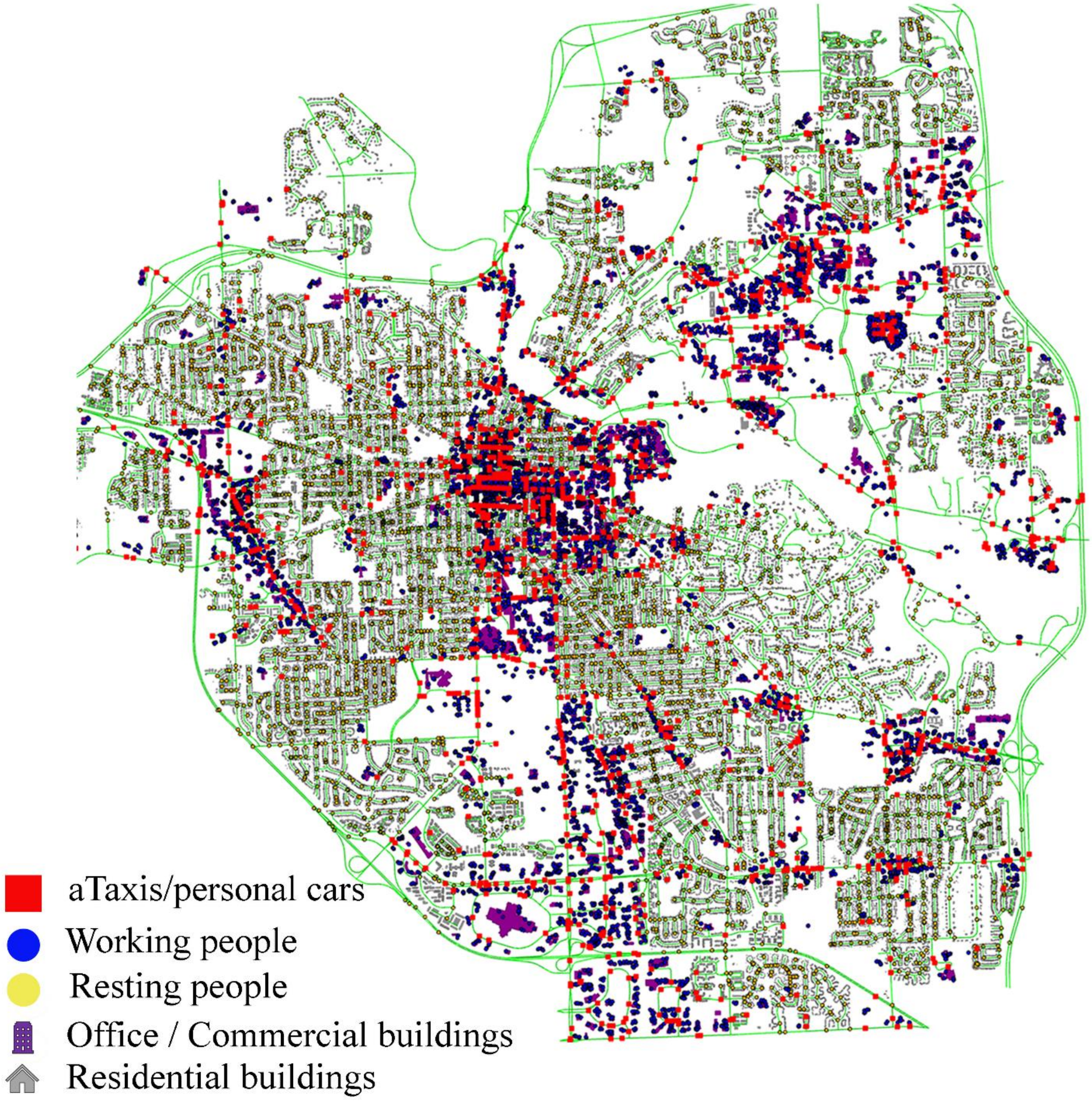

Figure 3-2. The display of Ann Arbor commute model

Table 3-3. Basic modeling parameters

Parameter	Value
Service area	6.97 mi. × 6.29 mi.
Average speed	27.6 mph
AM peak	6:00-9:00
PM peak	16:00-18:00
Free-flow speed	33 mph
Commute Period	0:00:00-23:59:59
Commuters' average hourly income	$28.4/hour
Maximum aTaxis occupancy	4

3.4.2 Model validation

Using real-world data to calibrate and validate the behavior model increases credibility and trust in this agent-based model and its results. Three components are used to validate the commuting model based on the BAU scenario: commute speed, commute time, and commute trips by time of day. The commute speed and commute time are collected from an Ann Arbor commuting survey (City-data, 2013). From the survey data, the average commute speed is 27.60 mph, and the corresponding simulation result is 27.52 mph. The average surveyed commute time within Ann Arbor is 10 minutes, and the commute time from the simulation results is 7.44 minutes, a difference that can be explained by the inclusion of boarding and alighting time in the survey data while the commute time from the simulation results only considers the driving time. Data from the 2009 National Household Travel Survey (NHTS) is used to validate the commute trips by time of day (**Figure 3-3**). These data contain extensive information about each commuting trip made by an individual living and working in small-medium cities, including the start times of daily trips to work and return trips home. In **Figure 3-3**, the morning peak hours of commuting travel are from 6 am to 9 am, and the evening peak hours are from 4 pm to 6 pm. In the simulation, the start time of trips to work and to home both follow a normal distribution. The simulation data in the figure have the best fit with the NHTS data.

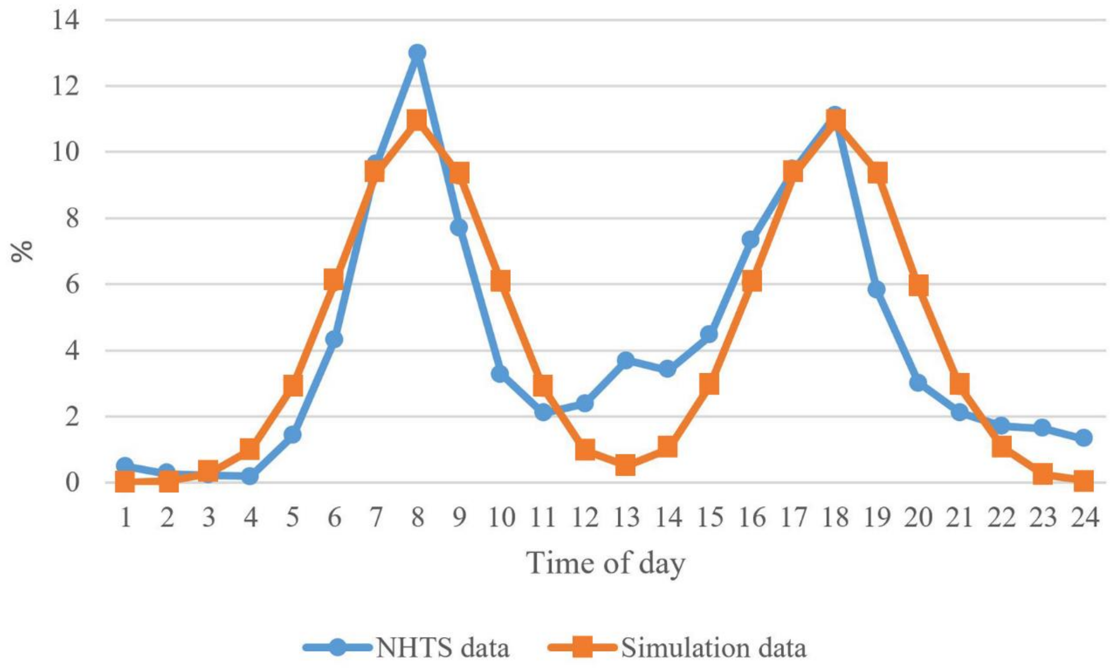

Figure 3-3. Commute trips by the start time of trip on weekdays within Ann Arbor

3.4.3 Scenario simulation

Several scenarios were used for the evaluation of autonomous taxi performance in commuting trips. The same random number is used in the simulation runs for different scenarios to ensure that any difference in outputs are not caused by noise from the random number seed that starts the simulation. All simulation results are generated from 100-run Monte-Carlo simulations. These scenarios are generated by varying three principal parameters in the simulation: fleet size, vehicle types, and operation strategies.

Fleet size: In the BAU scenario, the fleet size equals the commuting population (commuters who drive alone to work). In the SAV scenarios, the aTaxi fleet size is also related to the commuting population, which is varied from 10% to 90% of the BAU commuting population in 10% steps.

Vehicle types: The BAU scenario represents the current situation—20,000 people commuting alone by their personal cars. In the SAV scenarios, there are two kinds of scenarios simulated—an all aTaxi scenario and a mode choice scenario. In the all aTaxis scenario, all personal cars are replaced with aTaxis, and people can choose to share aTaxis with others or not. It means 50% of people driving alone to work only can choose aTaxis as their commute mode in all aTaxi scenarios, while the other 50% of people will still keep their previous commute modes, such as walking or cycling, which are not covered in this study. In the mode choice scenario, the 50% of people driving alone to work can choose aTaxis or personal cars based on their waiting time limit and waiting time for the closest aTaxi. The electric aTaxi system is also simulated, with the environmental impacts compared to the personal car system. Full battery-electric vehicles today still have limited range compared to gasoline vehicles and thus need time for recharging (OECD, 2015). Nonetheless, Taiebat et al. (2018) indicate that it is easier to integrate electric propulsion vehicle into a dynamic ride-sharing system than into a non-ridesharing system, as the former has longer and more frequent chargeable breaks during the daytime. Electric aTaxis are assumed to have a fast battery recharge time of 30 minutes (using Level III chargers) and a vehicle range of 110 miles (Chen et al., 2016).

Operation strategies: In the optimized fleet size scenario, several vehicle operation strategies are tested for further performance optimization. At the beginning of the simulation, idle aTaxis are randomly distributed in the city (Zhang et al., 2015a), or the empty aTaxis are spatially clustered according to the population density or building density. During the simulation, the aTaxis park directly at the last passenger's destination if not assigned to the next trip (OECD, 2015), or the aTaxis gravitate toward high-demand areas based on population density or building density after sending the last passenger to its destination (Zhang et al., 2017).

Figure 3-4 shows the travel time of the SAV and BAU scenarios (the average wait time of the BAU scenario is 0 minutes as people can drive their car anytime they like). In the SAV scenarios when all the commute modes are aTaxis (all aTaxis scenario), the waiting time is reduced from 2.88 minutes to 0.70 minutes since the fleet size is larger. In the SAV scenarios when passengers have mode choice, the waiting time of the aTaxi fleet size is relatively short, between 0.61 minutes and 0.13 minutes, as the passengers can choose the convenient mode. The minimized in-vehicle time in the all aTaxis scenario is achieved when the aTaxis fleet size is 4000. There are two essential elements related to the in-vehicle time: ride-sharing rate and vehicle speed. The in-vehicle time is reduced greatly when the fleet size is increased from 2000 to 4000 because the ride-sharing rate of aTaxis is reduced from 1.94 to 1.30. However, the in-vehicle time is slightly increased when the fleet size is increased from 4000 to 18,000. In explaining this outcome, we might first notice that the increased in-vehicle time is closely related to the ride-sharing rate, and the ride-sharing rates are nearly equal to 1.0 in the all aTaxis scenarios with fleet sizes equal or greater than 6000. Thus, the ride-sharing rate has less of an effect on the in-vehicle time in these scenarios. However, the vehicle speed has significant influence on the in-vehicle time in these scenarios. The increased in-vehicle time is mainly due to the lower speed, and the lower speed of the aTaxis is due to the increased road occupancy.

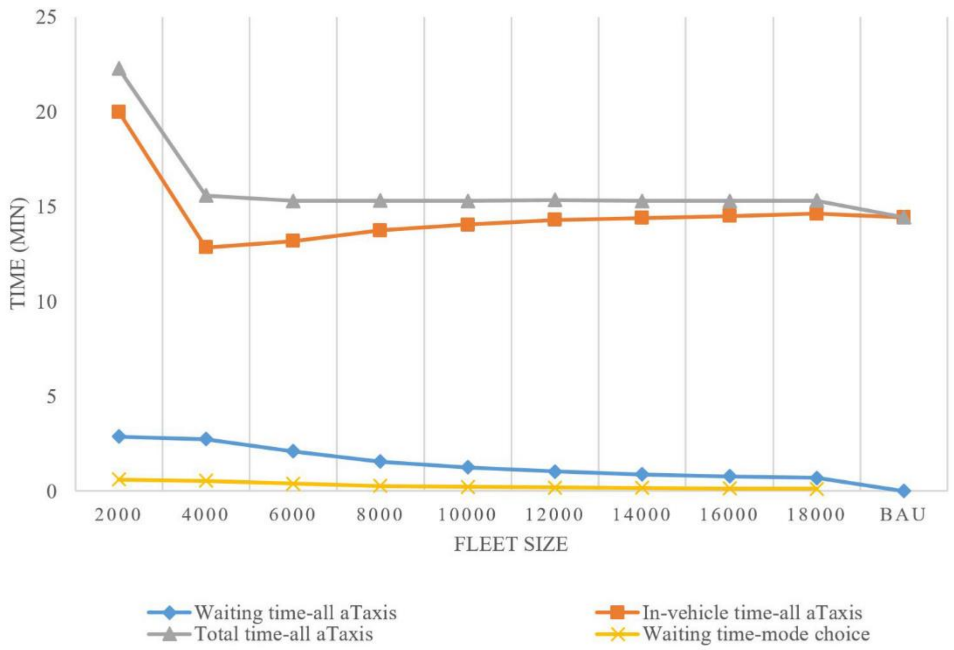

Figure 3-4. Travel time of SAV and BAU scenarios

Table 3-4 shows the VMT of the SAV and BAU scenarios. Compared with the BAU scenario, as fleet size is increased in the SAV scenarios, the total VMT is increasing, and the unoccupied VMT is also increasing. This is a result of the cruise distances that aTaxis accumulate when commuters request a ride. The total cruise distance will be longer when there are more aTaxis. But the total VMT is not increased drastically with the larger fleet size, as the service aTaxis provide overlaps with the commuting activity already performed without aTaxis.

Table 3-4. Vehicle mile traveled (VMT) of SAV and BAU scenarios

SAV	VMT-aTaxi (mile)		VMT-PC (mile)		Unoccupied VMT (mile)		Total VMT (mile)	
Fleet size	All aTaxis	Mode choice	All aTaxis	Mode choice	All aTaxis	Mode choice	All aTaxis	Mode choice
2000	160394	123047	0	32799	3247	746	160394	155846
4000	170246	113118	0	55822	8686	1253	170246	168940
6000	171652	111735	0	59839	9691	1315	171652	171574
8000	171457	111174	0	60289	9643	1264	171457	171463
10000	171419	111650	0	59693	9666	1306	171419	171343
12000	171334	111900	0	59455	9624	1302	171334	171355
14000	171193	112481	0	58736	9602	1308	171193	171217
16000	171463	112111	0	59353	9671	1292	171463	171464
18000	171450	111735	0	59775	9670	1267	171450	171510
BAU	0		127462		0		127462	

Note: VMT-aTaxi is the VMT traveled by the aTaxis. VMT-PC is the VMT traveled by the personal cars (PC). Unoccupied VMT is the cruise distances between car location at time of request and pick-up location that aTaxis accumulate when commuters requesting for a ride.

In the SAV scenarios, the simulation results of all aTaxis and mode choice scenarios are compared. In the mode choice scenario, the unoccupied VMT is much smaller than in the all aTaxis scenarios. The total VMT in the all aTaxis and mode choice scenarios are very close. However, significantly larger fleet size (more vehicles) is needed in the mode choice scenario. For example, only 4,000 aTaxis are needed to serve 20,000 passengers in the all aTaxis scenario, while in the mode choice scenario, 10,555 personal cars and 2539 aTaxis are needed. This is because passengers with mode choices turn to personal cars as the commuting mode when aTaxis cannot arrive within their waiting time limit. It can be concluded that the waiting time is still a big challenge for aTaxis compared with the personal cars.

3.5 Results and discussion

The final ideal fleet size is determined by passengers’ wait time, in-vehicle time and total VMT. The optimized fleet size is determined when the average waiting time is less than 3 minutes, the average in-vehicle time is less than 15 minutes per trip, and the VMT is minimized throughout the simulation day (Zhang et al., 2015a, 2015b). The optimized fleet size here is 4,000, 20% of that in the BAU scenario. The average wait time is 2.74 minutes, and the VMT is increased by 33.6% because of the unoccupied vehicle travel of the aTaxis. As there is little difference in total VMT for the all aTaxi and mode choice scenarios, and many fewer vehicles are needed in the all aTaxis scenario, the optimized scenario uses 4,000 aTaxis in the all aTaxis scenario.

In order to further minimize the total VMT and average wait time, several operation strategies are tested. **Figure 3-5** shows the operation algorithm of aTaxis. The blocks highlighted by yellow represent the operation strategies mentioned before: the location of initial parking and the behavior after serving the last passenger. High-demand areas refer to the high population density areas or high building density areas. The green blocks show the ride-sharing conditions. It can be found the ride-sharing only occurs when all the conditions are satisfied. The low rate of ride-sharing can be explained. Some representative simulation results are shown in **Table 3-5**. The first column shows the origin condition: the empty aTaxis are randomly distributed in the initial stage and park at the location of the last passenger's destination before receiving the new request. The second column shows the best simulation results, the total VMT is minimized, and the average wait time is less than 3 minutes. Although the fourth and fifth columns show less wait time and higher ride-sharing rate, the total VMT is significantly large. Thus, the operation algorithm in the second column (the empty vehicles park based population density at the beginning of the simulation, and wait at the location of the last passenger's destination until receiving the new request) are used for the following simulation.

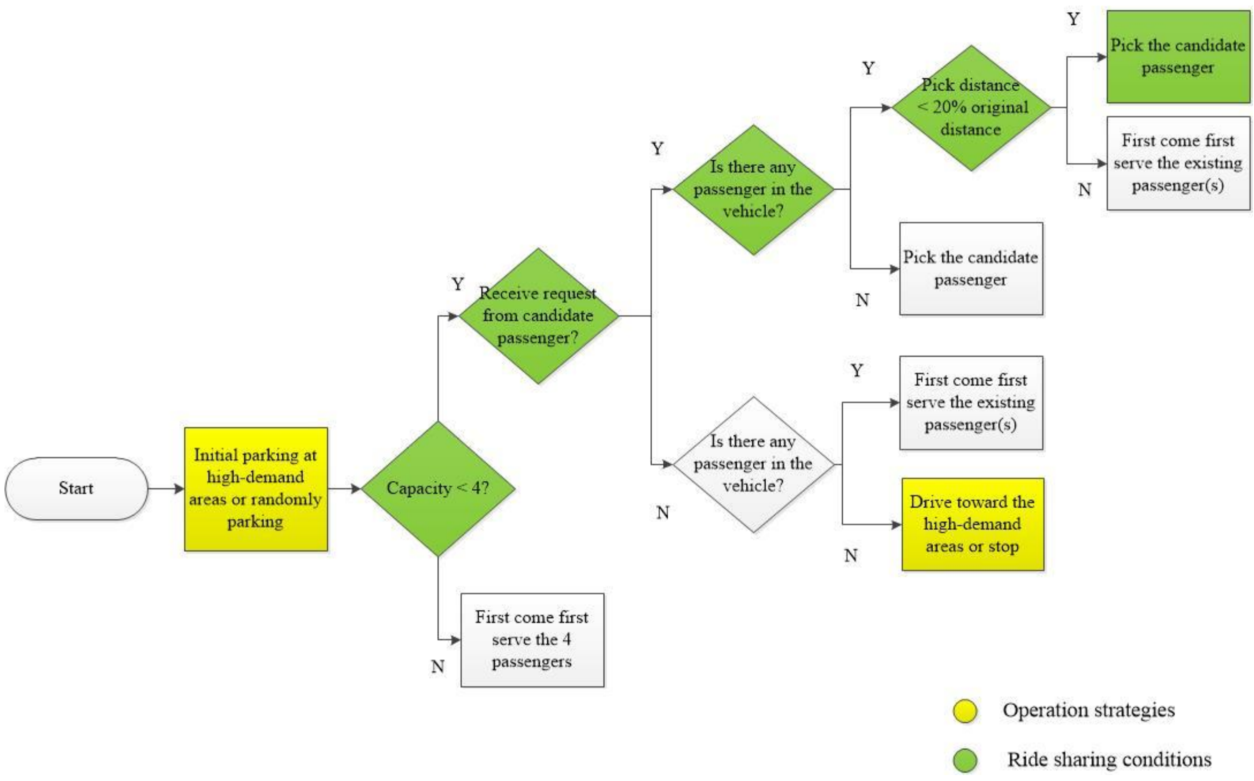

Figure 3-5. Operation strategies of aTaxis

Table 3-5. The simulation results of respective operation strategies

No.		1	2	3	4	5
Initial parking	Population density	N	Y	N	Y	Y
based on	Building density	N	N	Y	N	N
Drive toward	Population density	N	N	N	Y	N
areas with high	Building density	N	N	N	N	Y
Fleet size		4000	4000	4000	4000	4000
Total VMT (mile)		170246	168233	168293	290331	290680
Unoccupied VMT (mile)		8686	8635	8681	8246	8389
In-vehicle time (min)		12.85	12.94	12.93	14.26	14.29
Wait time (min)		2.74	2.68	2.69	1.54	1.54
Total ride-sharing		4112	4195	4063	4582	4472

Note: Y refers to Yes, and N refers to No.

In the optimized fleet size scenario, the vehicle utilization for daily commuting is improved to 92 minutes, as opposed to the BAU scenario of privately-owned vehicles typically used for 14 minutes in daily commute travel. The average occupancy is 1.3 in the optimized fleet size scenario. This may reflect the low probability of matching trips that satisfy the ride-sharing algorithm, a phenomenon in accord with the findings of Zhang et al. (2015a).

The total travel cost is composed of explicit costs and hidden costs, which are highly sensitive to the level of VMT and VOT. The more vehicle miles traveled, the greater the total travel cost. The VMT in aTaxis is increased due to the distance that vehicles travel while unoccupied as they drive to pick up passengers. The lower the value of time, the lower the total travel cost. For aTaxis, passengers are relieved from driving, and they can use their time as desired. Their productivity can be improved through working in the aTaxis. Therefore, the VOT of the aTaxi is greatly reduced. Overall, for the ride-sharing trips in the optimized SAV scenario, the average total cost per mile is approximately \$1.29 (\$1.0 for explicit cost and \$0.29 for hidden cost), which is 38% lower than the non-sharing trips in the BAU scenario.

In contrast, the environmental performance of the aTaxis system is not positive, since the environmental impacts of the transportation system are highly related to VMT, and the VMT is increased even in the SAV scenarios because of the unoccupied vehicle travels. In the optimized SAV scenario, the system energy consumption, GHG emissions, and SO_2 emissions are 16%, 25%, and 10% higher, respectively, than in the BAU scenario. The environmental results are consistent with Miller and Heard (2016): autonomous vehicles could become more environmental-friendly on a functional unit basis (i.e., per-passenger-mile), while overall transport-related GHG emissions increase as VMT increase. Environmental outcomes do not improve in the electric aTaxi scenario when the fleet size is also set to 4,000. While corresponding system energy consumption and GHG emissions are 7% and 1% lower than those in the BAU scenario, the total SO_2 emissions are increased by 560% compared to BAU scenario. This is mainly due to the carbon emission intensity of Michigan's grid mix. Thus, the environmental performance does not improve as expected with the introduction of autonomous vehicles for commuting in Michigan.

It is also found that aTaxis require far fewer vehicles than are currently on the road, while the total distance traveled is greater due to the unoccupied aTaxi travel as they accommodate the geographical distribution of demand. In order to explore road conditions with the introduction of aTaxis, road occupancy was studied (see **Figure 3-6)**. Road occupancy represents the total number of vehicles using the specific road during one weekday. In the optimized SAV scenario, the average road occupancy increases by 12% compared with the BAU scenario, but as suggested by Zakharenko (2016), increased traffic would not necessarily cause a congestion increase, as the SAVs are expected to run efficiently. The traffic congestion should be further investigated with more factors, such as travel directions. This unexpected traffic problem is due to the low rate of ride-sharing and increased VMT in the SAV scenarios. This result indicates that policymakers and planners should not view vehicle automation through rose-colored glasses as a solution to traffic jams and environmental implications.

In the case of Ann Arbor, aTaxis are only used for end-to-end trips as there is no transit. Using aTaxis to connect the first/last mile trips of transit will be explored further in ongoing work. Given the relatively small size of Ann Arbor, the results from this work are not representative for other cities, especially large metropolitan areas where average commute time is over one hour per day. Future study will develop similar agent-based models for large metropolitan areas with long, complex commute patterns. In addition, we consider only the income of commuters affects their willingness to share. Social and racial factors, in fact, play equally important roles in ride sharing, which will be further examined in the future. Meanwhile, more realistic features can be added to this modeling framework, such as the consideration of traffic signals and further validation of the model through vehicle trips crossing the main intersection.

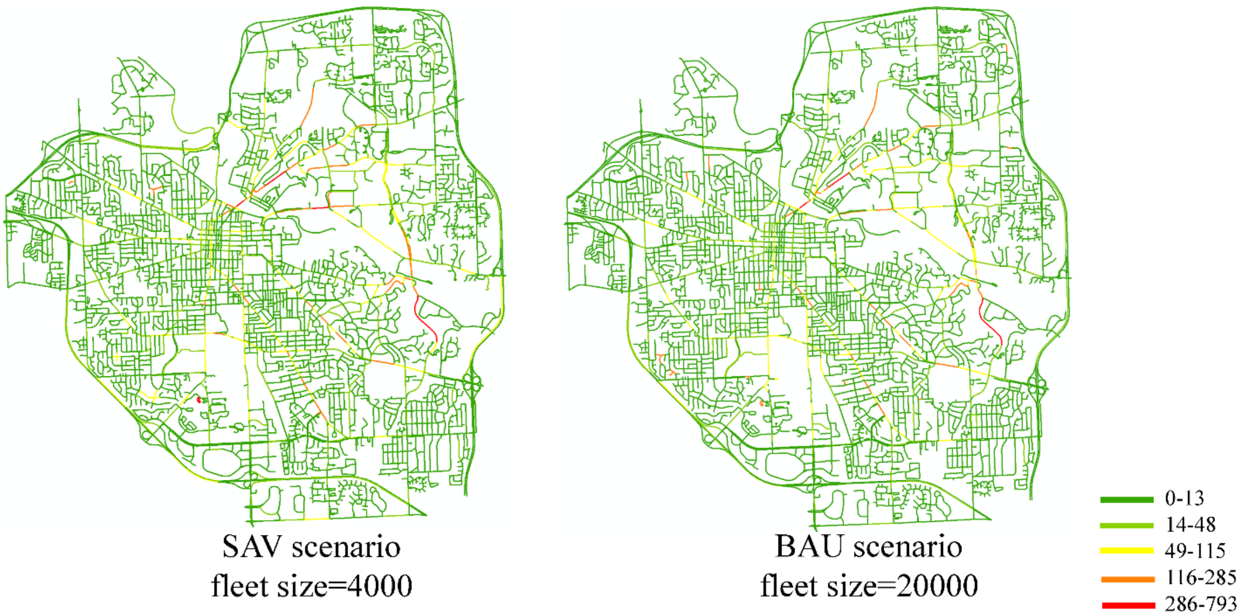

Figure 3-6. Road occupancy of the optimized SAV scenarios and BAU scenario

3.6 Summary

This study developed a simulation model to evaluate the travel costs and environmental impacts of aTaxis for commuting. The major contribution of the model described in this study is to simulate aTaxis traveling on a real road network, where all vehicles start and end their trips and travel on the road. Moreover, hidden travel costs related to commuters' value of time are considered, and the environmental impacts of aTaxis are estimated to compare electric aTaxis, gasoline aTaxis, and conventional gasoline cars.

The optimized fleet size is obtained with minimized VMT and reasonable average wait times for passengers—which this study determined to be 20% of the fleet size of the BAU scenario. The results of the optimized fleet size scenario show that total commute costs are reduced by 38% and the daily vehicle utilization is increased from 14 minutes to 92 minutes, but the daily road occupancy is increased by 12%. This system's energy consumption, GHG emissions, and SO_2 emissions increase by 16%, 25%, and 10%, respectively compared to the BAU scenario. This is mainly due to increased unoccupied VMT and less ride-sharing. The unsatisfactory environmental performance of aTaxis is not improved when gasoline aTaxis are converted to electric aTaxis: the corresponding energy consumption and GHG emissions can be 7 % and1% lower than those in the BAU scenario, while SO_2 emissions increase to 560% compared to BAU scenario.

Our simulation results show that aTaxis do not exhibit significant improvements in environmental performance compared to personal car use, until more people are willing to share aTaxis rides. Whether more aTaxi ride-sharing will occur when aTaxis are integrated into overall daily travel (for recreation and shopping in addition to commuting) and what the consequent impacts might be are important questions for future research. A clear policy implication of this study is that aTaxi fleets do not naturally lead to the higher environmental performance of transportation system. Thus, tailored regulations must be in place before deployment of this technology to ensure that the design and operation of the aTaxi system are environmental-compliant.

Our model is not designed as an accurate forecasting tool but rather as an initial test of the potential application of aTaxis to commuting travel. The model can be used to evaluate other prototypes in order to inform policy discussions among planners and decision-makers, as well as to highlight gaps in existing methods that other model developers can consider improving future simulations.

Chapter 4 Improving the Sustainability of Integrated Transportation System with Bike-Sharing

4.1 Introduction

The rapid growth in world population and increasing demand for transportation is putting great pressure on the transportation and fuel sectors, resulting in heightened traffic congestion, increasing fuel prices, and degraded air quality. In response, worldwide consciousness has risen on land use management, environmental emissions abatement, and climate change alleviation. It has become essential to develop new modes of transport and adapt existing ones to move people in more sustainable and economically feasible ways (Bauman et al., 2016; DeMaio, 2009; Shaheen et al., 2010).

Bike-sharing, or public bicycle programs, is emerging as a partial solution. Bike-sharing allows people to rent a bicycle from one of many stations that are situated throughout a city, then ride and return it at any one of these stations. Bike-sharing services have grown in Europe, North America, South America, Asia, and Australia (Liu et al., 2012). Today over 500 cities in 49 countries have well-established bike-sharing programs that in aggregate provide more than 500,000 bicycles. Bike-sharing systems have evolved over time, often beginning as free-to-use bike services that later became coin-deposit systems. Today's bike-sharing services are typically IT-based systems, with some city services including demand-responsive and multi-modal functionalities with real-time information, among other enhancements (Shaheen et al., 2010). Bike-sharing can be characterized as a "three-S" system: a Sustainable transport mode that can Substitute for short trip modes and Seamlessly connect with public transit (Hu & Liu, 2014). The reported benefits of bike-sharing include reduced greenhouse gas (GHG) emissions; reduced fuel consumption; enhanced accessibility; increased public transport use; decreased traffic congestion and noise; lower travel cost; increased physical activity and consequently improved health and physical fitness; and improved image of the urban environment (Bauman et al., 2016; Caulfield et al., 2017; DeMaio, 2009; El-Assi et al., 2017; Faghih-Imani et al., 2017b; Kumar et al., 2016; Pal & Zhang, 2017; Shaheen et al., 2010; Shaheen et al., 2013)

However, some studies show that the benefits of bike-sharing are overstated. The mode shift to bicycling has clear health benefits, but it also may lead to a reduction in walking for some short-distance trips, while walking has greater health benefits (Fishman et al., 2014a; Woodcock et al., 2014). The effects of bike-sharing on public transit are not consistent; in a dense urban area bike-sharing may replace rather than supplement public transit use and offer quicker, cheaper, and more direct connections for short distances. In suburban areas, where public transit can be sparse, bike-sharing may provide better access to enhance the use of the existing public transit system (Martin & Shaheen, 2014). One promoted benefit of bike-sharing, namely reduction in carbon emissions, is often overstated given the limited mode share of bicycling (Ricci, 2015). Médard de Chardon et al. (2017) also found that bike-sharing has only a limited positive impact on health and modest impact on carbon dioxide emissions.

It should be noted that every urban area has its own distinct attributes and thus the benefits of bike-sharing can vary from city to city. Research on the impacts of bike-sharing in East Asia is particularly limited. Current studies also generally do not assess the interactions between bicycling and other modes with methods that incorporate the influence of passenger behaviors. Thus, it would be valuable to explore the effects of bike-sharing in an integrated transportation system in Asian cities.

The objective of this study is to understand how bike-sharing changes user travel behaviors and minimize the environmental and social impacts of an integrated transportation system. This study draws upon spatial agent-based modeling to observe how travel behaviors change in response to different bike-sharing strategies. Two kinds of behavior theories that are widely used in travel behavior modeling and prediction, which are random utility maximization and bounded rationality, are applied to study passenger mode choice behaviors. The key factors influencing passenger mode choices, including travel cost, travel time, accessibility level, and automobile ownership, are evaluated and integrated into the model. After defining travel behaviors, two scenarios are constructed to simulate different operation strategies for bike-sharing, including bike infrastructure extensions, and bike-sharing incentives. These scenarios are evaluated by environmental and social impacts. The greenhouse gas (GHG) emissions, and air pollution emissions, such as SOx, NOx, and CO emissions of each mode are calculated to set benchmarks. The human health benefits from physical activity including cycling and walking are investigated. **Figure 4-1** shows the model framework based on a Taipei City map. As the model responds to real parameters, the user may amend basic input information to generate an optimum outcome and understand the required parameters, e.g., the most sustainable transportation scenario that has the minimum environmental impacts.

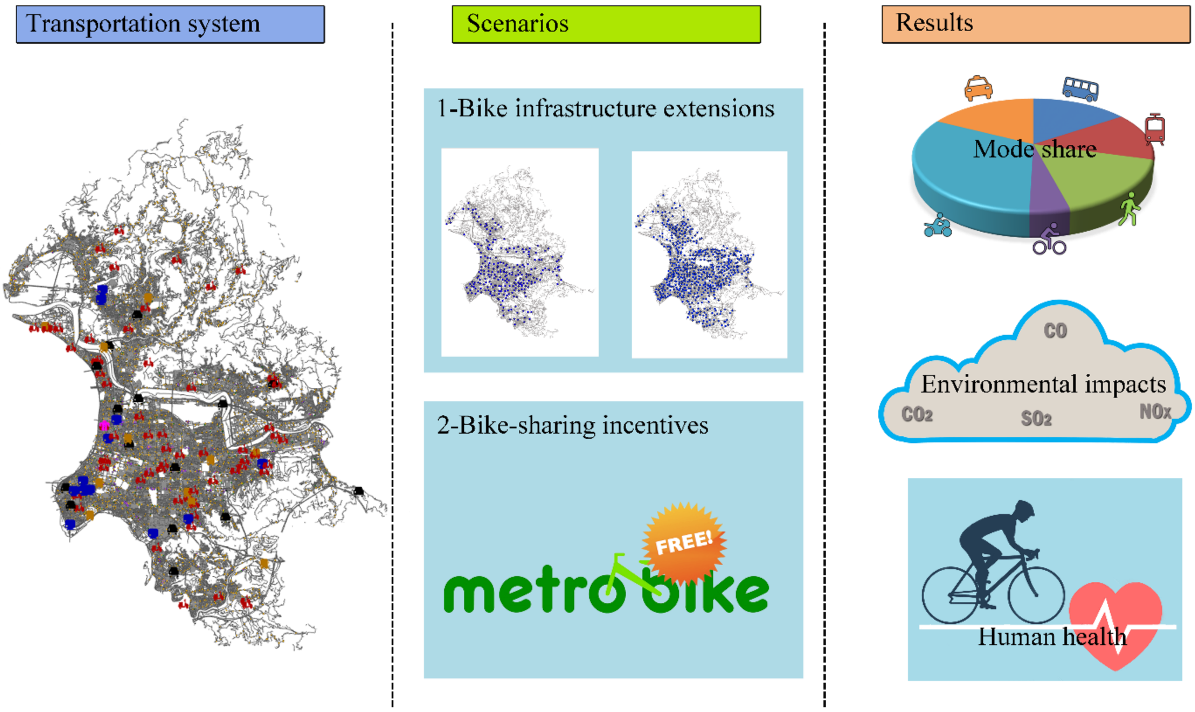

Figure 4-1. Model framework

4.2 Literature review

Some studies have evaluated the environmental and cost impacts of bike-sharing separately. Montreal's Bixi has claimed that its program has saved over 3 million pounds of GHG emissions since its launch in May 2009 (DeMaio, 2009). Lyon (2009) stated that its program, which began in 2005, had cut the equivalent of 18.6 million pounds of CO_2 emissions from the atmosphere. Meanwhile according to the Earth Policy Institute, each shared bike user in Washington DC saves $800 in transportation costs per year on average (Davis, 2014).

The environmental impacts of bike-sharing can instead be investigated more accurately when taking into consideration its mode share in an integrated transportation system. Some studies indicate that bike-sharing mainly acts as a competitor to private modes. As Martin and Shaheen (2014) stated, bike-sharing has been found to decrease driving. A survey conducted by Shaheen et al. (2013) revealed that 41% of respondents in Montreal, Canada reported using public transit with bike-sharing to complete a trip that would have previously been made by car. Faghih-Imani et al. (2017a) also found that during weekdays bike-sharing for over half of trips less than 3 km is either faster or comparable to taxi service. The impacts of bike-sharing on shifts in public transit have been mixed. Campbell and Brakewood (2017) found that for routes in Manhattan and Brooklyn, every thousand bike-sharing docks along a bus route were associated with a 2.42% decline in daily unlinked bus trips. Martin and Shaheen (2014) found that bike-share members living in Washington D.C.'s high population density urban core were more likely to report reductions in bus use as a consequence of bike-sharing, while members living in lower-density regions in the urban periphery were more likely to report additional bus use. However, this pattern did not emerge in the results for Minneapolis, where respondents reported rising and falling usage in almost equal proportion regardless of residence in the urban core or periphery. Modal shifts identified in Hangzhou bike-sharing can act as both a competitor and complement to other available public transport options (Shaheen et al., 2011). Some studies also found that bike-sharing has a greater impact on transit in these competitive relationships. Fuller et al. (2013) found that bike-sharing was associated with a small (0.3 – 0.4%)

modal shift away from car use, but most of the apparent behavioral shift was seen from public transport, walking or private bike use. Similarly, Pai (2012) also reported that in Taipei, with the introduction of YouBike, 35.97% of YouBike trips shifted from bus traveling and 34.60% of YouBike trips shifted from walking. Only 8.72% of YouBike trips shifted from riding a private bike and 6.81% from riding a motorcycle. In order to more accurately evaluate the impacts of bike-sharing, the mode shares between bike-sharing and other transpiration modes were explored during the first stage of the current study.

The key factors that influence mode share choices have been investigated. Heinen et al. (2011); Kumar et al. (2016) found that time, price, and convenience were the main concerns of travelers in the mode choice process. Adverse weather conditions such as cold temperatures, heavy rain, high humidity, and stormy weather decreased bike-share activities and more regionally specific comfortable temperatures (close to 90°F) increased bike-share trips (Godavarthy & Taleqani, 2017). Zhang et al. (2016) also found that precipitation had a significant short-term impact on trip numbers: after heavy rainfall, bookings declined considerably below average and would take around three hours before rebounding to average trip rates again. But research by Heinen et al. (2010); Miranda-Moreno and Nosal (2011); Nankervis (1999) suggested that weather does not typically deter regular cycle commuters unless conditions are particularly severe, i.e., temperatures below 4-5°C or above 35°C. Raviv and Kolka (2013) asserted that the primary factor that determines the success of a bike-sharing system is the ability to meet the demand, which can be pursued by providing a sufficient number of available bicycles and vacant lockers at each station. Inadequate cycling infrastructure decreased bike-sharing and private utility cycling (Goodman & Cheshire, 2014). As Heinen et al. (2011); Stinson and Bhat (2003) found, travelers' mode choice is not only influenced by the external environment, but also by travelers' socio-demographic characteristics. In particular, car ownership has been shown to have the greatest impact on bicycle usage among all studied socio-demographic variables, accounting for significantly low use of a bicycle as a mode for commuting. The same applies to motorcycle owners. McFadden (1979) emphasize that it is important to identify factors whose values may be changed through proactive policy decisions. Passenger environmental awareness, attitude towards bad weather, and other psychological factors are not considered in this study, as these factors are more challenging to quantify and incorporate into this model. Thus, in this study, the four factors influencing mode choice include travel cost, travel time, accessibility level, and automobile ownership.

4.3 Material and method

4.3.1 Definition of the simulation

This study simulates the impacts of bike-sharing under alternative transport policy initiatives by using agent-based modeling—a bottom-up approach that draws upon spatial information. Bike-sharing embedded in transportation systems has been studied from a top-down viewpoint, either for system optimization (such as optimization of station locations), or for a deeper statistical understanding of their working mechanisms (such as logistics operations to identify and remedy zones with a surplus or shortage of bikes). Yet bottom-up approaches to studying bike-sharing that incorporate the behavior of users have not typically been applied so far (Shimizu et al., 2014). Agent-based modeling (ABM) is used for simulating the evolution of passenger mode choices as influenced by different transport policies (Lu & Hsu, 2017). An integrated transportation model is thus generated to simulate the interactions between passengers and transport modes. As distinguished from system dynamics, ABM can reflect the heterogeneity of travelers' characteristics and the complex interactions in a passenger transportation market (Manley et al., 2014). The behavior theories of random utility maximization and bounded rationality, which are widely used in travel behavior modeling and prediction, are applied to model passengers' mode choice behaviors. A geographic information system (GIS) is also employed to enhance the reality of the ABM model.

In the model, there are two types of agents: passengers and transport modes. The passengers commute during weekdays based on their different socio-economic status, which is generated from a representative distribution in the model (Guo, 2015). Each passenger has its preferential weights for choosing a mode for a commute. Six kinds of transport modes are included in the model. The first four modes are used for end-to-end trips, including bicycle, walk, motorcycle, and car. The other two modes are transit, i.e., bus and metro, which might need first/last mile connections to complete a trip. This study focuses on walk and bicycle serving as the first/last mile connect modes for the public transit modes. To show the mode choice processes based on the interactions between passenger and mode agents, the model excludes other irrelevant factors that may occur in reality.

To calibrate the agents' traveling behaviors, two kinds of data are collected. The first kind encompasses the attributes of passenger agents, which include income level, automobile ownership, time to travel, and the origin and destination of the trip. The second kind consists of the variables of model agents, which include travel speed; travel cost; emission factors; spatial distribution of bike stations, metro stations and bus stops; and the corresponding routes. The spatial distribution data for bikes, metro, and bus is especially important in accurate transportation map construction and highly related to the performances of transport modes. The model enables life-cycle impact assessments of these transport modes by using environmental performance data for the transport modes, including SOx, NOx, CO, and GHG emission factors.

As indicated previously, the key factors that influence passengers' mode choice are travel time, travel cost, accessibility level, and automobile ownership. Travel time in the model refers to the onboard time of the travel mode. The travel cost sums up all the explicit costs incurred during the commute trip. Accessibility level represents a locational characteristic that permits a station to be reached through the effort of those at other places using connected modes such as walking or bicycling. Automobile ownership means the ownership of a private car or motorcycle. For ease of comparison, the travel time and accessibility level are evaluated by how each agent values its time, defined as the value of time (VOT). Empirical studies have firmly established that travelers are much more sensitive to out-of-vehicle time than to in-vehicle time, meaning that a higher disutility is generated from a minute of out-of-vehicle time compared to a minute of in-vehicle time (Koppelman

& Bhat, 2006). In this study, the VOT in vehicle and out of vehicle are evaluated as 60% and 100% of the passenger's hourly salary level. The four factors are defined in Eq. (1) to Eq. (4).

$$\text{time} = d_{travel}/v_{travel} \times s \times 60\% \tag{1}$$

$$\text{cost} = c_{travel} + c_{connect} \tag{2}$$

$$\text{access} = d_{connect}/v_{connect} \times s \times 100\% \tag{3}$$

$$\text{own} = \begin{cases} 1\ (has\ the\ mode, e.g. car\ or\ motorrcycle \\ \quad\quad 0\ (otherwise) \end{cases} \tag{4}$$

Where d_{travel} and $d_{connect}$ represent the travel distance and connect distance, c_{travel} and $c_{connect}$ represent the cost of travel mode and cost of connect mode respectively, and s refers to the hourly salary of the passenger agent.

The four factors of the transport modes vary between time periods due to changes in the external environment. For example, the bike accessibility level could change due to the redistribution of bike stations. In addition to the four factors, actual traffic conditions affect travelers' choices (Orsi & Geneletti, 2016). Faghih-Imani et al. (2017a) found that individuals were unlikely to consider bike-sharing for long trips (>5 km or so). Thus, the bike mode is only deemed of utility if the one-way trip distance is under 5 km. Similarly, as stated by Pushkarev and Zupan (1977), walking is considered of utility when the one-way trip distance is less than 1 km. Based on statistics of trip information (Department of Transportation, 2016), only when the end-to-end trip distance is longer than 500m will it be regarded as one trip. For example, if one traveler rides a bike to a nearby store and the cycling distance is less than 500m, the bike is not considered a transport mode in this study. In the first/last mile trips, the connect mode is also counted when the connection distance is longer than 500m. For example, in the case of one traveler taking a public bike from home to a metro station to connect to a metro trip, the bike is regarded as the connect mode when the cycling distance is longer than 500m. Hence, 500m is taken as the minimum trip distance for one specific mode.

4.3.2 Behavior theories

With the key factors influencing the passengers' mode choices defined, two behavior theories constructing the passengers' mode choice processes were implemented: random utility maximization (RUM) and bounded rationality (BR). RUM represented as perfect rationality (PR) has been widely applied in modeling travel behavior, assuming people assess and choose the best available mode of transport by considering all related factors such as cost, time, and the person's socioeconomic traits. However, this approach is not able to explain why individuals in similar situations and with similar socioeconomic traits make different mode choices. As opposed to RUM, BR takes into account the cognitive limitations of the decision-maker, limitations of both knowledge and computational capacity. When one person with bounded-rationality "satisfices," he seeks the alternatives that are satisfactory or "good enough" and not necessarily optimal. These two behavior theories were applied to the passengers' travel behavior simulation for comparison. And based on the historical data, the theory with the best fitness simulation results was selected for the subsequent scenario simulations.

Random utility maximization

Daniel Mcfadden parameterized and applied random utility maximization (RUM) into transportation demand in the early 1970s, work for which in part he later won the Nobel Prize in Economics. The utility maximization rule rests on two main concepts. The first is that the attribute vector characterizing each alternative can be reduced to a scalar utility value for each of those alternatives. The second concept is that the individual chooses the alternative with the highest utility value (McFadden, 1979). In the following equations (Eqs. (5) to (8)), we denote i for people, and $i \ni N^*$, and we define j for transport mode, and $j \ni N^*$. In a RUM model, the utility of one alternative mode is comprised of two parts: (1) the utility solely related to the attributes of alternatives, (2) the utility solely related to the characteristics of the decision maker, as shown in Eq. (5):

$$V_{i,j} = \mathrm{V}(M_j) + \mathrm{V}(P_{i,j}) \quad (5)$$

Where $V_{i,j}$ is the utility of mode *j* of the people *i*, $V(P_i)$ is the utility associated with the characteristics of people *i*, and $V\left(M_j\right)$ is the utility associated with the attributes of mode *j*. Based on the above four key factors, the mode utility is extended in Eq. (6):

$$V_{i,j} = \beta_1 \times cost_{i,j} + \beta_2 \times time_{i,j} + \beta_3 \times access_{i,j} + \beta_4 \times own_j \quad (6)$$

Where β_k is the weights of corresponding attributes; $cost_{i,j}$, $time_{i,j}$ and $access_{i,j}$ are the travel cost, travel time, and accessibility level of mode j of people i respectively, which are normalized between zero and one; and own_j is a dummy variable for automobile ownership (automobile here refers to the car or motorcycle), one if the passenger has a car or motorcycle and zero otherwise.

Finally, the people choose the mode has the highest utility after comparing all the modes' utilities. The RUM model is assumed to have uniform cross-elasticities, that is, the cross elasticity of the choice probability of alternative i with respect to an attribute of alternative j is the same for all alternatives i≠j.

Bounded rationality

Bounded rationality (BR) was introduced by Herbert Simon in the 1950s. It has recently recaptured researchers' attention since it was first introduced in transportation research in the 1980s due to its ability to more realistically model and predict travel behavior. Through a comparative analysis of commuter departure time and route choice switch behavior between laboratory experiments and field surveys in Dallas and Austin, Texas, Mahmassani and Jou (2000) were able to demonstrate that boundedly rational route choice modeling generates valid representations of real commuter daily behavior. However, there is no standard BR framework for travel behavior research (Di & Liu, 2016). Gifford and Checherita-Westphal (2008) indicated that the underlying challenge of incorporating bounded rational travel behavior in transportation research is that it does not seem to behave very well from a modeling standpoint. Manson (2006) also concluded that research on BR is less theoretically developed and methodologically integrated than research for perfect rationality.

In order to reflect BR-based behavior, a simple behavior procedure was devised for this study (see **Figure 4-2**). Three principle parameters were used in modeling the BR behavior. They are aspiration level, stress threshold, and activation level. The aspiration level also called an indifference band, can change in the process of learning and interaction with the environment (Gifford & Checherita-Westphal, 2008). The deviation between the aspirations of an agent and the utility of a mode is defined as “stress” (Habib, Elgar, & Miller, 2006). If stress exceeds the stress threshold, the agent selects the choice with the maximum expected utility and its aspiration level falls. As long as the stress is within the stress threshold of the agent, the alternative will be selected and implemented again. Memory activation level is a habit indicator, as the mode with the maximum activation level in the choice set becomes the habitual option for that individual (Psarra et al., 2015). The updated activation level of mode *j* of people *i* in time *t* is defined as follows:

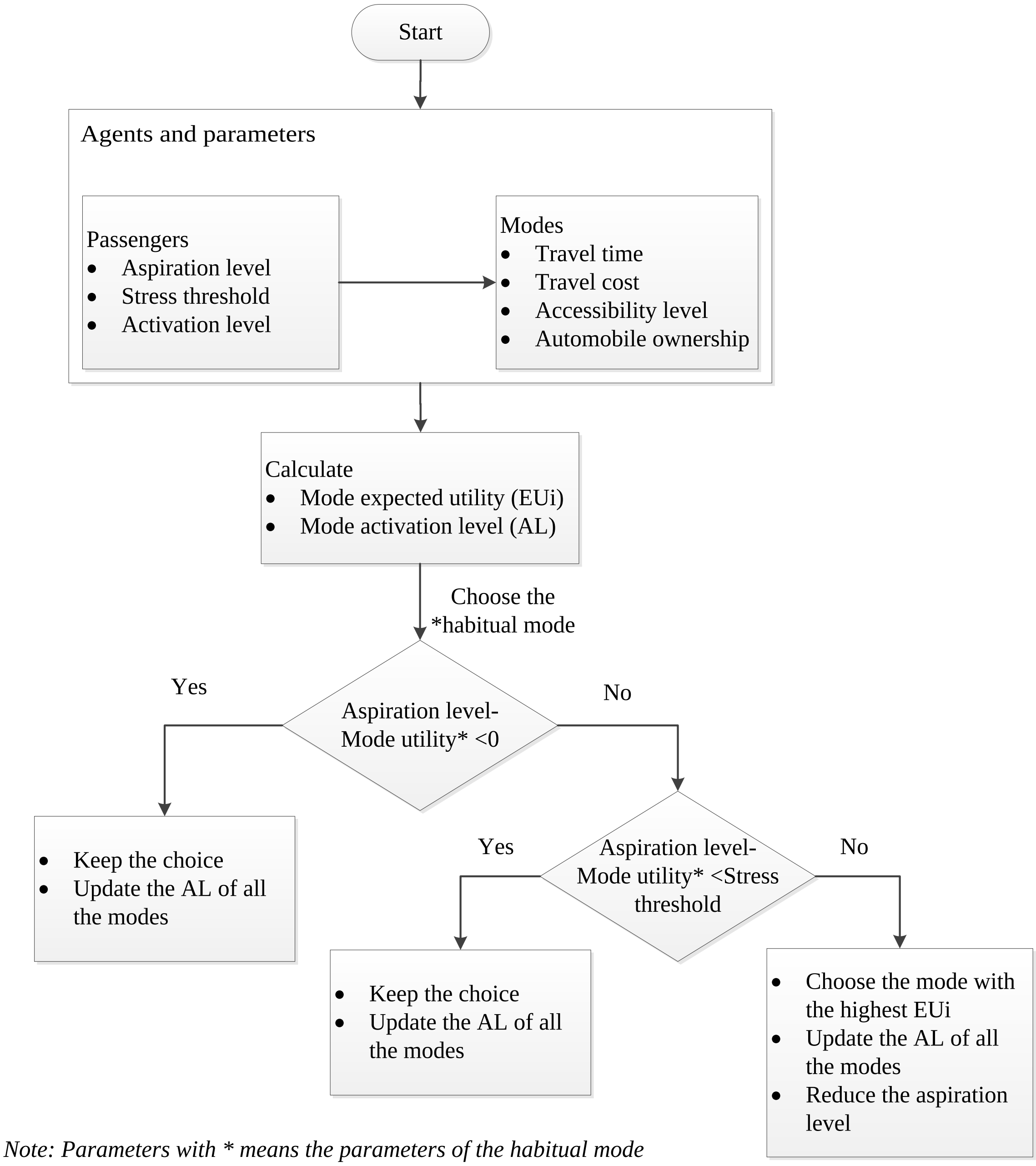

Figure 4-2. Bounded rationality behavior framework

$$AL_{i,j}^{t} = \log\left(AL_{i,j}^{t-1} + 1 + \beta\right), \tag{7}$$

if the model has been selected by people i at this time step

$$AL_{i,j}^{t} = \log\left(\alpha AL_{i,j}^{t-1} + 1\right), otherwise \tag{8}$$

where $\beta > 1$ is the recency weight and $0 < \alpha < 1$ is the retention rate.

A logarithmic transformation is used because it is assumed that when the mode is newly selected, its activation level rapidly increases until it reaches a saturation point at which the activation level surge slows down. On the other hand, when the mode is no longer selected, its activation level dramatically falls (Psarra et al., 2015).

4.3.3 Case study of the Taipei city

The majority of people in Taiwan rely on cars, motorcycles, and scooters as the preferred mode of transport. Growing populations in cities have resulted in increased traffic congestion, air pollution, and car accidents. To address the negative impacts of motorized transport, the Taipei City Government has started promoting sustainable transport modes since 2008. The Public Bike System "YouBike" was officially launched in Taipei City in 2009. Taking advantage of Taipei Open Data, the spatial information of bike stations and bike lanes from 2009 to 2015 were collected. Other modes' stations and corresponding traffic lines were also incorporated into the model. The trips simulated are mainly based on the home-based work trip. The main transportation modes in Taipei include bike, walk, motorcycle, car, bus, and metro, which account for more than 95% of market share in the Taipei transportation system. The operating parameters such as the speed and cost of the studied modes were derived from Chang and Guo (2007); Huang (2016).

4.3.4 Model calibration and validation

The model was calibrated and validated through the comparison of two types of empirical data: a travel survey of respondents' daily used transport modes, and findings from previous Taipei transport system research literature. The statistical analysis was applied to measure the goodness of fit according to quantitative values and patterns (Grimm et al., 2005). The travel surveys of daily used transport modes were collected from 2009 to 2015 in Taiwan, which include the mode shares of the walk, bike, motorcycle, car, bus, and metro (Department of Transportation, 2010, 2011, 2012, 2013, 2014, 2015, 2016). In this survey, more than 30,000 people were interviewed by telephone every year. These historical mode shares were used for model calibration. The calibration experiment was conducted by varying the combinations of three parameters, the weights of travel cost, travel time, and accessibility level, to find parameter combination which best fit the historical mode shares. The weight of automobile ownership can be calculated automatically with the above three weights. In addition, two kinds of behavior theories were applied to construct the mode choice behaviors.

Maximum likelihood estimation is a widely used method for finding the parameters of Multinomial Logit Model (MNL) models; it finds the value of the parameter β which that maximizes the log-likelihood value. However, the complicated formulation and estimation process is difficult for practitioners to use when there are more than two parameters β_i. The solution to this difficulty is typically to use an iterative procedure such as generalized iterative scaling to find β_i. In our study, since we have four key factors that comprise the mode utility, it is difficult to estimate the corresponding weightings of β_i by the maximum likelihood method. Instead of that, exhaustive algorithms and heuristic algorithms were implemented to find the best parameter combination with the help of the computation power. The historical data of mode share in 2013 and 2015 were used as representative data to compare with the respective simulation results. The four key factors of the transport modes varied between 2013 and 2015. For example, bike stations increased from 136 to 212. In addition, before April 2015, using YouBike was free for the first 30 min. Since April 1, 2015, the charge for the first and each subsequent 30-minute increment use was 5 NTD (New Taiwan Dollar) (roughly 1.66$). Thus, the travel cost, travel time, and accessibility level of bike and its connected transit changed accordingly. The ownership of motorcycles and cars also varied between these two years. Motorcycle ownership fell from 411 to 363 per 1,000 people from 2013 to 2015, while car ownership rose from 283 to 293 per 1,000 people. **Table 4-1** shows the parameter combinations which generate from Monte-Carlo simulation outputs fitting the historical data best in terms of minimizing squared residuals. The corresponding weights of the key factors—travel cost, travel time, accessibility level, and automobile ownership are 0.43, 0.39, 0.08, 0.10, respectively. We can find commuter has the high value of travel cost and travel time. **Figure 4-3** compares the historical mode shares and their corresponding simulated mode shares of these two behavior theories with the best fitting parameter combination 0.43/0.39/0.08 in 2013 and 2015. Based on the total squared residuals, the behavior theory of bounded rationality can better represent the commuters' mode choice behaviors.

Table 4-1. The best 100-run Monte-Carlo simulation outputs fitting the historical mode shares

Mode share	Bike	Walk	Motor-cycle	Car	Bus	Metro	RSS
2015H	5.40	16.40	27.30	16.90	17.20	16.90	N/A
2015S-RUM	5.51	19.69	26.77	11.02	20.47	16.54	0.00565
2015S-BR	5.56	20.63	25.40	10.32	19.84	18.25	0.00736
2013H	5.50	15.40	29.10	15.90	18.90	15.30	N/A
2013S-RUM	10.66	16.39	22.95	9.02	26.23	14.75	0.01667
2013S-BR	5.98	14.53	29.06	10.26	23.93	16.24	0.00589
SUM of RUM RSS				0.022330			
SUM of BR RSS				0.013260			

Note: 2015H/2013H means the historical date of the year 2015 and 2013. 2015S/2013S means the simulated results of the year 2015 and 2013. RSS is residual sum of squares.

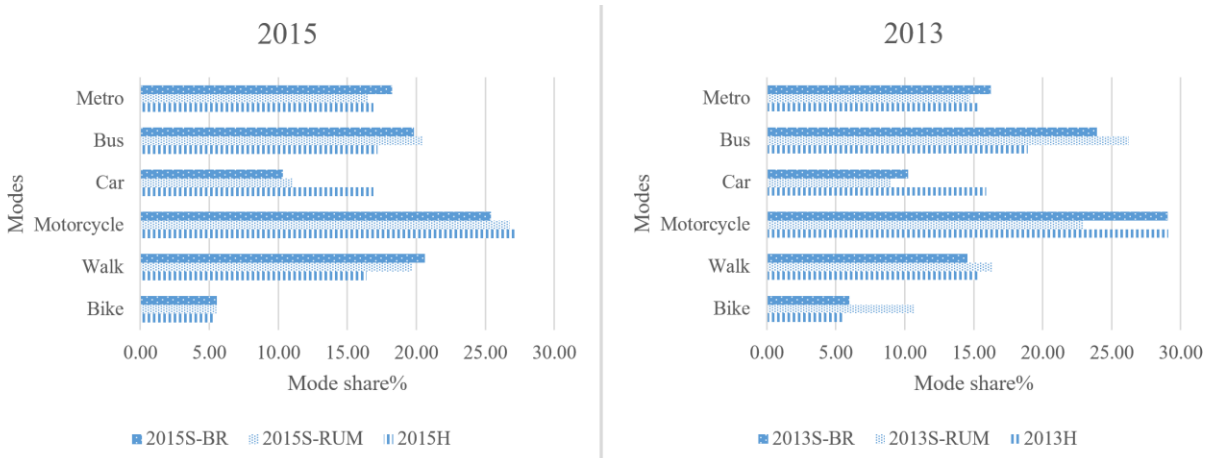

Figure 4-3. Calibration results of mode shares in 2013 and 2015

Note: 2015H/2013H means the historical date of the year 2015 and 2013. 2015S/2013S means the simulated results of the year 2015 and 2013.

To validate the chosen parameter combination, the modes' travel distances were simulated to fit the actual travel patterns. As for the research findings from the literature review, in Taipei City, the average trip distances of bike, metro, motorcycle, and car are 2 km, 8.1 km, 9 km, and 12 km, respectively (Huang, 2016). The studies found that the cars and motorcycles in Taiwan are usually used for long-distance traveling given their faster speed and higher accessibility level. These travel patterns are used for model validation (see **Table 4-2**). Another Monte-Carlo simulation with 100 runs was conducted to quantitatively validate the weight combination of 0.43/0.39/0.08 with the respective behavior theories.

Table 4-2. Validation results of average trip distance in 2015

Average trip distance (km)	Empirical study (Huang, 2016)	2015S-BR	2015S-RUM
Metro	8.10	7.29	7.19
Car	12.00	10.42	7.93
Motorcycle	9.00	7.64	10.92
Bike	2.00	1.72	2.31

The simulation results for BR demonstrated better fitness according to both of the validation procedures applied in this study. Thus, the weight combination of 0.43/0.39/0.08 with behavior theory of bounded rationality was applied to the scenario simulation.

4.3.5 Scenarios

Based on the calibrated configuration of the model, two scenarios related to the key factors were simulated. The following scenarios are represented quantitatively in the simulation. **Table 4-3** summarizes the simulation results of the following scenarios.

Table 4-3. Simulation results of the two scenarios

Mode	2015 BAU	Scenario1	Scenario2	
		Infrastructure extensions	Free for transit connection	2 NTD coupon
Bike%	5.40	5.79	6.30	5.60
Walk%	16.40	15.70	20.47	20.00
Motor%	27.30	31.40	24.41	33.60
Car%	16.90	12.40	10.24	12.80
Bus%	17.20	21.49	19.69	14.40
Metro%	16.90	13.22	18.90	13.60

Notes: BAU represents business as usual, and NTD refers to the New Taiwan Dollar.

4.3.5.1 Bike infrastructure extensions

High bicycle modal share can be achieved through maintaining and continually improving safe and extensive bicycling infrastructure. Castillo-Manzano and Sánchez-Braza (2013) described Seville’s high bicycling modal share as the result of the implementation of extensive new bicycling infrastructure. Public bicycle stations are usually located on a sidewalk near a transit station (Liu et al., 2012). In Taipei, most of the bike-sharing stations are located at nearby metro stations, with a few also located at bus stations. Such integration of bicycling infrastructure with other modes of public transit could enable stakeholders economic and other benefits (Chow & Sayarshad, 2014; Pucher & Buehler, 2009). Thus, 369 new bike-sharing stations were added close to the bus stations except for the remote mountainous areas in the north of Taipei. With the spatial data-driven model, travelers (agents) can measure the distance between home/workplace and stations based on the real road network, which relates to one of the key factors—the accessibility level of the mode. Lin et al. (2013) showed that bicycle stations should not be located more than 300–500m from important origins and destinations of traffic. The average distance between the bike-sharing stations and users' home/workplace in 2015 was calculated to be approximately 818 meters. After the extension of bike-sharing stations, the average distance between bike-sharing stations and users' home/workplace decreased to 604 meters. The travel cost, travel time, and accessibility level of bikes and their connected transits changed accordingly. Compared to the BAU scenario in 2015, the bike mode share increased from 5.40% to 5.79%, and bus mode share increased from 17.20% to 21.49%. As an alternative mode to bus, metro market competitiveness thus weakened.

bike-sharing can extend the catchment area of public transit (Shaheen et al., 2013). Huang (2016) found that 48% of YouBike trips started or ended at a metro station in Taipei, which can be speculated that almost half of YouBike services were used in the first/last mile service of transit. In this scenario, with the extension of bike-sharing stations, 63% bike are used to connect the first/last mile of the transit. But it should be noted 85% connecting bike are used for the first/last mile service of metro although the strategy is focused on building more bike sharing stations around the bus stations. This phenomenon can be explained by the spatial function of the model. It can be found the average distance between bus stations and users' home/workplace in Taipei is 203m, which is less than 1,000m and can be connected by walk. While the average distance between home/place and metro is much longer, 1,373 meters, even longer than the maximum walking distance 1,000 meters, that's why most connecting trips occur around the metro stations.

4.3.5.2 Bike-sharing incentives

Huang (2016) found that average bike-sharing trips declined by 26%, and trip distances—around 1-2 km—did not significantly change, after the cancellation of the "free use in the first 30 min" policy in April 2015. With consideration of this finding, some incentive strategies to encourage people using bike-sharing could consist of the free use of YouBike when used to connect the transit with the smart travel card, or a 2NTD (roughly 0.66$) coupon for every completed trip that can be used on subsequent trips. With one or the other incentive strategies simulated in the present study, the travel costs of the bike and its connected transit changed accordingly.

Compared to the BAU scenario in 2015, the simulation results show that the bike mode share increases from 5.40% to 6.30% with the first incentive strategy, and the shares of bus and metro also increase by 2.49% and 2.00%. Correspondingly, the motorcycle mode share decreases by 2.89% with the first incentive strategies. The bike mode share increases from 5.40% to 5.60% with the second incentive strategy. With the first bike-sharing incentive strategy, 75% bikes are used to connect the first/last mile trips of the transit, but the connecting percentage in the second bike sharing incentive strategy is only 45%, which has little change compared with the BAU scenario. This is because bike-sharing and transit become complementary modes in the first incentive scenario, which can encourage more people to use bike and transit compared to implementing an incentive strategy that only targets cycling.

In Taiwan, motorcycles are the primary transport mode and known to be the biggest single source of vehicular pollution. Despite the introduction of bike-sharing through YouBike in 2009, bike-sharing exhibits limited influence on motorcycle use based on the simulation results for the above two scenarios. As for the motorcycle and car, there are no first/last mile problems. The travel speeds of motorcycle and car are even faster than the bus. However, it should be noted that the transit mode shares increased by 2%-4% with the strategies encouraging the use of bike-sharing to connect to transit.

4.4 Results and discussion

The environmental impacts of these two scenarios were analyzed, with the associated SOx, NOx, CO, and GHG emissions estimated. Thus, free use of bike sharing to connect transit could be more environmental-friendly than other traffic policies that only target bike-sharing. Thus, free use of bike sharing to connect transit could be more environmental-friendly than other traffic policies that only target bike sharing.

Table 4-4 shows the emission factors with the unit of per passenger-kilometer-traveled (PKT) (Chester et al., 2010; Lin et al., 2011), and **Table 4-5** shows the damage cost of the respective pollutant measured in NTD (Lin et al., 2011). Thus, the corresponding environmental impacts are transferred to the total damage cost for comparison (see Eq. (9)).

Table 4-6 shows the daily pollutant emissions of respective scenarios in Taipei transportation system. Compared with the 2015 BAU scenario, the S1 scenario (bike infrastructure extension) and S2 COUPON scenario (2NTD coupon for every complete trip) have less SO_X emissions because of the less metro mode share. The S2 FREE scenario (free use of bike sharing to connect transit) saves 142-ton GHG emissions from daily commute trips compared with the BAU scenario due to less mode shares of motorcycle and car.

Figure 4-4 shows the damage cost of these scenarios. NOx and GHG emissions are the two major sources of pollutant damage cost. The minimized total damage cost is achieved in the scenario of free use of bike sharing to connect transit. The total damage cost can be reduced by 16%, equal to 1.5 million US dollars reduction in transportation damage cost per year compared to the 2015 BAU scenario (see **Figure 4-4**). Thus, free use of bike sharing to connect transit could be more environmental-friendly than other traffic policies that only target bike-sharing.

Table 4-4. Emission factors of the respective modes

Modes	Bike	Walk	Motorcycle	Car	Bus	Metro
NOx (g/PKT)	0.00	0.00	0.34	0.64	0.60	0.09
SOx (g/PKT)	0.00	0.00	0.00	0.01	0.00	0.14
CO (g/PKT)	0.00	0.00	6.12	7.96	0.14	0.02
GHG(CO2eg/PKT)	0.00	0.00	138.51	231.28	78.24	77.48

Table 4-5. Damage cost of the respective pollutants

	Damage cost (2009NTD/g)
NOx	0.101342
SOx	0.252785
CO	0.001198
GHG	0.000590

$$\mathrm{TDC} = \sum EF_i \times DC_i \times Td_j \;\; for\ i = 1,2,3,4\ and\ j = 1,2,3, \ldots 6. \quad (9)$$

Note: Here TDC, EF_i, and DC_i represent total damage cost, emission factor of the pollutant i, and damage cost of the pollutant i. Td_j means the total travel distance of the mode j.

Table 4-6. Daily pollutant emissions of scenarios

Emissions	2015 BAU	S1	S2 FREE	S2 COUPON
NO_X (ton)	2.5	2.6	2.1	2.2
SO_X (ton)	0.2	0.1	0.2	0.1
CO (ton)	22.5	22.3	16.9	21.9
GHG (ton)	767.7	760.1	626.0	697.3

Note: 2015 BAU refers to the business as usual scenario in 2015, S1 represents the first scenario of bike infrastructure extensions. S2 FREE refers to the second scenario of free use of bike sharing to connect transit. S2 COUPON refers to the second scenario of 2NTD coupon for every complete trip.

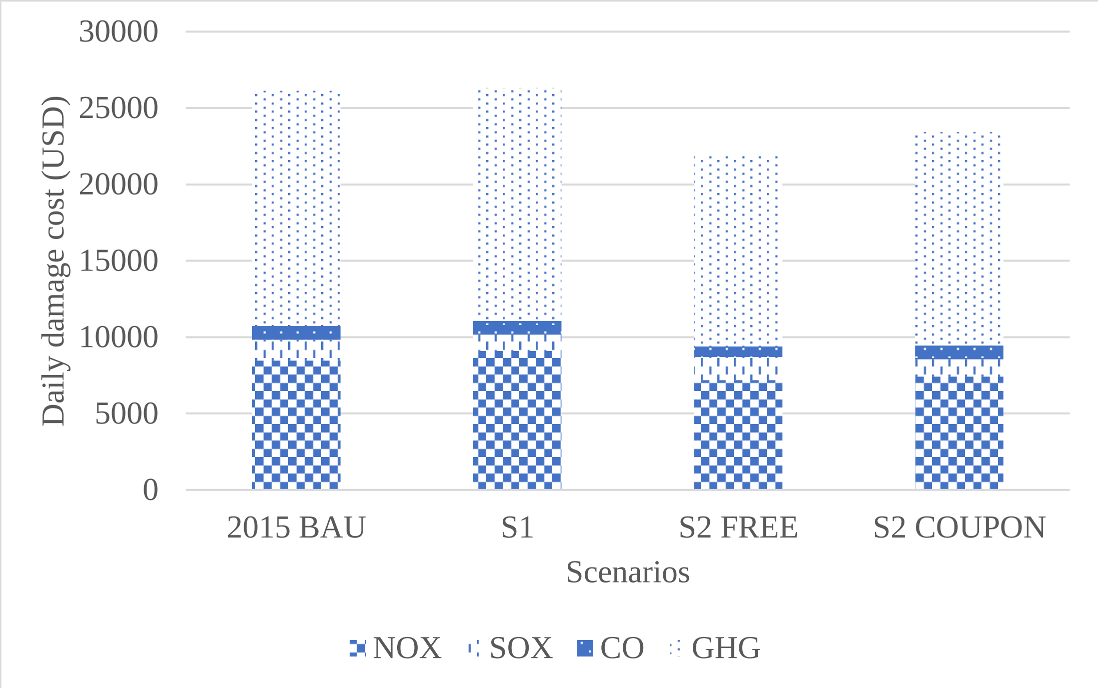

Figure 4-4. The damage cost of the respective scenarios

The benefits of physical activity including cycling and walking are compared between the minimized environmental impacts scenario (free use of bike sharing to connect transit) and the BAU scenario. The World Health Organization's Health Economic Assessment Tool (HEAT) was used to estimate avoided premature deaths due to physical activity from walking or cycling (World Health Organization, 2017). HEAT calculations are based on mortality rates for the age ranges of 20-74 years for walking, and 20-64 years for cycling. HEAT is designed for habitual behavior, such as cycling or walking for commuting, which is perfectly suitable for our commuter health assessment. With this tool, the economic values of the health benefits that occurs as a result of the reduction in mortality due to their physical activity are explored. In the minimized environmental impacts scenario, the average daily cycling and walking time for regular commuters are 16 and 36 minutes, respectively. Thus, the relative risk for cycling is 0.89 for regular commuter cycling for 16 minutes per week, that is, a population of regular cyclists are 11% less likely to die from all causes combined than a population of non-cyclists. In the same way, the relative risk for walking is 0.90 for regular walking of 180 minutes per week. Compared with the BAU scenario, 7,488 and 33,862 people shift to cycling and walking in the minimized environmental impacts scenario. As a result, in the minimized environmental impacts scenario, 22 premature deaths can be further prevented per year compared with the BAU scenario. The comparisons between BAU scenario and minimized environmental impacts scenario (free use of bike sharing to connect transit) are shown in **Table 4-7**.

Table 4-7. The health benefit comparisons between different scenarios

Items	2015 BAU	S2 FREE
Daily cycling population	44928	52416
Daily walking population	136448	170310
Daily cycling time (min)	17	16
Daily waking time (min)	36	36
Relative risk for cycling	0.89	0.89
Relative risk for walking	0.90	0.90
Prevented premature deaths (per year)	93	115

The human health impacts taking into consideration both physical activity and ambient air pollution were also analyzed. Woodcock et al. (2014) concluded that the health benefits of walking and cycling outweigh the negative effects on health from air pollution, even in cities with high levels of air pollution. Tainio et al. (2016) generated a different conclusion, finding that in areas with $PM_{2.5}$ concentrations of 100 μg/m3, harms would exceed benefits after 1 h 30 min of cycling per day or more than 10 h of walking per day. The average annual $PM_{2.5}$ concentrations in Taipei City is around 19 μg/m3 (World Health Organization, 2016). The real-time $PM_{2.5}$ concentrations in Taipei City can rise to 50 μg/m3 (Taiwan Environmental Protection Administration, 2017). **Table 4-8** shows the "tipping point" and "breakeven point" of cycling and walking in Taipei with different air qualities based on the findings of Tainio et al. (2016). The "tipping point" means an increase in physical activity (such as cycling and walking) will no longer lead to health benefits and the maximum benefits are reached. And the "breakeven point" represents no longer health benefits incurred by physical activity in such air polluted environment, harms higher than benefits when engaging more physical activity. When exposed to the average and maximum $PM_{2.5}$ level in Taipei, the maximum health benefit (tipping point) of cycling can be reached in 465 min and 75 min, respectively. Cycling becomes harmful (breakeven point) when exposed to the maximum $PM_{2.5}$ environment ($PM_{2.5}$ concentrations of 50 μg/m3) for more than 5 hours. Actually, 70% people in Taipei ride bikes for short trips within 30 minutes; 23% of people's riding time is between 30 and 60 minutes, and only 6% of people use a bike for trips over 60 minutes long (Pai & Pai, 2015; Pai, 2012). Thus, most bike users in Taipei City stay in a healthy exercise range even during a maximum $PM_{2.5}$ concentration environment.

Table 4-8. The "tipping point" and "breakeven point" of cycling and walking

$PM_{2.5}$(μg/m3)	Tipping point (min cycling/day)	Breakeven point (min cycling/day)	Tipping point (min walking/day)	Breakeven point (min walking/day)
19	465	>960	>960	>960
50	75	300	630	>960

There are number of limitations in this research. To resolve current methodological limitations, future model development could first incorporate weather effects. Individuals hesitate to ride a bike when facing adverse weather (Faghih-Imani et al., 2017a). When there is favorable weather, the number of trips and travel time have both been shown to be greater (Caulfield et al., 2017). Several weather conditions (such as precipitation) should be simulated based on comprehensive historical weather data. Second, in addition to the commute activities modeled in this study, leisure travel also contributes to the usage of bike-sharing. People using bike-sharing for tourism also have different values for travel time, travel cost, and so on, often being less sensitive to travel time compared to commuting citizens. Tourists' travel patterns can be modeled further in the course of bike-sharing system development. Third, some studies have revealed that psychological factors (such as comfort and perceptions of safety) have a significant influence on bicycling behavior and should be given further attention (Heinen et al., 2011). In future research, agent decision-making should also incorporate these psychological factors.

4.5 Summary

In this study, a multidisciplinary approach of spatial multi-agent simulation for improving the sustainability of an integrated transportation system with bike-sharing was developed using real spatial information and modeling disaggregated passenger behaviors. An ABM type model was developed to examine the usage of bike-sharing in a city's integrated transportation system by simulating the interactions between passengers and transport modes. The model can dynamically display how passengers' mode choices evolve under the influences of different transport policy strategies. In this model, all the modes operate in their traffic lines based on real road network data, and all the potential passengers commute by starting their trips from home and finishing at the workplace. The inclusions of these spatial behaviors enable the model to more accurately reflect the real transportation system.

Comparative analysis of the simulation results for two scenarios provide insights into the application of three traffic system measures, namely building more dockings near bus stations, free use of bike sharing to connect transit, and 2NTD coupon for every completed trip. The results indicate that the second strategy is the most sustainable one, with the corresponding total damage cost of commute pollution reduced by 1.5 million US dollars per year compared to the 2015 BAU scenario, and 22 premature deaths further prevented per year due to the mode shift to cycling and walking. However, bike-sharing has limited influence on the use of private modes in Taipei, especially for motorcycle owners. Discouraging motorcycle use may produce the most immediate positive effects from an environmental perspective. This study provides an advanced tool to simulate bike-sharing decision making and understand environmental consequences under various policy scenarios. The model can be applied to other cities to aid in improving the sustainability of integrated transportation systems with bike-sharing.

Chapter 5 Conclusions

Through three case studies (high-speed rail, autonomous taxi, and bike sharing), this thesis demonstrates that integrating individual travel patterns and spatial transportation maps into sustainability assessment can enhance our understanding of the economic, social, and environmental implications of these emerging transportation systems and better support decision making. Based on the results of this thesis, the following major conclusions can be drawn.

Taking into consideration the interactions between transportation modes can improve understanding of the life-cycle environmental performances of a multimodal transportation system.

Previous studies related to the environmental impacts of transportation systems mostly use LCA alone. For the case of HSR, market behaviors are integrated into the assessment of environmental performances of transport modes, with due attention to interactions between existing transportation modes and newly-built HSR. The results of the case study indicate that the Guangzhou-Shenzhen-Hong Kong HSR can gain 13% market share in the opening year. With the introduction of Guangzhou-Shenzhen-Hong Kong HSR, the system life-cycle energy consumptions, GHG emissions, and SO_2 emissions of the cross-boundary transportation system are increased by 17%, 16%, and 42%. In order to minimize the environmental impacts, HSR needs to sustain a high occupancy rate—more than 80%; the through train may need to be gradually closed, which would reduce the system life-cycle environmental impacts by 30%; and the boundary train may need to cut its daily frequency as its mode share decreases with the introduction of HSR. In contrast, airlines will need to increase their daily flight frequencies or capacity as it provides a different service than HSR.

Vehicle operation in traffic lines based on real road network data can lead to a more realistic representation of real-world transportation activities.

Most autonomous vehicle simulations are based on a highly-developed grid or hypothetical city with constant vehicle travel speed and uniform passenger behavior. In the autonomous taxi case, all the vehicles travel on the real road network at various speeds, and all the passengers have their own trip characteristics such as commuting from home to office at a specific time. The simulation results of the autonomous taxi study demonstrate that the optimized fleet size obtained with minimized VMT and reasonable average wait times for passengers is only 20% of the fleet size in the BAU scenario. The optimized fleet size scenario shows that total commute costs are reduced by 38%, and the daily vehicle utilization is increased from 14 minutes to 92 minutes, though daily road occupancy also increases by 12%. This system's energy consumption, GHG emissions, and SO_2 emissions increase by 16%, 25%, and 10%, respectively compared to the BAU scenario, which is mainly due to increased unoccupied VMT and less ride-sharing. These phenomena cannot be captured using aggregate travel patterns based on a hypothetical city.

Individual travel behavior information can guide bike sharing system development.

Evaluating the environmental and social performances of different bike sharing operation strategies requires detailed travel behavior information, which includes social-economic information on the passengers, and the origins and destinations of their commute trips. This information was generated from travel surveys and literature reviews. In the case of bike sharing, the interactions between bicycling and other modes that incorporate the influence of passenger behaviors were simulated. Results from this case study show that free use of bike sharing to connect the first/last mile trip of the transit is the most effective operation strategy, with cycling mode share increases from 5.6% to 6.3%, and the corresponding total damage costs of commute pollution reduced by 1.5 million US dollars per year, and 22 premature deaths further prevented per year due to the mode shifts to cycling and walking. As for the human-health aspect, most bike users in Taipei City stay in a healthy exercise range even during a maximum $PM_{2.5}$ concentration environment. These parameters can be directly calculated from the individual travel pattern data in this research.

Future research

In the HSR case study, given data availability constraints, the LCI of cross-boundary modes was estimated by adjusting the LCI of reference modes from the literature. In future research, a hybrid life-cycle analysis method integrating process-based LCA and economic input-output based LCA could be applied to more thoroughly evaluate the life-cycle environmental performances of these cross-boundary modes. At the current stage, only the occupancy rate is discussed as one dimension in scenario simulation. Future simulation scenarios could include other dimensions such as fuel production (different electricity mix), accessibility change (with or without feeder bus), market influences (passengers' sensitivity to ticket fare may be lower during holidays), and mode complementarities (HSR replacing short-haul airline as a transfer mode to an international airline).

In the autonomous vehicle case study, the autonomous taxi is only applied to commute travel. Whether more aTaxi ride-sharing would occur when aTaxis are integrated into overall daily travel (for recreation and shopping in addition to commuting) and what the consequent impacts might be are important questions for future research. In the present study the aTaxis are only used for end-to-end trips. Using aTaxis to connect the first/last mile trips of transit will be explored further in ongoing work. Meanwhile, more realistic features can be added to this modeling framework, such as consideration of traffic signals and further validation of the model through vehicle trips crossing the main intersection.

As for the bike sharing case study, weather effects will be incorporated in our future research, with several weather conditions (such as precipitation) simulated based on comprehensive historical weather data. Not only commute travel but also leisure trips will be simulated as passengers have different weights for the travel cost and travel time with different trip purposes. And some psychological factors (such as safety concerns) will be considered as one of the key factors influencing passengers' behaviors.

The three emerging sustainable transportation systems consisting of high-speed rail, autonomous taxis, and bike sharing are discussed separately in the research that we have so far performed. In our future work, these emerging transportation systems are integrated in the case of the Hong Kong Transportation system. The theory of system of systems is applied to develop the model. It is important to note that the theory of system of systems does not yet have a standard, widely accepted definition. One definition (Popper et al., 2004) is "a collection of task-oriented or dedicated systems that pool their resources and capabilities together to obtain a new, more complex 'meta-system' which offers more functionality and performance than simply the sum of the constituent systems." In the case of Hong Kong, several transportation systems including high-speed rail, bike sharing, mass transit railway (MTR), and other transportation systems operate independently but have to compete and cooperate to gain the passenger market shares. Based on the findings of the second case of autonomous taxis, we will not discuss driverless vehicles or electric vehicles in the case of Hong Kong, given their inefficient space utilization in operation and parking, and their unsatisfactory environmental performances. With double the space for pedestrians and cyclists and half the space for cars, Stockholm's vision can be used as a reference for Hong Kong to build a compact, green, and connected city.

Development of efficient mass public transport, along with promotion of non-mechanized modes like walking and cycling, is widely suggested as a sustainable solution to improve mobility in big cities (Dimitriou & Gakenheimer, 2011; Vuchic, 2005). People in Hong Kong are highly dependent on the MTR and bus system, with 90% of journeys ridden on public transport. First-/last-mile connectivity is one of the major issues in the current system of Hong Kong. These first and last mile journeys are mostly completed by walking, which is significant as an active mode of transportation used in the City of Hong Kong. However, the use of bicycling to connect the first/last mile trips of transit is below expectations. **Figure 5-1** shows the transit and bicycle network in Hong Kong.

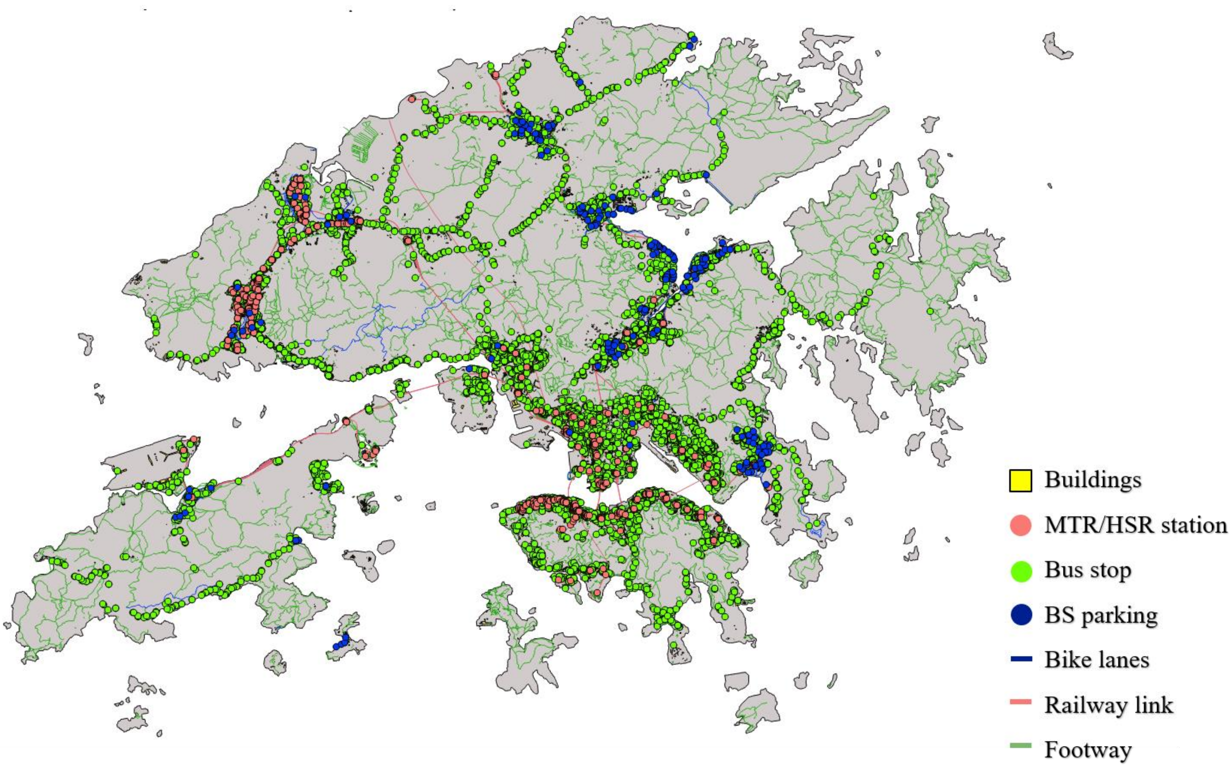

Figure 5-1. Hong Kong transit and bicycling network

Note: BS here means bike sharing

Public bike sharing was originally established as a means to facilitate better first- and last-mile connections between public transit stations and desired destinations (DeMaio & Gifford, 2004; Liu et al., 2012; Midgley, 2009; Shaheen et al., 2013). Nowadays there are more than four private bike sharing companies operating in Hong Kong, and all of them are free-floating bike sharing systems (FFBSs).

FFBS is different from station-based bike sharing (SBBS), in that bikes in the former system can be locked to an ordinary bicycle rack (or any solid frame or standalone), thus eliminating the need for specific stations. The users of FFBS can drop off the bike wherever they want. In practice, this has led to complaints from Amsterdam citizens, who are annoyed by the sheer number of bicycles taking up space in the city. In response, Amsterdam decided to impose a ban on rental free-floating bike sharing systems (Joris, 2017). Hong Kong has experienced the same problem as Amsterdam. Given the spontaneity characteristics of FFBS, some FFBS bikes are illegally parked and affect the townscape (Ye, 2017). Specifically designed parking spots for bike-sharing could address the issues described above. The location of the FFBS parking spots in relation to the public transport network is one of the keys to the success of such complementary programs (García-Palomares et al., 2012; Lin & Yang Ta-Hui, 2011; Martens, 2007). FFBS can act as a better seamless feeder service to public transit throughout Hong Kong City with such optimized parking spots. Thus, understanding the actual usage patterns of bike sharing and designing parking spots for FFBSs are the major objectives of this study. This study will propose a GIS-based ABM model to investigate the spatial distribution of the potential demand for first/last mile trips, locate parking lots in relation to the existing transit networks, and determine the station capacity based on real demand. Based on this model, the parking lots that are relatively isolated with low demand will also be eliminated in the system. Lin et al. (2013) used an iterative greedy-drop heuristic for locating bicycle stations based on a hypothetical transport network. García-Palomares et al. (2012) optimized the location of bike sharing stations with a GIS approach, but the passengers' behaviors not considered. To the best of our knowledge, there is relatively little literature integrating free-floating bikes into a public transportation system with consideration of the spatial structure of the transport network and users' interaction and adaptation behaviors at the same time, especially in the case of Hong Kong.

Free-floating bike services offer scholars unprecedented access to large-scale ridership data by tracking bikes in real-time with built-in Global Positioning System (GPS). Ridership data of free-floating bikes provide accurate origins and destinations of bike trips. The ridership data of free-floating bikes are collected via web-mining techniques from bike sharing websites.

A program has been built to simulate the requests from the client-side program and collect the server's response, containing a list of nearby available bikes. The hired bike will disappear from the pool, and if the trip terminates, it will reappear with a new coordinate. Therefore, after cyclical collection, the origin and destination of a bike trip can be obtained by searching for the geolocation change of each bike. We have collected ridership data with a total of approximately 8848 bikes from February 8th to 28th, 2018, except for the 14th when renewal of the service subscription caused a temporary suspension of data collection and access. Data-mining bike collocation with metro stations or bus stops can deepen our understanding about the extent to which bikes facilitate first- or last-mile connections to public transportation. The hotspots of bike usage located less than 300m from transit stations are identified as potential parking lots. Household Interview Survey (HIS) data are used to assign trip sequences to individuals and define the social-demographic characteristics of individuals. Each individual has a travel diary which consists of a sequence of trips that the person makes in a weekday (such as from home to transit station at 7 a.m. or from transit station to workplace at 8 p.m.). As the frequency of bus and MTR services are high (less than 10 min headway), the model assumes that passenger arrival time is independent of the bus and MTR schedule.

More recently, computation developments in seamless integration of GIS into ABM and the possibility of simulation of geospatial features have significantly improved the capacity of ABM to portray more realistic processes and patterns of urban environments (Taillandier et al., 2012). The agents in this model includes biker, walker, and parking lot. Biker agents move with a speed randomly set between 8 and 14 km/h. Walker agents move at a speed less than 5 km/h. While moving the agents, the model can draw the paths for visualization, and also save all paths as shapefiles for further analysis. There is the possibility of 'bike share programs showing some social contagion, spreading within social groups to increase their use' (Schoner et al., 2016). The small-world theory will be used to construct the passengers' social network (Watts & Strogatz, 1998). Passengers' mode choices will be influenced by each other according to their social networks.

The model will be developed to optimize the distribution and capacity of parking lots in the free-floating bike sharing system, to achieve a transport system as efficient and sustainable as economically and socially possible. The origin-destination first/last mile trips of the users consists of three links: (1) a user walks to pick up a bicycle at a parking lot near his/her origin; (2) the user rides the bicycle to another parking lot near his/her destination and locks the bike; and (3) the user walks from the check-in parking lot to the destination. The origin and destination here refer to the users' home and inbound/outbound transit stations. **Figure 5-2** illustrates the first/last mile trips between the transit stations and homes.

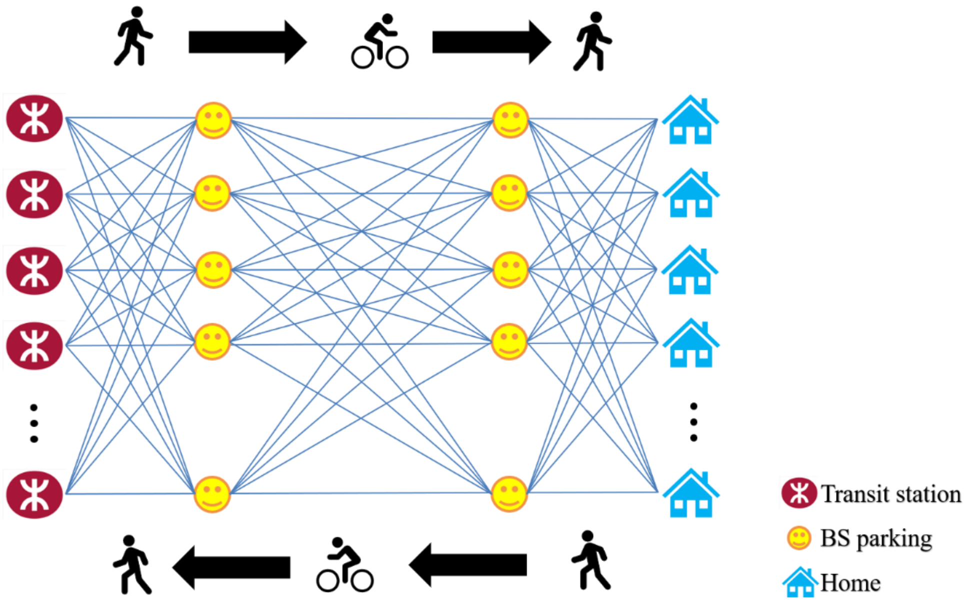

Figure 5-2. First/last mile trips connected by bike

The accessibility of FFBS parking lots is a crucial factor in encouraging bike sharing use. Shorter access time from origin to parking lots may persuade more people to use bike sharing to connect to transit, consequently making public transit more competitive than private transport modes. Lin et al. (2013) showed that bicycle stations should not be located more than 300–500 m from important origins and destinations of traffic. A preference survey conducted by the Melbourne and Brisbane bike sharing systems also indicated that users are more likely to use bike-sharing if a station is within 250 meters of their workplace (Fishman et al., 2014b). Compared with SBBS, FFBS is more convenient and the average walking distance of FFBS is shorter (Pal & Zhang, 2017). In Hong Kong, the main factors affecting the choice of transport mode are travel time and walking distance between location for getting on/off the mechanized transport and the locations of trip origin/destination. Owing to the heat and humidity in Hong Kong, the outdoor walking time and the waiting time are of high importance to service quality. The objective is to minimize the sum of the travel costs incurred in the first/last mile trips (including the explicit cost of cycling charge and the hidden cost related to passengers' value of time), capital costs of public bicycles, and the operating cost of the FFBS system. Thus, there is a basic tradeoff in determining the number and locations of bicycle stations. In comparison to the prevailing SBBS, FFBS saves on start-up cost by avoiding the construction of expensive docking stations and kiosk machines. Thus, the construction cost of parking lots is not considered in this study. The total cost is expressed in Eq. (1).

$$\text{Min TC} = w_1 \times (EC + HC) + w_2 \times (CC + OC) \quad (1)$$

Where TC refers to the total cost, and EC, HC, CC, and OC represent the explicit cost, hidden cost, capital cost of bike, and operating cost of the system, respectively. And w_1 and w_2 are the weights of user's cost and system's cost.

The capital cost of Mobike system is estimated at $466 per bicycle, and OfO is estimated to be $78 per bicycle. But OfO bikes do not have GPS tracking systems nor power generation systems. As for the operating costs, the cost of maintenance, distribution, staff, insurance, office space, storage facilities, website hosting, and maintenance are taken into consideration. The average operating cost of the bike sharing systems in New York and Minneapolis is around $1,600 per bicycle (New York City Department of City Planning, 2009; Twin Cities Bike Share, 2008). DeMaio (2009) and Midgley (2009) estimated that the annual operating costs per bike vary from $250 to $1,600, depending on the used technology.

The model will be calibrated with the real-time free-floating bike movements. Except for the business as usual scenario, some scenarios also will be simulated based on different operation strategies. Three different scenarios are considered: 1) Different demand scenarios during peak and non-peak hours. In this scenario, the busiest parking lots will be identified, and isolated parking lots with less utilization will be closed. Some suggestions will be proposed for better utilization of each lots. 2) Limited budget scenarios with different total numbers of parking lots will be explored to determine the most cost-effective scenarios. 3) Different incentive scenarios. This scenario will be conducted to introduce a subsidy to encourage the use of certain parking lots and stop bicycle from over-accumulating. **Figure 5-3** shows the first/last mile trip network with potential parking lots in Sha Tin, Hong Kong.

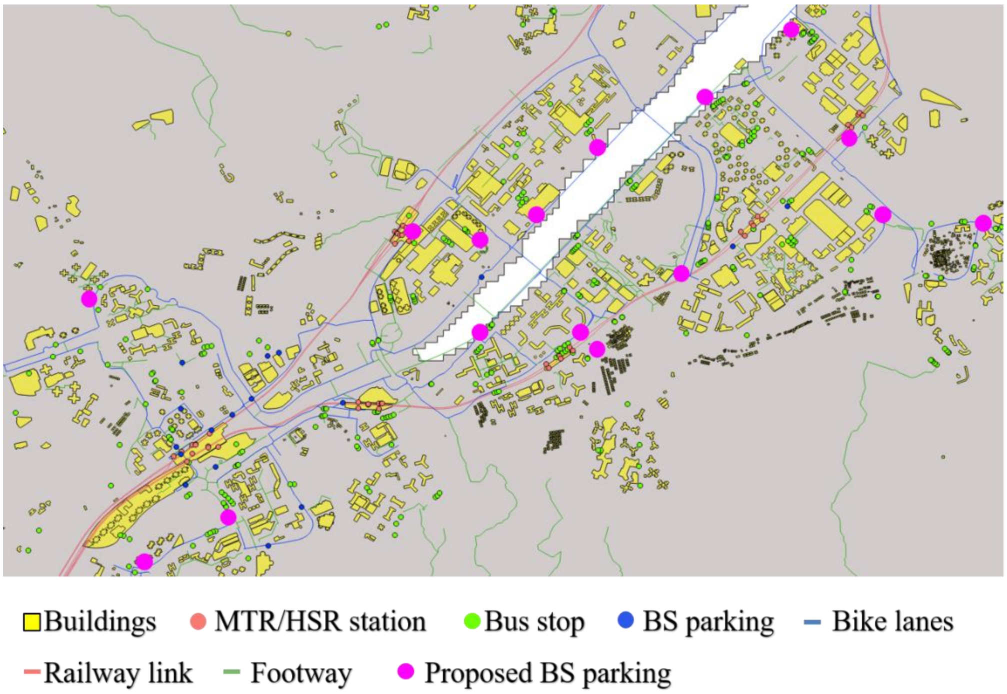

Figure 5-3. First/last mile trip network in Sha Tin, Hong Kong

The public transit usage before and after deployment of FFBS services will be evaluated, which is also consistent with the objective—to enhance the bicycle and transit connections and promote the usage of public transit.

Understanding how bike sharing and public transit systems are interrelated is vital for planning a mutually reinforcing sustainable transport network (Campbell & Brakewood, 2017). We hope that a better understanding of the relationship between these two different modes can improve the first/last mile access to mass transit in Hong Kong.

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Appendices

1. ALENT methodology overview

The process of the model simulation contains the following steps (see **Figure S1**). First, a cross-boundary mode choice behavior survey is conducted. Four most influenced key drivers for passenger mode choice are identified. There are travel time, ticket fare, service quality, and accessibility level. Specifically, the accessibility level of specific transport mode is calculated with this GIS map, which depends on Euclidian distances (Li & Liu, 2007) between the mode's station and urban centers. GIS map is used for mapping of Pearl River Delta and its main routes, especially for the airline, high-speed rail link, train link and highway systems in this case.

Second, a transport market is created including passengers and modes, in this case of different ways to choose their satisfied modes. Each passenger has social connections with other passengers who are called the "friends" of the passenger. The social networks we present here is from the model proposed by Watts and Strogatz (1998), which fits very well on both small-world and clustering characteristics. This "small-world phenomenon" was confirmed by a study of Milgram (1967). It is indicated that most people are separated by on average only six degrees. Social networks constructed in such a way can make the information spread much faster, then people can make decisions in a more holistic way.

Each mode has specific values of four dimensions, travel time, ticket fare, service quality, and accessibility level. While each passenger owns two specific parameters, U_{ij} and Un_{ij}. U_{ij} is the total utility of passenger i choosing mode j and Un_{ij} reflects how certain a consumer i is when choosing mode j. At the initial condition, each passenger is assigned one of the available modes. In the next step choice, U_{ij} and Un_{ij} are calculated based on the passenger's current choice and friends' choice. The values of total utility U_{ij} and uncertainty Un_{ij} are then compared with the passengers' own Umin-minimum satisfaction and Unmax-maximum uncertainty. One of the four cognitive processes is performed and a choice is accordingly made. These choice behaviors will continue until the model run is terminated, then the mode shares among transport modes are presented. Third, the corresponding operational and life-cycle environmental performances of transport modes are calculated based on passengers' mode choices. For example, passengers' choices may change as the opening of HSR, the following environmental impacts should be investigated. Finally, in order to minimize the environmental impacts, several scenarios at the operation stage are simulated based on simulated mode shares. Modes' environmental performance then get better by these environment-friendly actions. The ALENT model will lead to a virtuous cycle for the environmental performances of the transport system.

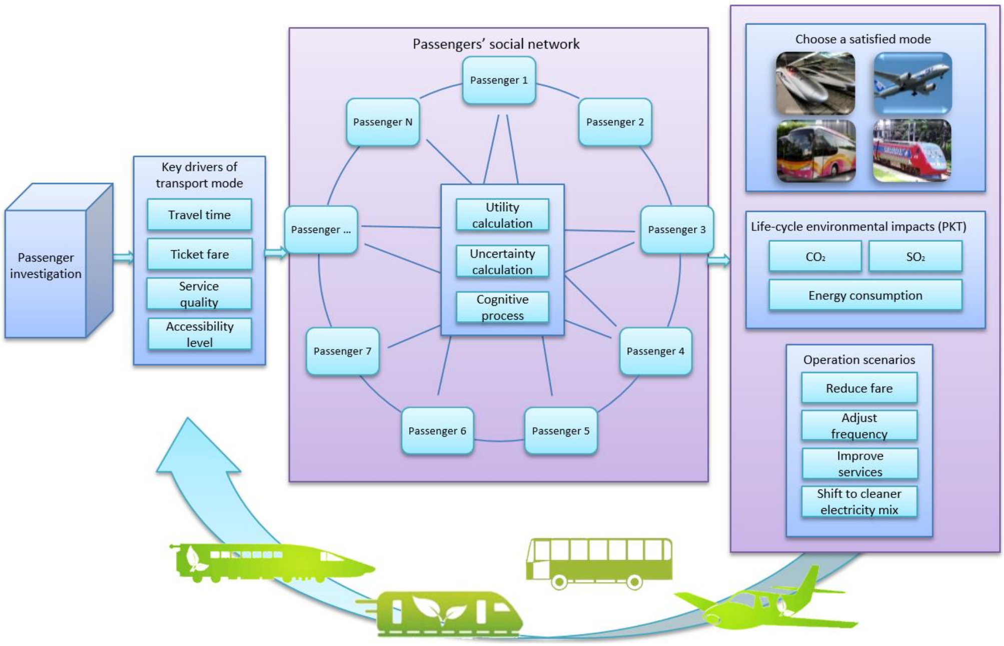

Figure S1. Process overview of the study

2. Introduction of referenced and studied modes in ALENT model

The basic information of the referenced and studied modes is listed in **Table S1** (MTR Corporation Limited, 2007; Wang & Ding, 2012). The Guangzhou-Shenzhen-Hong Kong HSR (GSH HSR), boundary train, and through train each have their own specific vehicle type. As for aircraft and boundary bus, Air A320 and urban transit bus are chosen as representatives based on sales data for the aircraft and buses that are the most commonly purchased vehicle types in China (China Association of Automobile Manufacturers, 2016; Fang, 2011). As for HSR, Inter-City Express 3 (ICE 3) or Intercity Express 3 is a family of Germany's Inter-City Express HSR vehicles. The LCI of GSH HSR vehicles is estimated by adjusting the LCI of ICE3, since GSH HSR vehicle CRH3 uses Siemens Velaro, or Germany's ICE 3, as a prototype with mostly the same structure and vehicle material (Siemens, 2005). The range in mode energy consumption is based on serval factors including the age of the modes and physical size (Givoni, 2007; Van Wee, Van Den Brink, & Nijland, 2003). Thus, the LCI for China's CRH3 vehicle is estimated by multiplying the LCI of Germany's ICE-3 vehicle with the weight ratio of China's CRH3 vehicle to the ICE-3 vehicle (Yue et al., 2015).

As for train, BART is San Francisco's Bay Area Rapid Transit System, whose environmental data comes from a heavy rail long distance system in the Ecoinvent 3.0 database (SimaPro, 2006). It is used to represent the boundary train and through train in this study. The differences between boundary train and through train are their different operate routes between Hong Kong and Mainland China. Boeing 737 is assumed as the representative of the Airbus A300s, Boeing 717, 727, 757, 777 (Chester, 2008). Urban buses are represented by a typical diesel-powered 40-foot vehicle (Federal Transit Administration, 2011). The referencing modes are selected to represent the studied modes as they have a similar size and speed to studied modes. So the LCIs of the studied modes—boundary train, through train, aircraft, and boundary bus are estimated in a similar way as far HSR.

Table S1. Basic information on referenced modes and studied modes

Modes	Vehicle type	Vehicle weight (Empty/full)/t	Operating speed (Km/h)	Total seats	Vehicle fuel
HSR*	ICE3	405/420	330	441	Electricity
GSH HSR	CRH3	433/473	300-350	556	Electricity
Train*	Rapid Transit (BART)	360/220	53	530	Electricity
Boundary train	SP1900	444/494	120	626	Electricity
Through Train	Lok 2000	564/617	120-160	648	Electricity
Midsize aircraft*	Boeing 737	37/48	780	140	Aviation kerosene
Midsized aircraft	A320	42	885	158	Aviation kerosene
Urban bus*	Urban transit bus	11/16	70-80	60	Diesel
Boundary bus	Urban transit bus	14/19	70-80	60	Diesel

*Modes for references

Table S2 and **Table S3** represent the operational and life-cycle environmental impacts of studied modes. These LCI results were estimated by adjusting the LCI of referenced modes (Chester & Horvath, 2010a, 2010b; Chester & Horvath, 2009; Chester, Horvath, & Madanat, 2010; Chester & Ryerson, 2014; Grossrieder, 2011; Yue et al., 2015). These LCI results per-VKT combined with dynamic mode shares were used for the environmental performance evaluation of the modes on a passenger-kilometer basis.

Table S2. Operational environmental impacts of studied modes

Modes	Energy (MJ/VKT)	GHG (gCO2e/VKT)	SO_2 (g/VKT)
HSR	428	31,750	188
Boundary Train	210	11,470	64
Through Train	266	14,570	80
Aircraft	300	20,200	6.5
Boundary bus	32	2,400	0.022

Table S3. Life-cycle environmental impacts of studied modes

Modes	Energy (MJ/VKT)	GHG (gCO2e/VKT)	SO_2 (g/VKT)
HSR	660	43,100	225
Boundary Train	380	22,200	105
Through Train	486	28,200	133
Aircraft	355	25,000	19
Boundary bus	43	3,300	1.9

3. Cross-boundary mode choice behavior investigation results

Table S4 presents a profile of the survey respondents. It shows that 55.0% of respondents are male and 45% are female. 16.9% of respondents are 20 years old or younger, 48.2% between 21 and 40 years old, 28.9% between 41 and 60, and 6.0% are 61 years old or older. The largest group indicated that the purpose of their trips is for leisure (57.2%=285), followed by commercial trips (20.5%=102), study (10.6%=53), visiting relatives (9.2%=46), and commuting (2.4%=12). The results are not surprising, given the growing tourism industry in Hong Kong. Respondents were asked how frequently they travel between Hong Kong and mainland China per month. More than 80% (80.9%) said once or less than once per month, 8.0% stated twice, 1.8% indicated three to five times, and 9.2% travel more than five times between Hong Kong and mainland China per month. Respondents were also asked to indicate their occupation. Almost a third (44.0%) are students, 17.1% work in the service sector, 13.3% work in the manufacturing sector, 9.6% are government employees, and 16.1% are other. When asked about their travel destination, 25.3%, 18.3%, 17.5%, 10.0%, 9.4%, and 19.5% report going to Shenzhen, Guangzhou, Hong Kong, Zhongshan, Dongguan, and other places respectively. As for their monthly income, nearly 50% (50.6%) of respondents report that it is HKD10,000 or less, 20.9% are between HKD10,000 to 2,5000, 17.7% are between HKD25,000 to 40,000, 10.4% are between HKD40,000 to 60,000, and 0.4% are more than HKD60,000. The weighting of four key drivers—travel time, ticket fare, service quality, and accessibility level are set as 0.3054, 0.4896, 0.0786, and 0.1264, respectively among the 498 respondents. Ticket fare is more important than other key drivers in mode choice consideration. A limitation of the online survey is that the surveyed people are not a representative sample of the total population of Hong Kong. For example, only 6% of the respondents are 61 years old or older, while in Hong Kong, people who are older than 60 make up 21% of the total population. This is because certain populations like the elderly are less likely to have internet access and to respond to online questionnaires.

4. Passengers' cognitive processes

Figure S2 shows the simulation results of the ALENT model—passengers' cognitive processes from 2003 to 2031. In the scenario simulation for 2003 to 2031, the mode choice of most passengers is primarily driven by repetition and deliberation behaviors. More than half of the passengers engage in repetition from 2003 to 2018, hence the market is stable (Janssen & Jager, 2001, 2003), as passengers choose transportation modes in a habitual manner. But since the opening of HSR in 2018, the fraction of passengers engaging in repetition is decreasing, with more and more passengers engaging in deliberation. The market consequently became unstable with the introduction of HSR. A certain number of passengers have become harder to satisfy but very certain to choose the most satisfied mode. They are making their own decisions without consideration of their friends' choices. From 2018 to 2031, this increase of passengers engaging in deliberation behaviors will cause growth in HSR mode share.

Table S4. Profiles of respondents (N=498)

Items	Number	Percent
Gender		
Male	274	55.0%
Female	224	45.0%
Age		
20 or less	84	16.9%
21-40	240	48.2%
41-60	144	28.9%
61 or above	30	6.0%
Trip Purpose		
Commercial trip	102	20.5%
Commute	12	2.4%
Study	53	10.6%
Leisure	285	57.2%
Visiting relatives	46	9.2%
Frequency travels per month		
Less than once or once	403	80.9%
Twice	40	8.0%
Three times - Five times	9	1.8%
Above five times	46	9.2%
Occupation		
Student	219	44.0%
Manufacturing sector	66	13.3%
Service sector	85	17.1%
Government employee	48	9.6%
Other - Write In	80	16.1%
Destination		
Hong Kong	87	17.5%
Guangzhou	91	18.3%

Shenzhen	126	25.3%
Zhongshan	50	10.0%
Dongguan	47	9.4%
Other places from Mainland	97	19.5%
Monthly incomes (HKD)		
Below $10000	252	50.6%
$10001-$25000	104	20.9%
$25001-$40000	88	17.7%
$40001-$60000	52	10.4%
Above $60000	2	0.4%
Relative weightings of key drivers		
Ticket fare	0.4896	
Travel time	0.3054	
Service quality	0.0786	
Accessibility level	0.1264	

(Monthly income reported in RMB is changed to HKD)

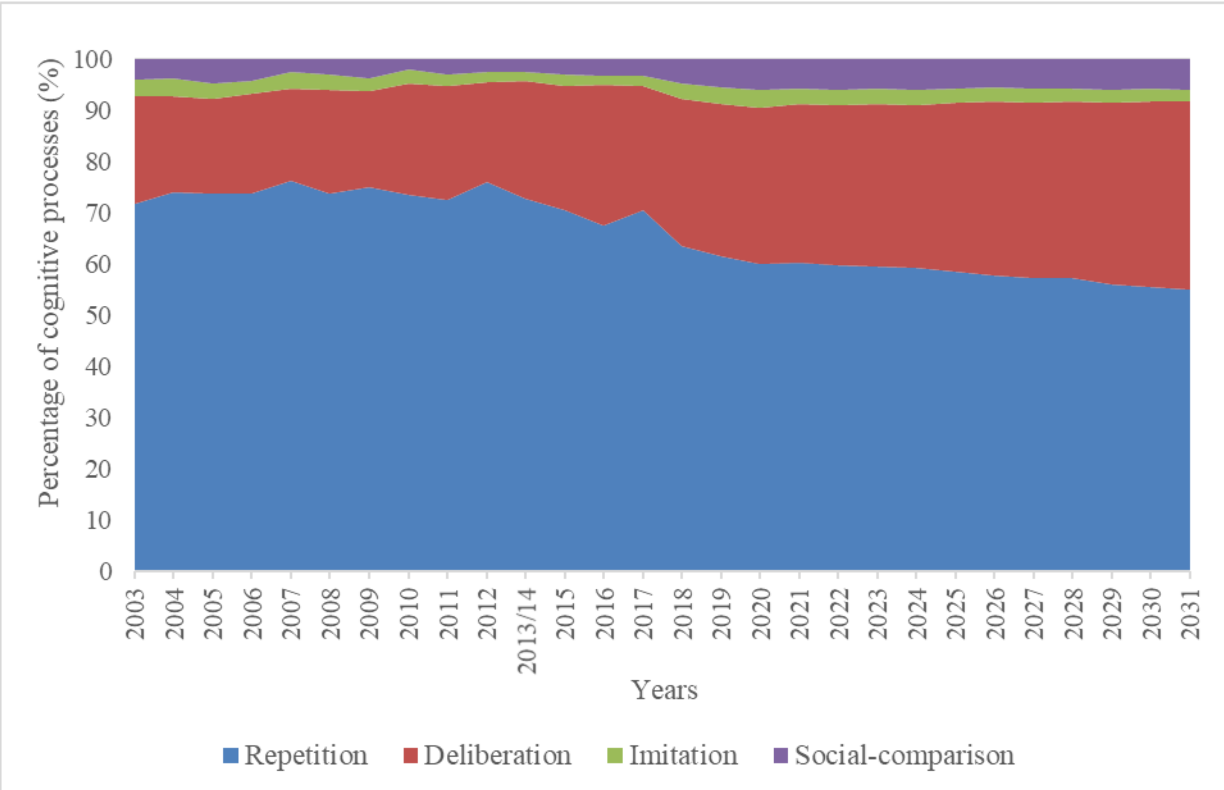

Figure S2. Fraction of cognitive processes from 2003 to 2018

Note: As there are 1000 agents exist in ALENT model, here uses ‰ per thousand to describe the simulation results rather than % percent.

5. Sensitivity analysis of ALENT model

Empirically based ABMs models often involve numerous parameters (Janssen & Ostrom, 2006). Sensitivity analysis is conducted to document the effectiveness of the parameters and increase the usability of the model (Ratto, Castelletti, & Pagano, 2012). Passengers' preferences for travel time and ticket fare are two significant parameters in this study. Each parameter is tested separately while leaving the other parameter in the calibrated configuration as described for the 2018 parameter settings. The perturbations imposed on the parameters are meant to consider the maximum realistic variations of modes' travel time and ticket fare in the cross-boundary transportation system. Then all the possible combinations of high and low values of the two parameters that mostly affect the mode shares are tested (**Table S5** and **Table S6**).

Table S5. Sensitivity analysis of passengers' travel time preference

Travel time dimension μ	Travel time σ	Corresponding mean travel time (min/100 Km)	Mode share changes				
			HSR	Boundary train	Aircraft	Through train	Boundary bus
0.160	0.300	134	—	—	—	—	—
0.187	0.300	130	19.3%	-3.8%	4.2%	10.2%	6.7%
0.214	0.300	126	18.9%	-3.5%	6.3%	14.6%	5.1%
0.241	0.300	121	49.6%	-7.6%	4.5%	4.6%	14.1%
0.268	0.300	117	61.3%	-11.1%	15.8%	10.8%	19.9%
0.295	0.300	113	65.7%	-11.2%	10.7%	10.3%	20.6%
0.322	0.300	108	71.3%	-15.8%	12.2%	4.6%	33.4%
0.349	0.300	104	94.5%	-16.4%	21.4%	10.2%	29.9%
0.376	0.300	100	148.7%	-21.5%	10.1%	9.8%	39.1%
0.403	0.300	96	154.7%	-22.5%	24.7%	-10.4%	40.4%
0.430	0.300	91	199.0%	-27.3%	27.9%	-9.2%	47.3%
0.457	0.300	87	209.0%	-27.7%	21.7%	3.2%	47.2%

0.484	0.300	83	254.7%	-30.9%	38.4%	-12.1%	48.4%
0.511	0.300	78	263.9%	-33.8%	20.7%	-1.2%	57.9%
0.538	0.300	74	325.2%	-37.0%	27.8%	-6.1%	58.0%

Table S6. Sensitivity analysis of passengers' ticket fare preference

Ticket fare dimension μ	Ticket fare σ	Corresponding mean ticket fare (HKD/100Km)	Mode share changes				
			HSR	Boundary train	Aircraft	Through train	Boundary bus
0.886	0.300	171	—	—	—	—	—
0.892	0.300	162	0.8%	-1.2%	-4.9%	-2.4%	2.8%
0.898	0.300	153	-3.9%	-1.2%	-4.1%	-8.7%	4.9%
0.904	0.300	144	-3.6%	-0.9%	-6.5%	11.0%	4.0%
0.910	0.300	135	-6.0%	2.1%	-10.6%	2.9%	2.6%
0.916	0.300	126	3.4%	-2.7%	-11.7%	-0.7%	5.4%
0.922	0.300	117	3.2%	-2.2%	-13.0%	8.1%	4.7%
0.928	0.300	108	-5.2%	-1.6%	-5.4%	4.8%	5.7%
0.934	0.300	99	-8.0%	0.5%	-18.3%	-12.2%	8.3%
0.940	0.300	90	-1.8%	-1.7%	-22.3%	7.8%	8.8%
0.946	0.300	81	-12.8%	3.3%	-27.0%	5.2%	8.3%
0.952	0.300	72	-4.3%	0.8%	-27.1%	-12.3%	8.8%
0.958	0.300	63	-7.9%	1.0%	-25.5%	-14.3%	9.7%
0.964	0.300	54	-3.3%	-2.2%	-30.5%	19.8%	11.6%
0.970	0.300	45	-3.8%	1.3%	-36.2%	5.6%	9.4%

First, Monte-Carlo simulations were conducted by varying the passengers' travel time preference dimension (from 0.160 to 0.538) based on calibrated preference trends, while keeping the ticket fare preference dimension the same as for 2018 setting—0.970. Owing to the faster travel time demand (from 134min/100Km to 74min/100Km), the mode shares of HSR, aircraft and boundary bus are increased by 325.2%, 27.8%, and 58.0%. Other competing modes may need to reduce their travel time by accelerating the transport vehicles, increasing daily frequencies, and/or improving the convenience of interchange.

Similar Monte-Carlo simulations were conducted by varying the passengers' ticket fare preference dimension (from 0.886 to 0.970) while keeping its travel time preference dimension the same as the 2018 setting—0.538. As the ticket fare varies among cross-boundary transport modes (from 0.260 to 0.970), the sensitivity of passengers' ticket fare preferences is not as obvious as travel time. Aircraft is the most affected mode with lower ticket fare preference of passengers (from 171 HKD/100Km to 45 HKD/100Km)-the market share is reduced by 36.2%, with HSR as the second most negatively affected mode. While cheaper ticket fare demand has positive effects for boundary bus's mode share.

Social networks also will influence the modes' market share in ALENT. The size of passengers' social networks, represented by the social connecting probability is also discussed to see the effect on model outputs. Social connecting probability set to 1%, meaning each passenger's social network is composed of its neighbors and 1% of non-neighbors. In general, the larger the social network, the faster information spreads, which implies that consumers will make more informed choices. **Table S7** shows the mode share results based on different social connecting probabilities with 2018 parameter settings. As social connecting probability increases, more and more passengers choose HSR with the comprehensive consideration of four key indicators. But based on 2003-2014 historical mode share data, a small-world network with 1% connecting probability, also studied by Janssen and Jager (2001), proves best able to accurately represent actual social networks in ALENT. This social connecting probability also can be applied simulations for future years.

Table S7. The effect of social networks on transport mode share in 2018

Social connecting pro	Mode shares (‰)				
	HSR	Boundary train	Aircraft	Through train	Bus
0.01	136	436	54	16	358
0.02	142	420	71	19	348
0.03	154	425	68	20	333
0.04	152	423	72	23	330
0.05	137	423	70	22	348
0.06	152	412	74	25	337
0.07	148	405	74	26	347
0.08	151	402	79	29	339
0.09	150	414	78	24	334
0.10	148	404	74	30	344
0.11	154	401	78	29	338
0.12	153	392	78	26	351
0.13	153	405	78	30	334
0.14	153	402	76	27	342
0.15	154	398	70	29	349
0.16	154	403	77	29	337
0.17	160	405	71	26	338
0.18	155	401	71	31	342
0.19	155	396	78	30	341
0.20	163	389	73	33	342

6. Other simulation results of ALENT model

Based on passenger preference trends, the mode shares of cross-boundary transportation systems from 2018 to 2031 also can be estimated (**Figure S3**). Here we assume the Passengers' expectations for the ticket fare dimension for the boundary bus is assumed to remain the same as in 2018—0.970 (45HKD/100Km), as it is the cheapest fare among cross-boundary modes, and the travel time dimension is expected to continue to grow by 0.01 per annual from 2018 to 2031 which is a bit slower than the annual growth of 0.027 was from 2003 to 2018. For example, the passengers' expectation preferences for travel time and ticket fare dimensions in 2031 are set as 0.668

(53mins/100Km) and 0.970 (45HKD/100Km). It should be acknowledged that the travel time, ticket fare, service quality, and accessibility level of the transport modes are assumed unchanged during these years as the high degree of freedom of the model.

Figure S4 shows that the mode share of HSR would grow continually from 2018 to 2031, reaching the largest mode share in 2031, at 20.7%. At the same time the mode share of the boundary train shrinks from 43.1% to 34.1%, a 21% reduction. Similarly, the mode share of the through train, which is influenced by HSR, decreases by 31%. These variations could in part be explained by the shuttle service that HSR provides, which is a similar service as the boundary train and through train in this cross-boundary transportation market. The HSR shuttle service linking Hong Kong to Shenzhen and Guangzhou, may grab boundary train and through train market shares due to the shuttle's faster speed. Meanwhile, the long-haul service of HSR may attract more passengers with the yearly increase of daily cross-boundary passenger trips. Compared to the through train and boundary train, the boundary bus and aircraft market shares are projected to experience a slight increase—6% and 5% respectively from 2018 to 2031. This shows that there are two different kinds of passengers existing in this market, bus passengers that are much more price sensitive, as HSR fares are two times greater than bus fares, and aircraft passengers that are much less concerned about ticket fares.

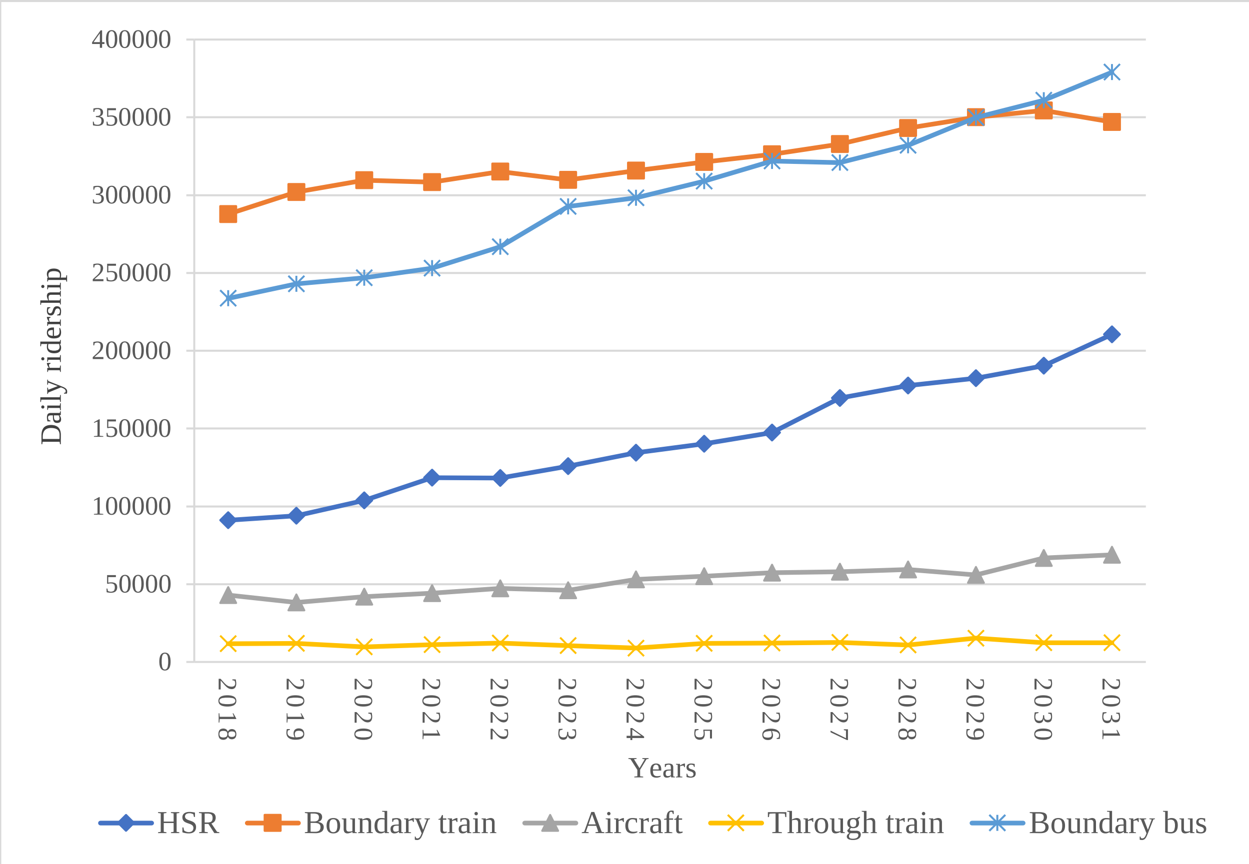

Figure S3. The mode shares of cross-boundary transport

Figure S3 shows the daily ridership forecasts of cross-boundary modes from 2018 to 2031 based on passengers' preference trends. The daily ridership of the boundary bus catches up with the boundary train after 2030. This is because the boundary bus has cheaper ticket fares compared to the boundary train. HSR also will become increasingly popular from the target opening year, whose daily ridership is projected to increase by 130% between 2018 and 2031. Thus, overall environmental performance will improve after 2018 with the high occupancy of HSR. Aircraft's daily ridership is also forecasted to increase by 60% from 2018 to 2031. However the through train's daily ridership has no obvious change during this time period.

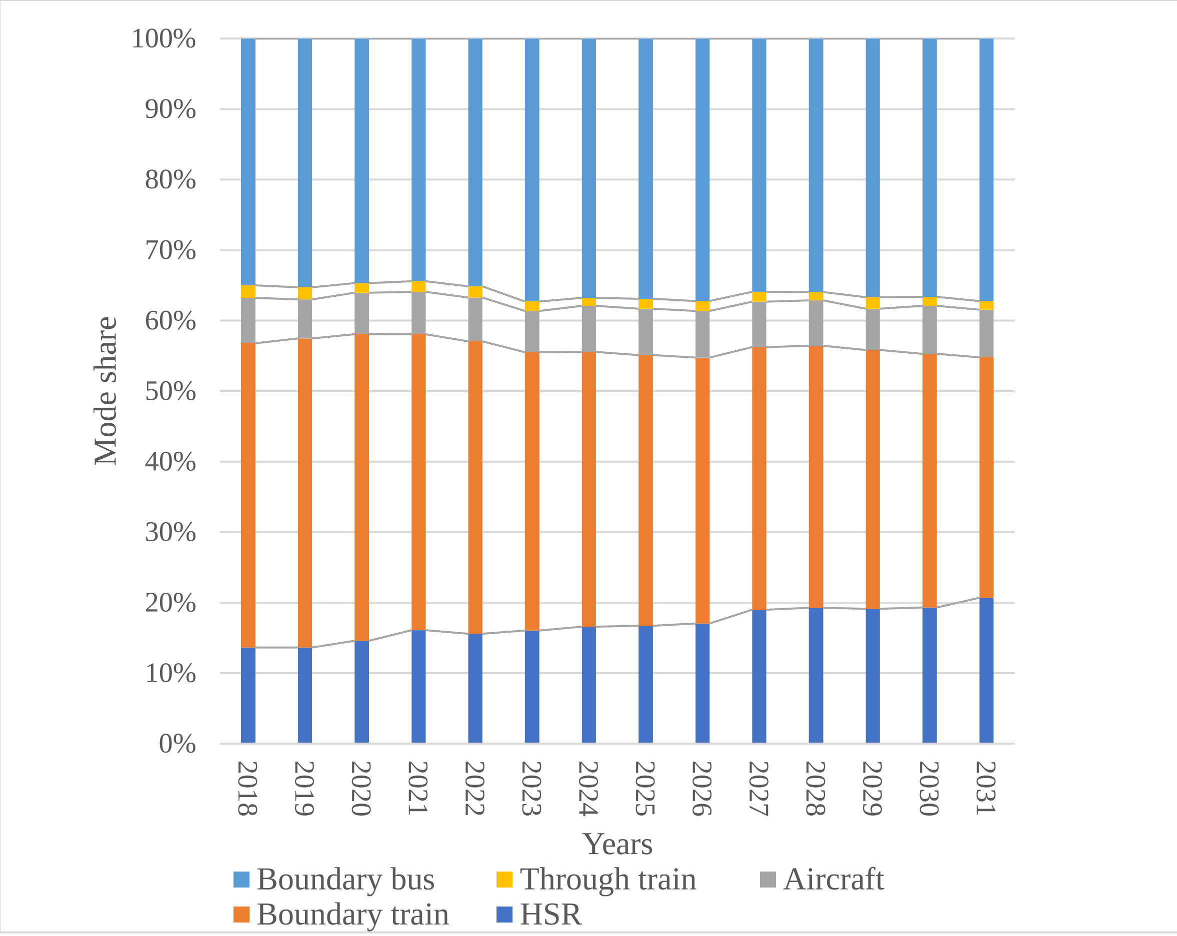

Figure S4. Daily ridership forecast of cross-boundary modes from 2018 to 2031

The following example analyzing of the impact of boundary bus travel time highlights the importance of considering passenger-mode-environment interactions. The boundary bus has the second longest travel time in this cross-boundary transportation system, following only the boundary train. This experiment is aimed at finding the relationships between the bus's travel time, the bus's occupancy rate, and system life-cycle environmental performance. When the bus's travel time is 70mins/100Km (the original travel time is 95mins/100Km), the occupancy rate of the bus is highest, increasing to 1.29. However, overall life cycle environmental performances worsen with the increase of the bus's occupancy rate, as well as specifically for HSR. The average life-cycle energy consumption, life-cycle GHG emissions and life-cycle SO_2 emissions are increased by 3%, 3%, and 1%, respectively based on the original scenarios.

These results thus may challenge the general assumption that a higher occupancy rate inevitably generates lower environmental impacts. These particular results can be explained by the reduced HSR market share with the acceleration of the boundary bus, as more and more passengers with cheaper ticket preference choose the boundary bus over HSR, consequently also reducing HSR's occupancy rate. The behavior of one mode not only influences its own environmental performance but can also affect overall conditions. Revealing such outcomes of passenger-mode-environment interaction is one of the distinctive features of ALENT. Thus, in this case maintaining the original, slower speed of the boundary bus may be more beneficial to the whole environment.

7. Cross-boundary passenger mode choice behavior survey

Background

In recent years, the Hong Kong government is becoming active in establishing the high-speed rail (HSR) to meet the increasing travel demand between Hong Kong and Guangzhou Pearl River Delta area.This survey is conducted to investigate the weighting of key drivers including run time, ticket fare, accessibility level and service quality which could affect passengers' travel mode choice travelling between Hong Kong and Pearl River Delta so as to estimate the passenger sharing of transport modes including high-speed rail, Guangdong through train, bus, airplane and East rail.

Key Drivers:

1. Run time:

The operation time of one transport mode travelling from starting point to destination with the unit of minute.

2. Ticket fare:

The non-discounted fare of one transport mode with the unit of HKD.

3. Service quality:

This includes car cleanness, neat appearance of employee, employee service attitude, comfort of air conditioning, on-time performance, and the convenience of reservation and ticketing.

4. Accessibility level:

This represents a locational characteristic that permits station or airport to be reached by the efforts of those at other places using various transport modes.

It is related to its geographical location (e.g. distance to urban center and other transfer station or airport) and the conditions of road networks.

The objective of this survey:

1. To identify the key drivers for passengers' choices and the respective weights of key drivers

2. To predict the basic passenger occupancy trend in the future so as to plan future transport service in Hong Kong

It is pleased if you could spend around 5 minutes to complete the questionnaire.

Statement of purposes

1. All data will only be used for research purpose. The confidentiality of information you provide will be carefully protected.

2. The personal data collected in this survey are only for uses stated above. Only aggregate information but not individual's details will be released to other parties or authorities.

Part A: Background Information

Please ✓ your information in the following. You should only ✓ one option unless specified.

1. Gender

- ○ Male
- ○ Female

2. Age

- ○ 20 or less
- ○ 21-30
- ○ 31-40
- ○ 41-50
- ○ 51-60
- ○ 61 or above

3. Usual Trip Purpose

- ○ Commercial trip
- ○ Commute
- ○ Study
- ○ Leisure
- ○ Other - Write In___________

4. Income per month (choose either one of HKD and RMB)

Hong Kong Area (HKD)

- ○ Below $10000
- ○ $10001-$25000
- ○ $25001-$40000
- ○ $40001-$60000
- ○ Above $60000

Pearl River Delta Area (RMB)

- ○ Below ¥4000
- ○ ¥4001- ¥8000
- ○ ¥8001- ¥15000
- ○ ¥15001- ¥20000

- ○ Above ¥20000

5. How often do you travel between Guangzhou and Hong Kong per month?

- ○ Less than once or once
- ○ Twice
- ○ Three times - Five times
- ○ Above five times

6. Occupation

- ○ Student
- ○ Manufacturing sector
- ○ Service sector
- ○ Government employee
- ○ Other - Write In___________

7. Destination

- ○ Hong Kong
- ○ Guangzhou
- ○ Shenzhen
- ○ Zhongshan
- ○ Dongguan
- ○ Other places from PRD area

8. Transport mode chosen for your usual trip

- ○ Guangdong through train
- ○ Bus

- ○ Airplane
- ○ East rail (Lo Wu/Lok Ma Chau)

9. Reasons to choose the transport mode you selected in Question 8 (You may choose more than one option)

- □ Shorter travel time
- □ Lower ticket fare
- □ Higher accessibility level (e.g. convenience of reservation and ticketing,
- □ stations accessibility)
- □ Service quality (e.g. staff service attitude, on-time performance, neat
- □ appearance of employee, car cleanness, comfort of air conditioning,
- □ convenience of reservation and ticketing)

Part B: Scenarios

For Question 10, please compare each pair of key driver according to our degree of concern when choosing a transport mode. (e.g. If you choose "0", this means you think the two key drivers are equally concerned. If you think that the key driver on the left is more important than the one on the right, please select a number between 1 and 8 on left side, and vice versa.)

0= equally concerned

2= moderately concerned

4= strongly concerned

6= very strongly concerned

8= extremely concerned

10. (a) Run time vs Ticket fare

Run time	-8	-6	-4	-2	0	2	4	6	8	Ticket fare

10. (b) Run time vs Service quality

Run time	-8	-6	-4	-2	0	2	4	6	8	Service quality

10. (c) Run time vs Accessibility level

Run time	-8	-6	-4	-2	0	2	4	6	8	Accessibility level

10. (d)Ticket fare vs Service quality

Ticket fare	-8	-6	-4	-2	0	2	4	6	8	Service quality

10. (e) Ticket fare vs Accessibility level

Ticket fare	-8	-6	-4	-2	0	2	4	6	8	Accessibility level

10. (f) Service quality vs Accessibility level

Service quality	-8	-6	-4	-2	0	2	4	6	8	Accessibility level

Part C: Suggestions

11. Please give a reasonable range for ticket fare about travelling between Hong Kong and PRD area (such as Guangzhou).

- Less than 120 HKD
- 120 HKD-180 HKD
- 181 HKD-250 HKD
- More than 250 HKD

12. Please give a reasonable range for travel time about travelling between Hong Kong and PRD area (such as Guangzhou). (Travel time includes walking time, waiting time, on-board time and interchange time)

- Less than 100 min
- 100 min - 150 min
- 151 min - 200 min
- More than 200 min

13. The Hong Kong High-Speed Rail will be operated in 2017. The travel time between Guangzhou and Hong Kong is estimated to be 48 minutes, the corresponding reasonable fare (one-way) will be:

- $50-$150
- $151-$300
- $301-$500
- $501-$800
- Above $800

14. Do you think there will still be a need to construct the Hong Kong Airport 3rd runway after the operation of the Hong Kong High-Speed Rail?

- O Yes
- O No
- O Not sure

Thank You!

End of Questionnaire

Thank you for your participation!

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