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A spatial agent-based model for environmental assessment of passenger transportation

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Abstract: This study presents an urban transportation simulation model for life-cycle environmental performance evaluation (ALENT). ALENT integrates geographic information to quantify stations' accessibility levels and construct real-world intercity transportation maps. A conceptual meta-theory from psychology is also adopted to form the behavioral rules of passengers choosing different transport modes as influenced in part by passengers' social networks. Operation scenarios are simulated for the year in which Hong Kong high-speed railway (HSR) is introduced, viewed from a life-cycle assessment perspective. 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%. ALENT can be used as a decision support tool for establishing sustainable passenger transportation systems.

Keywords: High-speed railway; Agent-based modeling; Logit model; Life-cycle environmental analysis

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

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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 operation of HSR is only a part of the whole life cycle of the HSR system, which also includes 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 and Ryerson 2014). Different levels of passenger occupancy can easily change the relative environmental performances of the various modes (Chester and Horvath 2009). 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 paper 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 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 paper 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.

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 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 considerable life cycle environmental benefits over other current transportation modes with state-of-the-art vehicles, renewable energy, and high ridership. Åkerman (2011) examined a proposed Swedish HSR track and found significant GHG emission reduction potential due to transportation modes shifting to HSR, even though new railway construction and maintenance could increase GHG emissions. Grossrieder (2011) 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 railway could go up to 50% (Chester and 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 and 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 of 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 and 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 and 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 a number of random non-neighbor agents. Here we use "friends" to represent social networks, implemented in line with the Watts-Strogatz model. The remainder of this paper 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.

Materials and methods

Figure 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 and Horvath 2009). 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 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 a number of "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.

Hybrid Logit and ABM model

As indicated previously, the motivation of this paper 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. The definitions of the model parameters are shown in **Table 1**. **Figure 2** shows the hybrid model design.

Compared to other discrete choice models, the utility of using a product in ALENT is that it not only considers the individual parts C_1 related to alternative modes' characteristics, but it also includes a social effect part C_2. 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 C_1 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):

$$U_{ij} = (1 - \beta_i) \times C_1 + \beta_i \times C_2 \tag{1}$$

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

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:

$$\begin{aligned} C_1 &= 1 - |P_i - d_i| \\ &= 1 - \sqrt{w_t \times (p_t - d_{i,t})^2 + w_f \times (p_f - d_{i,f})^2 + w_c \times (p_c - d_{i,c})^2 + w_a \times (p_a - d_{i,a})^2} \end{aligned} \tag{3}$$

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

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 (Yamaguchi and Yamasaki 2009; Levinson et al. 1997; De Palma and Rochat 2000; Liu and Li 2012), travel time (Levinson et al. 1997; De Palma and Rochat 2000), accessibility level (Chester and Horvath 2010a), and service quality (Levinson et al. 1997; De Palma and Rochat 2000). Ticket fare is the non-discounted fare of one transport mode. Travel time includes walking time, waiting time, on-board 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 and 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.

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

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

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):

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

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, 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.

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 and Horvath 2010a; Chester and Horvath 2009; Chester and Horvath 2010b; Yue et al. 2015; Grossrieder 2011; Chester 2008; Chester et al. 2010) 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 and **Table 3** 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.

Case study

Hong Kong-Mainland China 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 for 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, 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 3 shows a screenshot of ALENT. ALENT was built with Netlogo-one, 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 (Zhu 2015; Yin 2013; Southworth 2005). The accessibility level of the specific transport mode is also measured with this spatial map, which depends on Euclidian distances (Li and 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).

In ALENT, the modes' key drivers are normalized with real operation data and are represented in **Table 4**. Travel time and ticket fare are negative indicators, and accessibility level and service quality are positive indicators. The faster the mode, the larger the travel time dimension of the mode. The cheaper the mode, the larger the ticket fare dimension of the mode. All key drivers are normalized between 0 and 1. 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.

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 in terms of 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 5 shows the best parameter combinations which generate Monte-Carlo simulation outputs (100 runs) fitting the historical data best in terms of minimizing squared residuals. The calibration results with the best parameter combinations are shown in **Table 6**. The calibration experiment finds that passengers' average preferences for travel time and ticket fare improve incrementally over the years (see **Table 5**), 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.

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 and Housing Bureau 2009).

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**.

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 4**. The mode share of Boundary train is reduced by 10%, and HSR gains 13% market share in the opening year.

Table 7 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):

$$\text{Occupancy rate}_i = \frac{mode\ share_i \times total\ number}{daily\ frequency_i \times no.of\ seats_i} \qquad (10)$$

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 7** 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).

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.

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**.

$$\text{LCI result/PKT} = \frac{\text{LCI result/VKT}}{Occupancy\ \text{rate} \times \text{no. of seats}} \quad (Occupancy\ rate < 1.0) \tag{11}$$

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

In **Figure 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 8**, 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.

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 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.

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 9** 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.

Conclusions

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).

Programming Information

The ALENT model was developed using the Netlogo platform provided by Northwestern University (https://ccl.northwestern.edu/netlogo/). Program scripts are available upon request.

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List of Tables

Table 1. Definitions of the main calculation parameters

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

Table 2. 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
Midsize 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 3. 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
Midsize aircraft	312	22,000	17	60	70	2.2	7.0
Urban bus	43	3,300	1.9	11	22	1.4	3.8

Table 4. 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

Note: HSR refers to Guangzhou-Shenzhen-Hong Kong HSR. Boundary train refers to passenger train service starts at Hung Hom Station in Kowloon and terminate 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.

Table 5. 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 6. 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.

Table 7. 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

Table 8. 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: $Weighted\ average\ = \sum mode\ share_i \times LCI\ result/PKT_i$

Table 9. 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.