Sustainable Cities and Society 49 (2019) 101567

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Considering user behavior in free-floating bike sharing system design: A data-informed spatial agent-based model

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ARTICLE INFO

Keywords:
User behavior
Bike sharing system
Data-informed
Agent-based modeling

ABSTRACT

Although bike-sharing has been recognized as an active and sustainable transportation mode, the dramatic expansion of free-floating bike sharing (FFBS) services generates problems such as illegal parking and low utilization. An effective FFBS system needs to be highly regulated. This study combines Big Data and spatial agent-based modeling to understand the interactions between stakeholders to assist the bike-sharing system design. The key design decisions considered are the locations and capacities of bicycle parking lots in the system, as well as the connected bike lanes between parking lots. The model has been applied to the case of Hong Kong for demonstration. The results show that the parking lots with higher capacities are mostly close to the metro stations, and the cycleways are disconnected even for those that have high cycling occupancy. The results indicate that for most target people to be willing to change the parking location, the minimum fare discount rate for doing so should be set to 30%. The average trip time can be reduced by 3.8%, and per user cost can be reduced by 2.4% with an expected investment of 0.12 million USD to build new cycle tracks and connect existing cycleways.

1. Introduction

As fuel prices rise, traffic congestion worsens, populations grow, air quality worsens, land use management and greater world-wide consciousness arise around climate change, it will be necessary to find sustainable modes of transport and better adapt existing modes to move people in more environmentally sound, efficient, and economically feasible ways (Bauman, Crane, Drayton, & Titze, 2017; DeMaio, 2009; Shaheen, Guzman, & Zhang, 2010). Bike-sharing, or public bicycle programs, is emerging as a prominent alternative to assist in solving the above problems. Bike-sharing schemes have grown in Europe, North America, South America, Asia, and Australia (Liu, Jia, & Cheng, 2012). This mobility trend has experienced exponential growth over the last years, with over 1100 cities actively operating automated bike sharing systems as of 2017, deploying an estimated 1,900,000 bikes worldwide. Bike-sharing schemes have evolved over the years, initially consisting of free-to-use bike systems and followed by coin-deposit systems, while the majority of today's bike-sharing schemes are IT-based systems, with some cities incorporating additional functionalities such as demand-responsive and multi-modal systems with real-time information (Shaheen et al., 2010). The emergence of free-floating bike-sharing (FFBS) services has revolutionized the market. The new services make renting and returning bikes more convenient than ever.

As an FFBS fleet size is not constrained by the capacity of docking stations, it is much easier to increase fleet size in the FFBS system. The recent dramatic increase in bike fleets is far beyond the expectations of transportation and urban planners. Before the introduction of shared-bike service, Hong Kong did not have a city-wide public shared-bike system as the only one operates within a park. The rapid expansion of free-floating bike sharing systems in Hong Kong started in April 2017, when the first operator launched its service. There were 25,000 shared bikes distributed in Hong Kong at the peak in the first half year of 2018 (Leung, 2018). If there are too many bikes in the system while the utilization of the bikes remains at a low level, such services could be fiscally unsustainable or potentially harm the urban transport system. In Shanghai, China, there is a bicycle graveyard where 100,000 unused bikes were parked (Bird, 2018). In Hong Kong, the government also received more than 800 complaints about illegal parking and public space occupation of shared bikes in one year (Legislative Council Secretariat, 2018). Amsterdam decided to ban free-floating shared bicycles in September 2017 due to the sheer number of bikes taking up space in the city (Van Roy, 2017).

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https://doi.org/10.1016/j.scs.2019.101567
Received 18 January 2019; Received in revised form 28 March 2019; Accepted 22 April 2019
Available online 08 May 2019
2210-6707/

Therefore, the FFBSs should be carefully regulated, taking into the consideration FFBS infrastructure represented as parking lots and bike lanes. In our study, the designated parking lots for FFBS are different from the stations in a station-based bike sharing system (SBBS). As only bike racks need to be installed in parking lots for FFBS rather than expensive kiosk machines and docking stations for an SBBS, the infrastructure costs of FFBS are considerably lower than for SBBS. Generally speaking, the number of parking lots for FFBS is much greater than the number of stations in SBBS. As a result, without considering the land use constraint, the high-density distribution of proposed FFBS parking lots can be achieved, and consequently, the high accessibility level that FFBS provides will not be compromised. The Hong Kong Government endeavors to foster a “bicycle-friendly” environment in new towns and new development areas in Hong Kong. The Transport Department will provide not less than 3500 additional bicycle parking spaces at suitable locations to facilitate the public cycling need (Hong Kong Transport Department, 2018). At the same time, the government will develop the cycling network and improve existing cycling facilities to promote cycling as a green mode for short-distance commuting. It is critical to developing a high-performance agent-based model to understand bike users’ travel behaviors and support system design by assessing the impact of changes in bike-sharing infrastructure at a fine spatial resolution.

A novel approach that combines Big Data and ABM for efficient FFBS system design with spatial information is presented in this study. The availability of this “big data” (i.e. large-scale data sets) on individual bike-sharing travel patterns, represents untapped opportunities to consider individual travel behavior when improving bike-sharing system design. The contributions of this research to methodology mainly focus on three aspects: 1) spatial clustering; 2) high-resolution; and 3) spatial extensions. One of the spatial clustering algorithms, k-medoid clustering algorithm, is applied to spatially cluster the origins/destinations (O/D) points into bike-sharing parking lots. A high-resolution ABM was developed based on the collected bike-sharing travel information that generates agents with the real trip start time and O/D points. Geographic information system (GIS) extensions are incorporated to enhance the reality of the model. The transport modes including bike and walk are simulated in their own traffic lanes (cycleway and footway) based on the corresponding speeds. This study aims to understand the travel behaviors of bike-sharing users and assist decision making on FFBS system design through a data-informed spatial agent-based model.

2. Related research

The FFBS is originated from China, which has not been very popular in other countries. The system design studies related to FFBS are sparse, most are focused on SBBS. Some SBBS system design methods also can be used as references for FFBS system development. Thus, the system design studies related to FFBS and SBBS are both reviewed. One way of improving the service quality of a bike-sharing system (BSS) is to improve its system design. Key design decisions include station size, station location, number of bikes at stations, number of stations and bike lanes connecting the stations. Some studies are dedicated to optimizing these decisions against economic constraints, including facility cost and travel value of time, or demand constraints. García-Palomares, Gutiérrez, and Latorre (2012) used a GIS approach to identify the potential trip demand and locate stations using location-allocation models, but the passengers’ behaviors were not considered. Vogel and Mattfeld (2011) applied data mining to operational data to offer insight into typical usage patterns of BSS then to predicate the bike demand in improving strategical and operational planning. Yan, Lin, Chen, and Xie (2017) focused on leisure bike-sharing trips and presented four time-space models considering the stochasticity of demand and different optimization objectives. Nair and Miller-Hooks (2016) formulated an equilibrium network design model to determine the optimal system configuration of a bicycle sharing system in Washington, D.C. which involved a fleet of bicycles positioned at various stations across the large network. Romero, Ibeas, Moura, Benavente, and Alonso (2012) proposed a bi-level mathematical programming model to optimize the location of public bicycle docking stations, a genetic algorithm was used in the upper level to search for the distribution of a given number of docking stations that maximized the number of bicycle users, and the interactions through the modeling of the modal split between car and bike were considered in the low level. Martinez, Caetano, Eiró, and Cruz (2012) presented a heuristic, encompassing a Mixed Integer Linear Program (MILP) to simultaneously optimize the location of shared biking stations, the size of the vehicle fleet, and regulates the bicycle relocation activities in a regular operation day. Garcia-Gutierrez, Romero-Torres, and Gaytan-Iniestra (2014) determined the station's location based on these people mobility considerations, and the estimated number of bicycles/parking lots per station given the probability of using the BSS system based on the knowledge of the potential user preferences.

The measure for BSS design also depended on the objective of stakeholders (Ho & Szeto, 2014). From a government perspective, social benefits such as environmental benefits, user satisfaction, and demand coverage are important. For private BSS operators, revenue and return on investment rate are perhaps more essential. Lin and Yang (2011) presented a mathematical formulation considering the service level and investment cost, including station cost and bike lane cost. To make the model more practical, Lin, Yang, and Chang (2013) further formulated the design as a hub location inventory problem and presented a greedy drop heuristics method to solve the problem posed in a hypothetic transport network. The mathematical model proposed by Frade and Ribeiro (2015) aimed at maximizing the demand coverage and return on investments as an optimization target at the zone level.

Three recent papers on FFBS considering the system design were found. Reiss and Bogenberger (2016) identified the mobility patterns based on detailed GPS-Data Analysis for the FFBS and built a demand model to forecast the upcoming demand and reveal the optimal fleet distributions. A validation method was used to evaluate and proof the benefit of potential relocation. Caggiani, Camporeale, Ottomanelli, and Szeto (2018) proposed a methodology for the strategic design of FFBS whose facilities could be allocated in the territory according to spatial and social equity principles. Bao, He, Ruan, Li, and Zheng (2017) used a greedy network expansion heuristic to generate a bike lane network plan set to maximize the usage while remaining within a construction budget and considering connectivity constraints. This approach is not applicable when individual trajectories are not available.

To the best of our knowledge, there is little literature integrating free-floating bikes with a public transportation system with consideration of the spatial structure of transport network and users’ interaction and adaptation behaviors at the same time, especially in the case of Hong Kong.

In this research, agent-based modeling (ABM) is used to overcome the limitations of previous studies. ABM has been used to investigate many transportation science problems such as the mode choice problem (Lu & Hsu, 2017; Lu, Hsu, Chen, & Lee, 2018); traffic signal control (Aziz, Nagle et al., 2018), parking (Levy, Martens, & Benenson, 2013; Zhang, Guhathakurta, Fang, & Zhang, 2015) and hurricane evacuation (Ukkusuri et al., 2017). There have been a few studies applying agent-based approaches to model trips related to bicycling include supporting walk-bike infrastructure investment (Aziz, Park et al., 2018) and improving system sustainability with bike sharing (Lu et al., 2018). Traditional econometric and approximate proportional models do not as such accommodate agent level interaction. In contrast, ABMs can capture dynamic attributes such as learning from experience and spatial evolution in the system (Lu et al., 2018). For instance, in our study, bike operators can dynamically deploy the parking lots with optimal capacities based on daily demand. With the extension of GIS on an ABM platform, all the bicycling activities can be simulated on a real road

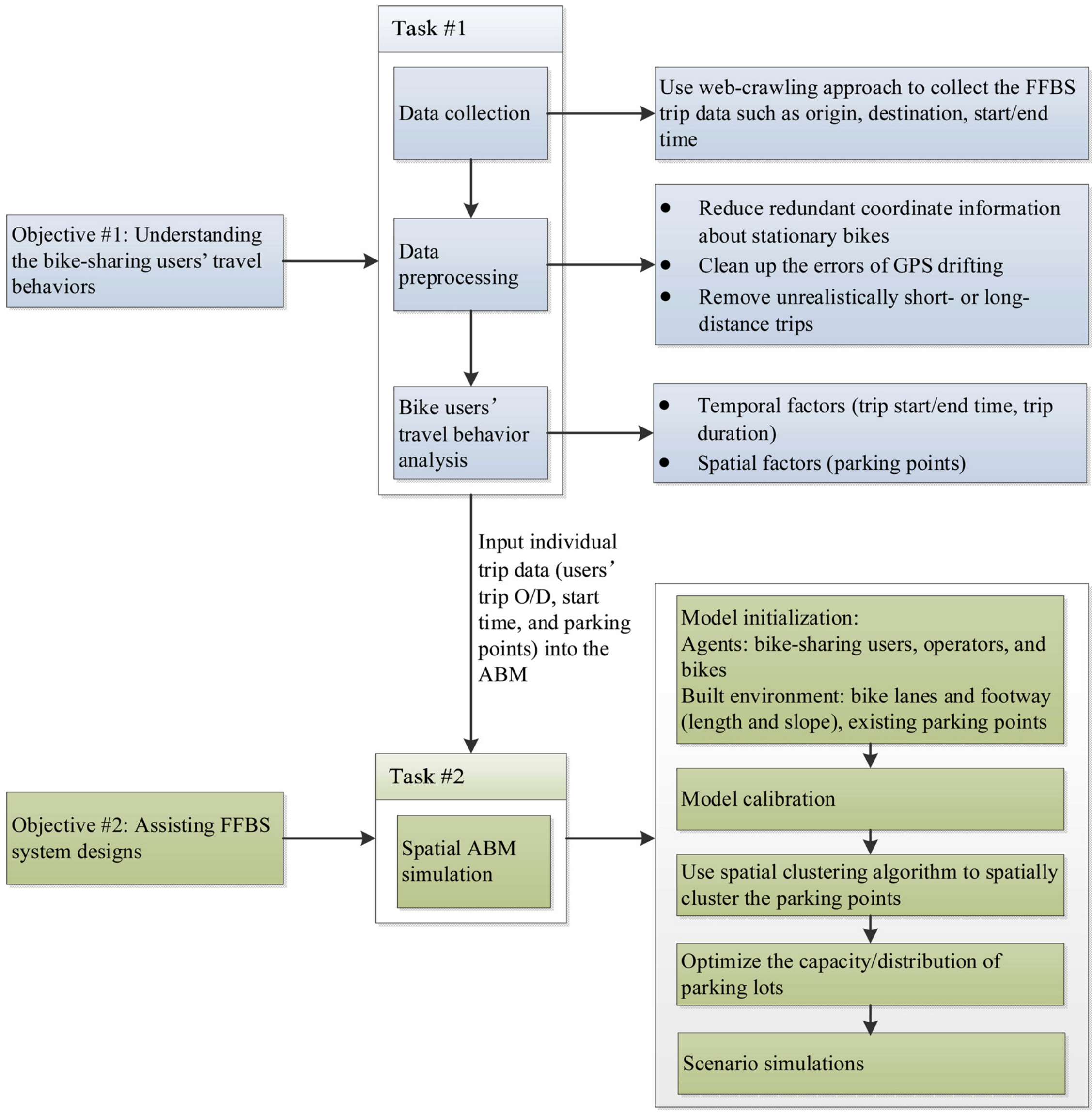

Fig. 1. Research workflow.

network. Moreover, the web-crawling method is used to collect the global positioning system (GPS) records of bike-sharing activities. The bike user agents' travel information (including trip origin/destination, trip start time) have a one-to-one correspondence to the individual-based bike-sharing travel data. Thus, a high-resolution spatial ABM is built to simulate and represent a BSS with a bottom-up approach, simulating the interactions between bike users, operators, and the government, and representing the evolutions of users' cycling choices as influenced by different FFBS system formulations.

3. The method

Fig. 1 shows the research workflow. In order to assist decision making for FFBS system design, two tasks are proposed: bike user travel behavior analysis and spatial ABM model development.

3.1. Descriptive analysis of bike users' behaviors

3.1.1. Data collection

As FFBSs are commonly operated by private companies, they usually do not grant the general public access to needed data. To solve this problem, a web-crawling method was developed to collect streaming data of bike-sharing trips in real-time. A program has been built to simulate the requests made in the smartphone app and systematically collect the server's response, containing the list of nearby available bikes. The hired bike will disappear from the pool, and if the trip terminates, it will reappear in 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 chronologically. The unique 9-digit bike ID and the real-time GPS location of every available FFBS bike in Hong Kong were continually recorded at a frequency of 5 min on average. Data from one of the largest FFBS bike operators in Hong Kong has been collected. The data for this study were collected from February 8 to February 28, 2018. The data are fully anonymous—no user information is associated. This research examines a large-scale dataset containing 58198 bike-sharing trip records in Hong Kong to explore the impacts of individual travel patterns. Each record has GPS coordinates of one specific bike and an observed timestamp.

3.1.2. Data preprocessing

Some redundant information and errors exist in the raw data, so we run a series of preprocessing steps. The first preprocessing step reduces redundant coordinate information about stationary bikes and cleans up some errors due to GPS drifting. For example, one kind of GPS drifting occurs from instabilities in civilian GPS sensors, which can cause a bike to seemingly teleport from one location to another before shifting back to the same location. We then removed some unrealistically short- or long-distance movement (riding time less than 1 min and longer than 3 h) because such movements might not be associated with an actual cycling activity (Shen, Zhang, & Zhao, 2018). For instance, the movement of a bike over a very short trip time could result from noncycling causes such as GPS instability, local bike relocation by bike-sharing operators, etc. And the movement of a bike for a very long trip time could result from bike maintenance and relocation by bike-sharing operators. After overly long/short trips based on duration were singled out, 98.6% of the BS trips were selected for subsequent analyses.

3.1.3. Travel behavior analysis

To provide insights into the modeling part, user behavior analysis is conducted. A descriptive analysis is conducted to identify the travel patterns of FFBS users in Hong Kong. The bike-sharing travel information, including temporal factors (trip start/end time, trip duration), spatial factors (O-D points) are extracted and saved in the dataset for population generation in the ABM model.

3.2. Spatial agent-based model development

3.2.1. Model experiment settings and initialization

The model was built using the GAMA platform (GAMA, 2016), which can construct spatially explicit agent-based simulations. In the ABM model, there are three agents: bike users, operators, and bikes. These agents interact with each other and also adapt to changes in the environment. The time step is one minute. The spatial resolution is 1 m × 1 m.

3.2.1.1. Bike users. The bike users' trip information including O-D matrix and trip start time are directly imported from the individual bike-sharing trip information in the dataset. Fig. 2 shows the import process of bike-sharing trip data. The disorganized trip origins and destinations from the bike-sharing trip dataset are identified as the parking points, which are saved in an ESRI shapefile format for the subsequent spatial cluster analysis. The bike users have different distributions of socio-economic status represented as different values of time (VOT) of cycling and walking. The cyclists' VOT are higher than the VOT for the car and public transport, as the time spent on cycling is comparatively unproductive. However, Van Ginkel (2014) claimed that VOT of cycling is lower because it brings health and convenience for the users. Koppelman and Bhat (2006) indicated that the 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. In this study, the VOT of cycling and walking are evaluated as 60% and 100% of the bike users' hourly salary level (Lu & Hsu, 2017; Lu et al., 2018). The user agents' hourly incomes are based on the distribution of hourly wage (all employees) from the *Report on Annual Earnings and Hours Survey* (Hong Kong Census & Statistics Department, 2017). But it should be acknowledged that most bike users are young people, whose hourly incomes may not fully correspond to the survey data on all employees across a wider age bracket.

The accessibility of FFBS parking lots is a crucial factor in encouraging bike sharing use. 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. We only consider the accessibility level as the key factor influencing the bike use. This is because the bike agents embedded in the model are already bike users based on the real bike-sharing trip data. The only difference is the changes in the parking lots' distributions, which is represented as the accessibility level, quantified by the distance between O/D and bike parking lots. Lin et al. (2013) showed that the bicycle stations should not be located more than 300–500 m from important origins and destinations of traffic. Thus, people will become a bike user if at least one bike-sharing parking lot is located less than 500 m from the user agent's origin/destination.

3.2.1.2. Bike operators. Bike operators deploy their bikes with the optimal distribution and fleet size to meet the daily demand. If the use frequency of the bike at a specific parking lot is zero, the operator will remove this bike in the next day, and the capacity of this parking lot will be reduced by one accordingly. In contrast, if a user cannot rent

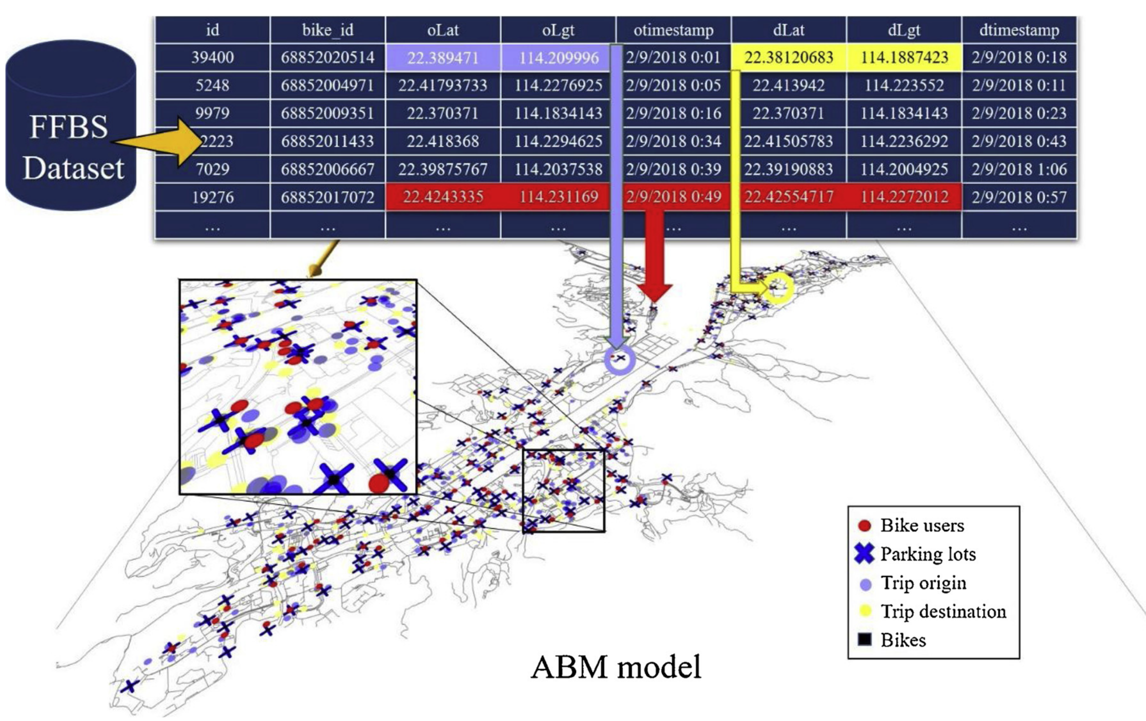

Fig. 2. The prototype of the spatial ABM model.

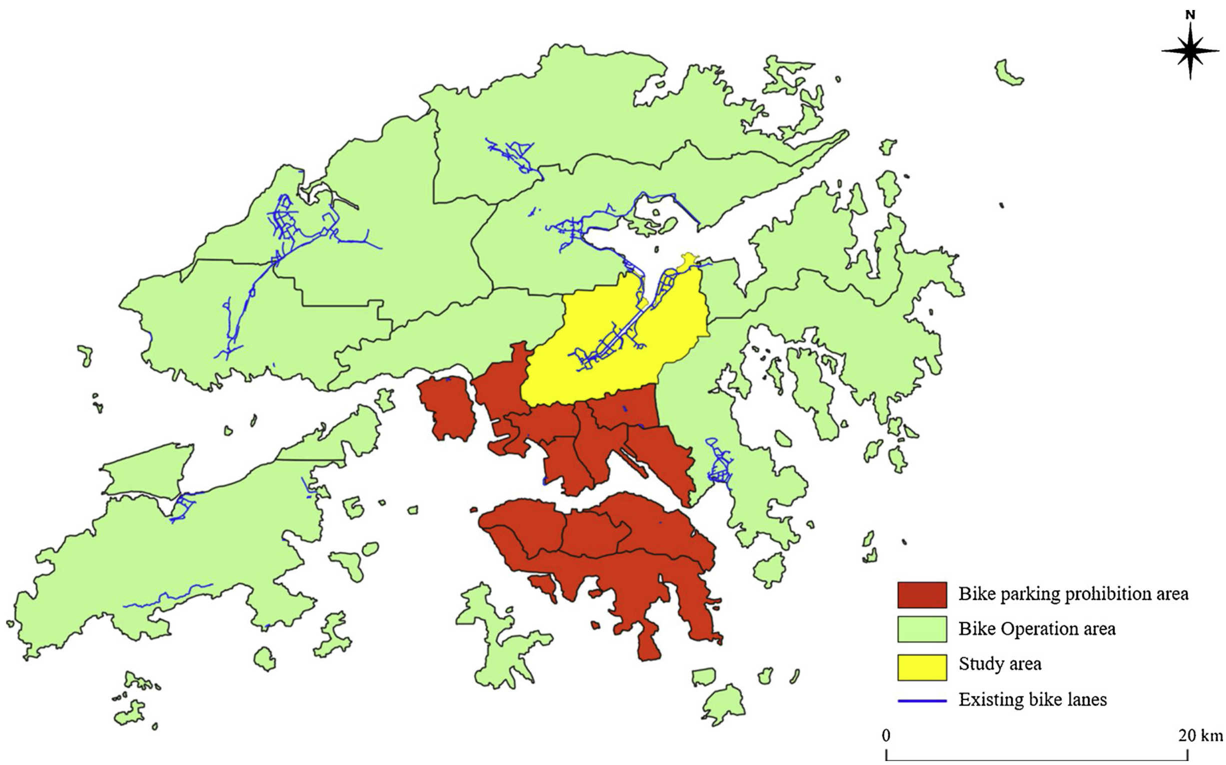

Fig. 3. The study area and nearby areas.

a bike at this parking lot, the operator will put one bike at this parking lot next day, the capacity of this parking lot increased by one accordingly. After several day-to-day adjustments, a supply and demand balance is achieved. The optimized locations and capacities of parking lots with the determined amount of parking lots can be realized.

3.2.1.3. Bikes. As FFBS bikes are not designed for racing, we use 15 km/h as a cycling reference speed on the level cycleway (Shen et al., 2018). Some cycle lanes are isolated and only connected by footway, where cycling is not allowed (Hong Kong Transport Department, 2018). Therefore, 5 km/h on average, a speed equivalent to walking, can be achieved on the footway. The dataset gives accurate time and geolocation date of the trip O-D, while it does not provide information about the route that users choose. The travel trajectories in this study are the shortest possible routes generated on a high-resolution GIS map.

3.2.1.4. The environment. The proposed model was applied to Sha Tin, Hong Kong for demonstration (see Fig. 3). The Sha Tin study area is highlighted in yellow in Fig. 3. The red area is the metro area, where bicycle parking is prohibited. Sha Tin is the most populous city in the New Territories of Hong Kong, with a 2011 population census of 630,273 within an area of 35.87 km^2. Sha Tin also has a "bicycle-friendly" environment with well-equipped bike infrastructures. The prototype of the spatial ABM model is shown in Fig. 2. The grey lines represent the footways and cycleways. The bike users are represented as red dots. The trip origin and destination exported from the bike-sharing trip dataset are shown as light-blue and light-yellow dots, respectively. The clustered parking lots are represented as blue crosses. The bikes are shown as the black squares, which are parked at the parking lots. A digital elevation model (DEM) has been constructed so that contiguous slopes along bike lanes can be obtained, which is used as a factor impacting bicycling speed in the estimation (see Fig. 4). Based on the real road network, the bike users who have specific origins and destinations are assumed to choose the shortest path for cycling. The shortest path here means the path with the shortest travel time by considering the length and slope simultaneously. Their trajectories are generated and saved as an ESRI shapefile format for the road occupancy analysis.

3.2.2. Model calibration

The day that used for calibration was selected randomly, based on the criteria that weather was suitable for cycling and most cyclists are observed on that day based on the bike-sharing trip dataset. The calibration method for picking one representative day is based on Wallentin and Loidl (2015). Finally, Friday 09 February 2018 was selected. On this date, the maximum temperature was slightly above 17 °C, and no precipitation was recorded.

The number of bike users, bicycling trip start time, and the origin/destination of the bicycling trip in the model are from the bike-sharing trip dataset collected with the web crawling method. Only two kinds of data, average trip time and a number of used bikes, were used to calibrate the bicycling trip behaviors. In the business as usual (BAU) scenario, there are no clustered parking lots, the bike users start their bicycling trips from their own trip origin at a specific start time and end their trips at their own trip destination. First, we compared the trip time generated from the BAU model and reality. Second, there are 540 bike users and 336 used bikes from real data, which means some bikes' use frequency is more than one. Based on the simulation results, the previous endpoint and current start point of the bike used by different users are sometimes not the same places. This phenomenon can be explained by the GPS error of the users' smartphones. The maximum GPS error range is 80 m. Table 1 shows the calibration results. The model has a good fitting degree with reality. The simulated average trip time is shorter than the real trip time, likely because the trajectories of bike users are defined as the shortest path, which may cause the simulated trip time to be shorter than the real trip time, especially for round-trips that have the same or very similar origin and destination.

3.2.3. Spatial cluster of the disorganized bike-sharing parking points

The trip O-D geolocation in the dataset suggests the demand to rent/

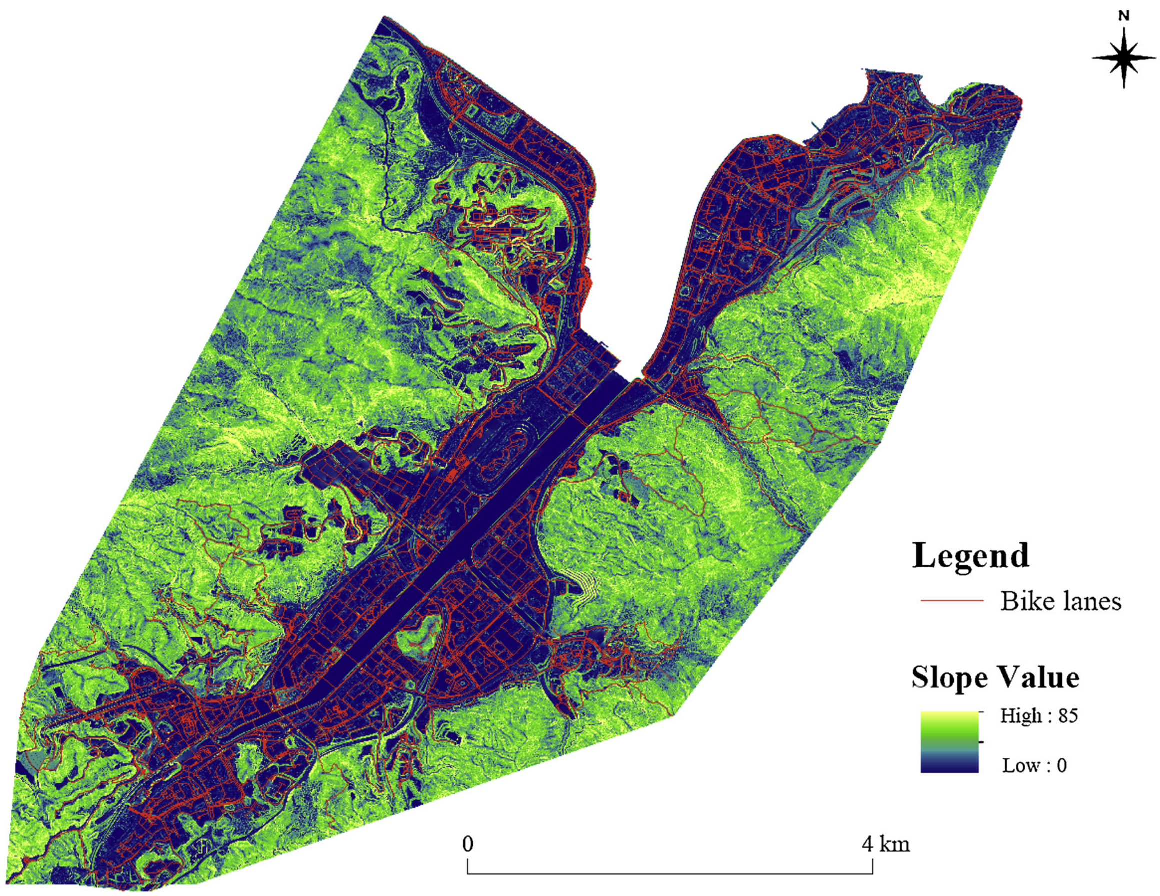

Fig. 4. Digital elevation model of Sha Tin.

Table 1
The model calibration.

Scenarios	Average trip time (m)	Number of used bikes
BAU	13	340
Reality	16	336

Table 2
The performances of hierarchical and k-medoid clustering algorithms.

Cluster threshold (m)	No. of parking lots (k)	Hierarchical performance	K-medoid performance
100	350	45	40
200	132	285	121
300	70	697	194
400	30	1178	320
500	18	1241	409
600	15	1256	450
700	10	1286	596
800	3	1405	1286
900	2	2989	1660
1000	1	3198	2678

return a shared-bike at such a spot. We use spatial clustering algorithms to cluster the disorganized trip O-D points into candidate parking lots. The bike users rent or return the bikes at these parking lots. The trip O-D points' distance between each other less than the cluster threshold is aggregated into one candidate parking lot. The cluster threshold is measured based on real road network distance. Thus, the spatial clustering algorithm such as k-means and DBSCAN based on Euclidian distance are out of consideration. Two spatial clustering algorithms, hierarchical and k-medoid clustering algorithms, are tested. The hierarchical clustering algorithm, specifically, means the hierarchical single-linkage agglomerative algorithm, which works on the location attribute and considers that a group is composed of points following this property: a point belongs to a group if there is at least one point in this group that is at a distance lower or equal to the cluster threshold. The center of hierarchical clustering is the point with the minimum distances between other points in the cluster. The k-medoids algorithm is a clustering algorithm related to the k-means, with the only difference being that k-medoids chooses data points as centers instead of the centroid of that cluster. The average accessibility distance of the bike users to the bike parking lots are changed with these spatial cluster processes, and bike usage is also influenced. Table 2 shows the performances of these two spatial clustering algorithms. The performance here refers to the average distance between points labeled to be in a cluster and a point selected as the center of that cluster, indicating how compact each cluster is. The number of parking lots is generated from hierarchical clustering algorithm with the different cluster threshold from 100 m to 1000 m with the step of 100 m. The k in the k-medoid clustering algorithm is defined with this number of parking lots. We can see that the k-medoid algorithm has better performance with the same number of parking lots. Fig. 5 shows the clustering results of these two algorithms with the same number of parking lots. Different colors represent different clusters. We can see that the clustered parking lots are distributed more uniformly with the k-medoid clustering algorithm, and the better performance—higher accessibility level—can be explained. Thus, the k-medoid clustering algorithm is selected to generate parking lots.

3.2.4. *Optimization of the location and capacity of parking lots*

The criteria for optimization of the location and capacity of the parking lots are defined as 1) minimizing the users' travel cost incurred

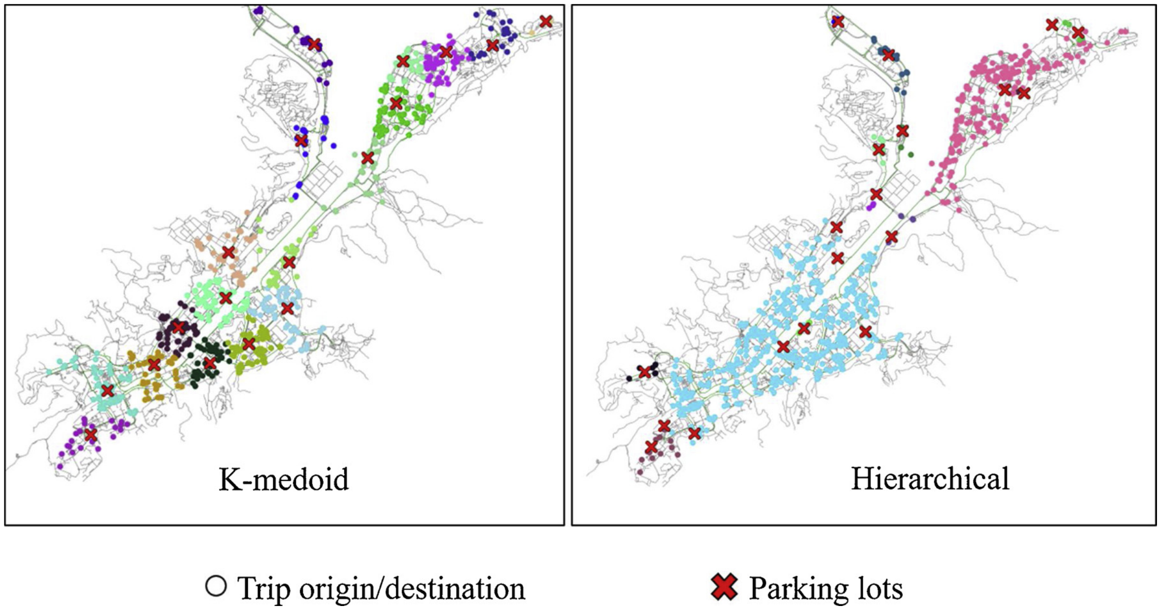

Fig. 5. The distributions of the parking lots with the two clustering algorithms.

in the bicycling trips, and 2) minimizing the system cost of the bike sharing operator. In comparison to the SBBS, FFBS saves on start-up costs by circumventing the construction of expensive docking stations and kiosk machines. Thus, the construction cost of parking lots is not considered in this study.

There is a basic tradeoff in determining the locations and capacities of bicycle parking lots. The user cost can be reduced with the increase of the parking lots and bike fleet size, but the system cost may be increased with the expansion of the FFBS. Determining the optimum distribution of the parking lots is a multi-objective optimization problem. The problem formulation is presented as follows:

Objective functions:

$$\text{Min} \quad UC = EC + HC \tag{1}$$

$$\text{Min} \quad SC = OC + CC - (EC + \text{deposit} \times \text{no.} \quad \text{users} \times 5\%) \tag{2}$$

UC and SC refer to the user cost and system cost. EC and HC represent the explicit cost and hidden cost of users. Explicit cost refers to the service fees of bike-sharing. And the hidden cost is related to the travel time and access time (the walking time to take or park the bikes at the designed parking lots) of bike users multiplied by their corresponding VOT. OC and CC represent the operating cost and capital cost of the bike-sharing system, respectively. Operating costs incur from maintenance, distribution, staff, insurance, office space, storage facilities, website hosting and maintenance (DeMaio, 2009). Capital costs include purchase and fabrication of the bikes (DeMaio, 2009). The lifespan of bicycles is assumed to be three years. The straight-line depreciation method is applied to calculate the yearly capital cost, which can distribute the fixed assets evenly to each year according to the service life. We also assume there is a 5% annual rate of return from the bike users' deposits.

The number of possible solutions to the optimized distribution of parking lots is too large for enumeration, as much as the total number of bike-sharing points in reality. Thus, a heuristic technique known as Pareto optimization is proposed to solve optimization problems. Heuristic methods have several advantages, such as that they are easy to implement on a computer, and they can be applied to virtually any ABM. This is particularly important for models that are too complex for conversion to other mathematical forms (Oremland & Laubenbacher, 2014). In this study, a genetic algorithm (GA) is applied to search the control space in an attempt to find the Pareto frontier. Fig. 6 shows the Pareto frontier.

Solutions on the Pareto frontier represent those that cannot be improved upon in terms of one objective without some sacrifice in another. In this sense, each solution on the Pareto frontier is optimal concerning some choice of weights. Fig. 7 shows one of the optimum distributions of the parking lots (k = 135). The corresponding average accessibility performance is 106 m, which is below the maximum walking distance. Based on the parking lots distribution, we can find certain parking lots are located around the metro stations and riverside. As we mentioned before, the bike will be removed if its daily utilization is zero and the corresponding capacity of these parking lots will be reduced by one, and a parking lot's capacity will be increased by one if one user cannot rent a bike in this parking lot. The optimized capacities of parking lots are obtained with the day-to-day adjustment. Because human mobility behavior is 93% predictable (Song, Qu, Blumm, & Barabási, 2010), we can foresee an individual's future whereabouts based on his or her previous trajectory, especially for the commuter trips during weekdays. Thus, the optimum locations and capacities of parking lots can meet the daily bike-sharing demand well. The corresponding capacities of parking lots based on the optimum distribution (k = 135) are presented in Fig. 7. We can see that the parking lots close to metro stations have higher capacities, which means bike-sharing may be used as first/last mile connections of the transit.

3.3. Scenarios simulations

3.3.1. Parking incentive

Based on the simulation results, the parking lots with higher capacities are mostly close to the metro stations, which leads to the problem of over-clustering of bicycles around public transit stations during peak hours. To solve this problem, parking incentives are proposed based on the cycling trajectories in the ABM model. For example, bike user A always uses FFBS to connect the first-mile metro trip from home to the metro station on weekdays. Because the presence of too many bikes obstructs the entryways of metro stations during the morning peak, the cheaper-parking incentive will be sent to the people A's smartphone to encourage him to park the bike at other parking lots with an acceptable walking distance to the metro station. The bike user's utility can be changed, which is represented as the user cost, where the explicit cost—the cycling fee—may be reduced with the incentives, but the hidden cost related to the walking time may be increased. If the utility is improved, in other words, the user cost is reduced, the bike user will

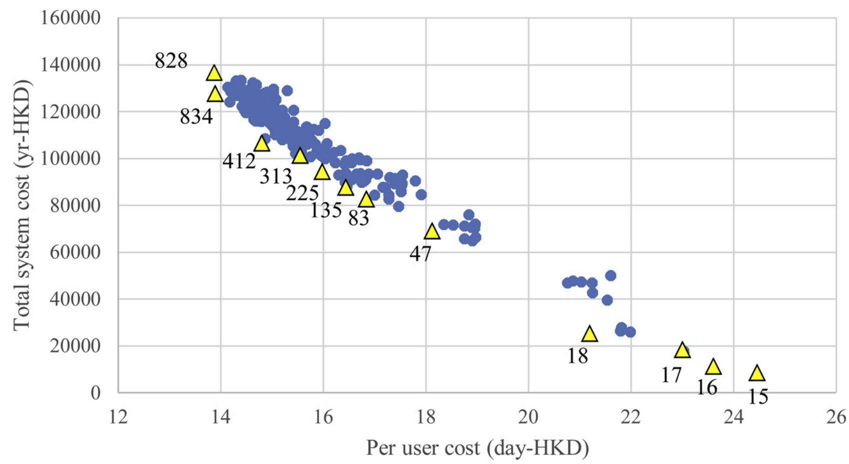

Fig. 6. The Pareto frontier of the number of parking lots.
Notes: Frontier points are marked with a triangle and non-frontier points with a circle; the number in the figure is the k in the k-medoid algorithm, which also equals the number of parking lots. Here 1 HKD ≈ 0.13 USD as in April 2019.

Fig. 7. The locations and capacities of parking lots (k = 135).

park the bike in other parking lots rather than near the metro station entryway.

Subsidies to encourage the use of certain parking spots and to stop bicycles from agglomerating are studied. As delineated in Hong Kong Transport Department regulations (Hong Kong Transport Department, 2018), bike-sharing operators must facilitate the return of their bicycles to designated bicycle parking places through incentive schemes for good bicycle parking practices and penalties for non-compliance. The Portland State University TREC Center (2018) found that nearly two-thirds of bike-sharing riders considered the discount important in their decision to sign up for membership. Lyft, the company that has purchased the largest bike-sharing operator in the US, offers discounts to people who use the bikes and scooters to connect to transit (Hawkins, 2018). One bike-sharing operator in Hong Kong has also claimed that customers can earn 30 min of free riding credits when they park certain bicycles in designated areas (Sun, 2017). In the present study, two incentive strategies are tested including 30 min of free riding, and a fare discount (as compared to the original fee).

Table 3
Simulation results of different parking incentive strategies.

Incentive strategies		Target people	Num willing to change	Average accessibility distance (m)	Access increase%
Discount rate (%)	100	19	15	169.9	60.5
	90	19	15	169.9	60.5
	80	19	15	169.9	60.5
	70	19	15	169.9	60.5
	60	19	15	169.9	60.5
	50	19	15	169.9	60.5
	40	19	15	169.9	60.5
	30	19	15	169.9	60.5
	20	19	14	162.7	53.7
	10	19	8	131.0	23.7
	0	19	5	134.8	27.3
Free 30 min		19	15	169.9	60.5
BAU(k = 135)		n/a	n/a	106.0	0

Notes: Here Num willing to change refers to the people from the target people group are willing to change the parking location with corresponding incentives. The average accessibility distance means the average distance between O/D and selected parking lots.

Based on the simulation results (Table 3), a discount scenario with a 30% reduction in price (or higher discount) has the same effect on parking behavior as the 30-minute free riding scenario, with most people are willing to change the parking location. Target people here means the bike users who would ordinarily park their bikes close to the metro stations with a distance less than 100 m during peak hours (7am-9am and 6pm-8pm). Thus, the operators are suggested to provide a 30% fare discount to solve the over-clustering parking problem. 26% of bike users are willing to change their parking location far away from the metro stations when the discount rate is zero, which means no incentives for the parking. Because their cycling distance is shorter, although the walk distance is longer, the corresponding total user cost is still reduced. Compared with the BAU scenario (k = 135), the accessibility distances of these scenarios are increased, which means this parking regulation brings a certain inconvenience for the bike users. For example, in the scenario of 30-minute free riding, the accessibility distance is increased by 60.5%.

3.3.2. Bike lane extension

Based on the simulated road occupancy, a bike lane extension scenario was simulated. The major problem of bicycle infrastructure in Hong Kong is that cycle tracks are underutilized and disconnected. Bike users need to wheel their bikes on the footway. High cycle modal share may be achieved and sustained with a safe, extensive, and continually improving cycling infrastructure (Ashwani, 2015). Castillo-Manzano and Sánchez-Braza (2013) stated that Seville's high cycling modal share was the result of the development of extensive new cycling infrastructure. There are some projects on clustering/summarizing trajectories on the road network (Han, Liu, & Omiecinski, 2012; Kharrat, Popa, Zeitouni, & Faiz, 2008), which help urban planners to know the popular routes and improve the public transportation system.

In our model, new bike lanes are suggested to be built parallel to the popular footways that have intensive trajectories. Thus, disconnected bike lanes can be connected. Identifying the heterogeneity (occupancy here) can assist in ranking candidate locations for infrastructure, which is a standard process in investment choices with a limited budget. There is a monetary cost $c_i$associated with each road segment R_i in converting a footway segment into a bike lane (e.g., building the railings and clearing the space). The cost for the construction of bike lanes and cycle tracks are 90HKD (11.7USD) and 630HKD (81.9USD) per meter, respectively (Weigand, McNeil, & Dill, 2013). Most cycleways in Hong Kong are cycle tracks that separate the cyclists from motor traffic and provide a high level of security. Thus, the cycle tracks construction cost is selected for bike lane extension investment. Fig. 8 shows the road occupancy of the existing cycleway and footway. Road occupancy represents the total number of bike trips that occur on a specific road on one weekday. The roads next to the river has higher occupancy, but these roads are not all cycleway; some are footways, which connect the cycleways. The candidate cycle tracks are indicated with an ID number corresponding occupancy in the Fig. 8. The candidate cycle tracks and the corresponding construction cost are shown in Table 4. We can find most high-occupancy roads have gentle slopes, which is consistent with the findings that cyclists tend to avoid slopes (Hood, Sall, & Charlton, 2011; Li, Wang, Liu, & Ragland, 2012; Menghini, Carrasco, Schüssler, & Axhausen, 2010). If 0.12 million USD were invested to build new cycle tracks and connect existing cycleways, the average trip time could be reduced by 3.8%, per user cost reduced by 2.4%, and the number of used bikes reduced from 227 to 211. Bike users' satisfaction could be improved accordingly, attracting more potential bike users.

4. Discussion and conclusion

This research presents a novel approach which integrates Big Data techniques into ABM to assist FFBS system design with spatial information. The k-medoid clustering algorithm is applied to spatially cluster the origins/destinations (O/D) points into bike-sharing parking lots. A high-resolution ABM was built that utilizes bike-sharing trip data to generate agents with real trip start time, trip O/D, and socio-demographic attributes. The bicycling and walking are based on a real transportation network with specific attributes such as road length and slope. The model acts as a laboratory to assess the impact of different strategical designs for bike lanes and parking lots.

Based on the simulation results generated in this study, as the number of designed parking lots increases, the per-user cost decreases accordingly, while as the total system cost increases, the optimum distribution of parking lots was found based on the Pareto frontier results. Then the capacities of parking lots are optimized considering the interactions between bike users and operators. The parking lots with higher capacities are mostly close to the metro stations, which leads to the problem of over-clustering of bicycles around public transit stations during peak hours. The roads, including footways and cycleways, have higher occupancy and are mostly near the riverside. The cycleways are disconnected, even those with high occupancy. Cycleways with intensive cycling trajectories are suggested to be built parallel to popular footways. Two scenarios were simulated to examine the effect of such decisions. The scenario of parking incentive shows encouragement of user agents not parking the bikes block the metro stations during the peak hour may bring certain inconvenience for the users represented as the increased accessibility distance. The minimum discount rate for encouraging most target people to change the parking location is 30%. 26% of bike users are willing to change their parking location farther from the metro stations even if the discount rate is zero. In the bike lane extension scenario, the average trip time can be reduced by 3.8%, and the per user cost reduced by 2.4% with a 0.12 million USD investment in building new cycle tracks and connecting existing cycleways.

The results of the study provide an advanced tool to assist in FFBS system design and understand the behaviors of bike users under various policy scenarios. The method used to develop this model can be used for FFBS system design in other cities. The potential benefits of this research are broader than providing comprehensive information for BSS development. Data availability of detailed GPS records including O/D points and generated trajectories can benefit other parties. By aggregating cycling trips, transportation planners can identify mismatches between cycling demand and infrastructure supply. In addition, the framework has the potential to be applied to other infrastructure systems and help inform the complex decision making for developing and improving integrated transportation systems such determining joint ticket formulation for metro-bike traveling and bike-sharing parking lot distributions around metro stations.

As with all modeling exercises, we are generating scenarios to

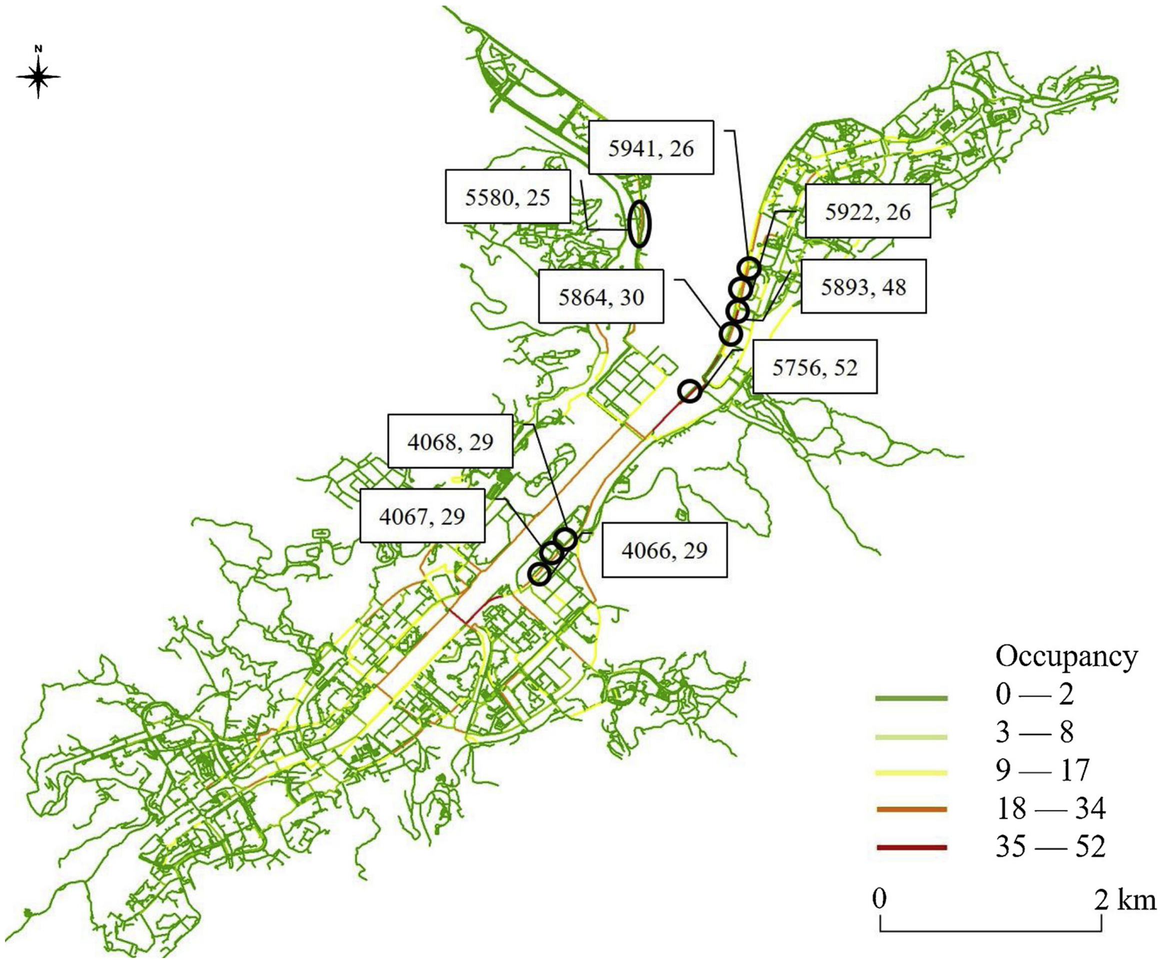

Fig. 8. The road occupancy (k = 135).

Table 4
Candidate cycle tracks and corresponding construction cost.

ID	Length	Slope	Occupancy	Construction cost (USD)
5756	260.62	9.65	52	21345
5893	134.30	7.48	48	11000
5864	119.84	1.98	30	9815
4066	169.49	0.88	29	13882
4067	132.69	1.27	29	10868
4068	186.88	2.75	29	15306
5922	152.10	1.67	26	12457
5941	114.70	2.12	26	9395
5580	245.50	10.69	25	20107
Total cost (USD)				124175

explore possible future options, not to predict actual futures. However, some limitations should be acknowledged. The current model only considers the operation cost based on statistical data, and the detailed dynamic rebalances cost will be simulated in future work. The impacts of FFBS strategic designs in the scenarios will be validated by travel survey data from before-after project completion analysis in our future work.

Acknowledgments

The authors appreciate the financial support from the Hong Kong Research Grants Council (Grant No. 25220615).

Appendix A. ODD protocol table of FFBS model

Elements of ODD protocol		Description
overview	1.Purpose	Free-floating bike sharing system design
	2.1 Entities	Bike users, bike operators, and bikes
	2.2 State variables	*Bike users*: Trip origins/destinations, selected parking lots, hourly salary, bicycling fee, walking/bicycling time, accessibility level of selected parking lots, travel trajectories *Bike operators*: parking lots location/capacity, operating cost, capital cost, bike fleet size *Bikes*: use frequency, speed, start/end parking lots
	2.3 Scales	Space: Sha Tin, Hong Kong (6 km * 6 km) Spatial: location of agents, resolution 1 m * 1 m Temporal: one-minute interval update of activities

	3. Process overview and scheduling	1. Bike users population synthetic based on the bike-sharing trip dataset. 2. Spatial clustering of existing O/D points to candidate parking lots. 3. Bike operator assigns bikes in different parking lots based on bike-sharing travel demand (the number of bike users whose distance to the parking lots are less than 500 m). 4. Bike users rent/return bikes at certain parking lots. 5. Bike operators optimize the location/capacity of parking lots until the supply and demand balance is achieved. For example, the parking lots with the zero daily capacity and bikes with the zero daily use-frequency are removed from the system the next day. If one bike user cannot rent the bike at parking lot A, the bike operator will add one bike at this parking lot next day. 7. Scenarios simulation of parking incentives: Encourage the bike users to use certain parking lots and stop bicycles from agglomerating around metro stations with two incentive strategies including 30-minutes free riding, and fare discount. Observe the minimum discount and the average accessibility distance. 8. Scenario simulation of bike lane extension: New bike lanes are suggested to be built parallel to the popular footways that have intensive trajectories. Then the disconnected bike lanes can be connected. Observe the total construction cost and the corresponding user cost and bicycling time.
Design concepts	4. Theoretical and empirical background	1 The bike user agents' hourly incomes are based on the distribution of hourly wage (all employees) from the Hong Kong annual earning survey. 2 The bike users who have specific origins and destinations are assumed to choose the shortest path for cycling. 3 The bike users only select the bike-sharing parking lots located less than 500 m from the user agent's origin/destination. 4 The lifespan of bikes is assumed to be three years. 5 The bike operators can get 5% annual rate of return from the bike users' deposits. 6 The criteria for optimization of the location and capacity of the parking lots are defined as minimizing the users' travel cost incurred in the bicycling trips and minimizing the system cost of the bike sharing operator. 7 The bike users decide to change parking locations or not based on utility maximization theory.
Details	5. Initialization	• Transportation map with bike lanes, footways and metro stations • Bike-sharing parking points (trip O/D) • Spatial clustering of disorganized parking points into candidate parking lots with a definite number (equals k in the k-medoid algorithm). • Bike user walks to its start parking lot and starts its trips from trip origin with the respective start time.
	6. Input data	• Bike user agents' travel behaviors (trip origin/destination, trip start time) are defined by the bike-sharing trip dataset. • Bike user agents' social-economic characteristics, especially for the hourly income, which are defined by the distribution of hourly wage (all employees) from the Hong Kong annual earning survey • The existing bike lanes, footways and metro stations are defined by the Hong Kong transportation map. • The slopes information of bike lanes and footways are defined by the Hong Kong digital elevation model. • Existing parking points are defined by real bike-sharing O/D points. • Cost parameters of bike-sharing system including system operating cost and capital cost of bikes are summarized from the open data of bike-sharing companies in China. • The construction cost of the cycle track is defined by studies related to bicycle facilities cost.
	7. Sub-models	• The scenario of parking incentive: *Purpose*: Encourage the bike users to use certain parking lots and stop bicycles from agglomerating around metro stations *Process*: Two incentive strategies are tested including 30-minutes free riding and fare discount. The bike users choose to change the parking lots depend on their utility (travel cost). The travel cost is composed of the explicit cost and hidden cost. Generally speaking, the hidden cost is increased, as the walking distance from the parking lot to the destination (metro station here) is increased. But the explicit cost (bicycling fee) is decreased with these two incentive strategies. If the user cost is reduced, the bike user will park the bike at other parking lots rather than near the metro station entryway. *Observation*: The most effective incentive strategy (the minimum discount rate of bicycling fee with the most target people willing to change the parking locations) and the average bike users' accessibility distance • The scenario of bike lane extension: *Purpose*: Construct new cycle tracks parallel to the popular footways that have intensive trajectories. Thus, the disconnected bike lane network can be connected. *Process*: Bike users need to wheel their bikes on the footway when the bike lanes are disconnected. The candidate cycle tracks are identified by the daily bicycling occupancy of the existing footways. The footways with the high occupancy are given priority for cycle track construction. The construction cost of cycle tracks is 630HKD (81.9USD) per meter. *Observation*: The total construction cost and improved system performance (including bicycling cost and time).

References

Ashwani, K. (2015). *A systems approach to assess and improve the last-mile access to mass transits* (Ph.D.)Singapore: National University of Singapore.

Aziz, H. A., Nagle, N. N., Morton, A. M., Hilliard, M. R., White, D. A., & Stewart, R. N. (2018). Exploring the impact of walk–bike infrastructure, safety perception, and built-environment on active transportation mode choice: A random parameter model using New York City commuter data. *Transportation, 45*(5), 1207–1229.

Aziz, H. A., Park, B. H., Morton, A., Stewart, R. N., Hilliard, M., & Maness, M. (2018). A high resolution agent-based model to support walk-bicycle infrastructure investment decisions: A case study with New York City. *Transportation Research Part C: Emerging Technologies, 86*, 280–299. https://doi.org/10.1016/j.trc.2017.11.008.

Bao, J., He, T., Ruan, S., Li, Y., & Zheng, Y. (2017). *Planning bike lanes based on sharing-bikes' trajectories. Paper presented at the proceedings of the ACM SIGKDD international conference on knowledge discovery and data mining*.

Bauman, A., Crane, M., Drayton, B. A., & Titze, S. (2017). The unrealised potential of bike share schemes to influence population physical activity levels—A narrative review. *Preventive Medicine, 103s*, S7–S14. https://doi.org/10.1016/j.ypmed.2017.02.015.

Bird, T. (2018). *China's bike sharing bubble has burst.* Retrieved from https://www.scmp.com/magazines/post-magazine/long-reads/article/2156975/chinas-bike-sharing-bubble-has-burst-drone.

Caggiani, L., Camporeale, R., Ottomanelli, M., & Szeto, W. Y. (2018). A modeling framework for the dynamic management of free-floating bike-sharing systems. *Transportation Research Part C: Emerging Technologies, 87*, 159–182. https://doi.org/10.1016/j.trc.2018.01.001.

Castillo-Manzano, J. I., & Sánchez-Braza, A. (2013). Managing a smart bicycle system when demand outstrips supply: The case of the university community in Seville. *Transportation, 40*(2), 459–477. https://doi.org/10.1007/s11116-012-9424-7.

DeMaio, P. (2009). Bike-sharing: History, impacts, models of provision, and future. *Journal of Public Transportation, 14*(4), 41–56.

Frade, I., & Ribeiro, A. (2015). Bike-sharing stations: A maximal covering location approach. *Transportation Research Part A: Policy and Practice, 82*, 216–227.

GAMA (2016). *GAMA, modeling made easy.* Retrieved fromhttp://gama-platform.org/.

Garcia-Gutierrez, J., Romero-Torres, J., & Gaytan-Iniestra, J. (2014). Dimensioning of a bike sharing system (BSS): A study case in nezahualcoyotl, Mexico. *Procedia – Social and Behavioral Sciences, 162*, 253–262.

García-Palomares, J. C., Gutiérrez, J., & Latorre, M. (2012). Optimizing the location of stations in bike-sharing programs: A GIS approach. *Applied Geography, 35*(1-2), 235–246. https://doi.org/10.1016/j.apgeog.2012.07.002.

Han, B., Liu, L., & Omiecinski, E. (2012). NEAT: road network aware trajectory clustering. *Paper presented at the 2012 IEEE 32nd International Conference on Distributed Computing Systems*.

Hawkins, A. J. (2018). *Lyft will offer discounts to people who use bikes and scooters to connect to transit.* Retrieved fromhttps://www.theverge.com/2018/7/16/17577498/lyft-bikes-scooters-public-transportation.

Ho, S. C., & Szeto, W. (2014). Solving a static repositioning problem in bike-sharing systems using iterated tabu search. *Transportation Research Part E: Logistics and Transportation Review, 69*, 180–198.

Hong Kong Census and Statistics Department (2017). *Report on annual earnings and hours survey*Retrieved from Hong Kong:https://www.censtatd.gov.hk/hkstat/sub/sp210.

jsp?productCode=B1050014.

Hong Kong Transport Department (2018). *Code of practice (CoP) for automated dockless bicycle rental services.* Retrieved fromhttps://www.td.gov.hk/mini_site/cic/files/others/code_of_practice_en.pdf.

Hood, J., Sall, E., & Charlton, B. (2011). A GPS-based bicycle route choice model for San Francisco, California. *Transportation Letters, 3*(1), 63–75. https://doi.org/10.3328/TL.2011.03.01.63-75.

Kharrat, A., Popa, I. S., Zeitouni, K., & Faiz, S. (2008). Clustering algorithm for network constraint trajectories. In A. Ruas, & C. Gold (Eds.). *Headway in Spatial Data Handling. Lecture Notes in Geoinformation and Cartography*. Berlin, Heidelberg: Springer.

Koppelman, F., & Bhat, C. (2006). *A self instructing course in mode choice modeling: Multinomial and nested logit models.* Retrieved fromhttps://books.google.com.hk/books?id=DiAIkAEACAAJ.

Legislative Council Secretariat (2018). *Bicycle-sharing in selected places.* Retrieved fromhttps://www.legco.gov.hk/research-publications/english/1819in02-bicycle-sharing-systems-in-selected-places-20181015-e.pdf.

Leung, K. (2018). *As Gobee.bike packs up, is it the end of the road for bike-sharing services in Hong Kong?* Retrieved fromhttps://www.scmp.com/news/hong-kong/hong-kong-economy/article/2154877/gobeebike-packs-it-end-road-bike-sharing-services.

Levy, N., Martens, K., & Benenson, I. (2013). Exploring cruising using agent-based and analytical models of parking. *Transportmetrica A: Transport Science, 9*(9), 773–797. https://doi.org/10.1080/18128602.2012.664575.

Li, Z., Wang, W., Liu, P., & Ragland, D. R. (2012). Physical environments influencing bicyclists' perception of comfort on separated and on-street bicycle facilities. *Transportation Research Part D: Transport and Environment, 17*(3), 256–261. https://doi.org/10.1016/j.trd.2011.12.001.

Lin, J. R., & Yang, T. H. (2011). Strategic design of public bicycle sharing systems with service level constraints. *Transportation Research Part E: Logistics and Transportation Review, 47*(2), 284–294. https://doi.org/10.1016/j.tre.2010.09.004.

Lin, J. R., Yang, T. H., & Chang, Y. C. (2013). A hub location inventory model for bicycle sharing system design: Formulation and solution. *Computers & Industrial Engineering, 65*(1), 77–86. https://doi.org/10.1016/j.cie.2011.12.006.

Liu, Z., Jia, X., & Cheng, W. (2012). Solving the last mile problem: Ensure the success of public bicycle system in Beijing. *Procedia – Social and Behavioral Sciences, 43*, 73–78. https://doi.org/10.1016/j.sbspro.2012.04.079.

Lu, M., & Hsu, S. C. (2017). Spatial agent-based model for environmental assessment of passenger transportation. *Journal of Urban Planning and Development, 143*(4), https://doi.org/10.1061/(ASCE)UP.1943-5444.0000403.

Lu, M., Hsu, S. C., Chen, P. C., & Lee, W. Y. (2018). Improving the sustainability of integrated transportation system with bike-sharing: A spatial agent-based approach. *Sustainable Cities and Society, 41*, 44–51. https://doi.org/10.1016/j.scs.2018.05.023.

Martinez, L. M., Caetano, L., Eiró, T., & Cruz, F. (2012). An optimisation algorithm to establish the location of stations of a mixed fleet biking system: An application to the City of Lisbon. *Procedia – Social and Behavioral Sciences, 54*, 513–524.

Menghini, G., Carrasco, N., Schüssler, N., & Axhausen, K. W. (2010). Route choice of cyclists in Zurich. *Transportation Research Part A: Policy and Practice, 44*(9), 754–765. https://doi.org/10.1016/j.tra.2010.07.008.

Nair, R., & Miller-Hooks, E. (2016). Equilibrium design of bicycle sharing systems: The case of Washington D.C. *EURO Journal on Transportation and Logistics, 5*(3), 321–344. https://doi.org/10.1007/s13676-014-0055-3.

Oremland, M., & Laubenbacher, R. (2014). Optimization of agent-based models: Scaling methods and heuristic algorithms. *Journal of Artificial Societies and Social Simulation, 17*(2), 6. https://doi.org/10.18564/jasss.2472.

Portland State University TREC Center (2018). *Outreach and discount programs alert residents to bike share, says study.* Retrieved fromhttp://betterbikeshare.org/2018/03/20/outreach-discount-programs-alert-residents-bike-share-says-study/.

Reiss, S., & Bogenberger, K. (2016). Validation of a relocation strategy for Munich's bike sharing system. *Transportation Research Procedia, 19*, 341–349. https://doi.org/10.1016/j.trpro.2016.12.093.

Romero, J. P., Ibeas, A., Moura, J. L., Benavente, J., & Alonso, B. (2012). A simulation-optimization approach to design efficient systems of bike-sharing. *Procedia - Social and Behavioral Sciences, 54*, 646–655. https://doi.org/10.1016/j.sbspro.2012.09.782.

Shaheen, S., Guzman, S., & Zhang, H. (2010). Bikesharing in Europe, the Americas, and Asia. *Transportation Research Record,* 159–167.

Shen, Y., Zhang, X., & Zhao, J. (2018). Understanding the usage of dockless bike sharing in Singapore. *International Journal of Sustainable Transportation, 12*(9), 686–700. https://doi.org/10.1080/15568318.2018.1429696.

Song, C., Qu, Z., Blumm, N., & Barabási, A. L. (2010). Limits of predictability in human mobility. *Science, 327*(5968), 1018.

Sun, N. (2017). *Bike-sharing operator Gobee.bike offering free rides in Hong Kong amid parking woes.* Retrieved fromhttps://www.scmp.com/news/hong-kong/economy/article/2105341/bike-sharing-operator-gobeebike-offering-free-rides-hong-kong.

Ukkusuri, S. V., Hasan, S., Luong, B., Doan, K., Zhan, X., Murray-Tuite, P., et al. (2017). A-RESCUE: An agent based regional evacuation simulator coupled with user enriched behavior. *Networks and Spatial Economics, 17*(1), 197–223. https://doi.org/10.1007/s11067-016-9323-0.

Van Ginkel, J. (2014). *The value of time and comfort in bicycle appraisal* (Master) Netherlands: University of Twente.

Van Roy, J. (2017). *Amsterdam to ban free-floating bicycle-sharing.* Retrieved fromhttps://newmobility.news/2017/08/03/amsterdam-ban-free-floating-bicycle-sharing/.

Vogel, P., & Mattfeld, D. C. (2011). Strategic and operational planning of bike-sharing systems by data mining—A case study. *Paper presented at the computational logistics: second international conference*.

Wallentin, G., & Loidl, M. (2015). *Agent-based bicycle traffic model for Salzburg City. Paper presented at the GI_Forum J. Geogr. Inf. Sci.*558–566.

Weigand, L., McNeil, N., & Dill, J. (2013). *Cost analysis of bicycle facilities: Cases from cities in the Portland, OR region.* Retrieved from Portland, OR:https://activelivingresearch.org/cost-analysis-bicycle-facilities-cases-cities-portland-or-region.

Yan, S., Lin, J. R., Chen, Y. C., & Xie, F. R. (2017). Rental bike location and allocation under stochastic demands. *Computers & Industrial Engineering, 107*, 1–11. https://doi.org/10.1016/j.cie.2017.02.018.

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