The behavioral impacts of uncertain access to free floating bicycle services

YAO ZIANG

2022

京都大学工学研究科

都市社会工学専攻博士論文

Ph.D. Thesis

Department of Urban Management

Graduate School of Engineering

Kyoto University

THE BEHAVIORAL IMPACTS OF UNCERTAIN ACCESS TO FREE FLOATING BICYCLE SERVICES

アクセスの不確実性がフリーフロート型のシェアサイクルの行動にもたらす影響に関する研究

YAO ZIANG

2022

ACKNOWLEDGMENTS

The journey towards the completion of this dissertation has been one of the most significant academic challenges I faced. A great many people have contributed to its production. Without their guidance and support, this study sure not to be completed.

First of all, my sincere and hearty thanks and appreciations go firstly to my supervisor, Associate Prof. Jan-Dirk Schmöcker, in Kyoto University for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research, in life, and writing of this thesis. It has been a great privilege and joy to study under his guidance and supervision. Furthermore, it is my honour to benefit from his personality and diligence, which I will treasure my whole life. My gratitude to him knows no bounds.

Besides my advisor, I would like to thank the rest of my thesis committee and co-supervisors: Prof. Yamata and Prof Fujii in the Kyoto University, for their insightful comments and encouragements, but also for the questions which inspired me to widen my research from various perspectives.

Also, my sincere thanks also go to Prof. Uno, Assistance Prof. Nakao in the Kyoto University, Associate Prof. Nakamura in Nagoya University who advised me at several stages. Without their precious support it would not be possible to conduct this research.

Regards the assistance of administration process, I hope to give this opportunity to express a deep sense of gratitude to thanks to the secretaries, Mrs. Shii, Mrs. Nishikawa, their various helps have made me concentrate on my research.

Above all, I would like to thank members of ITS laboratory and all friends who have a great time and willing to share their thoughts and ideas with me in Japan. I would like to thank my family for supporting me spiritually throughout writing this thesis and my life in general.

I would like to thank my family members. I would like to thank my cat, Cai Suantou, who has been my spiritual support when times are tough. Last but not least, I would like to thank wife, Ph.D. candidate Peng Xue, for her love, tolerance, encouragement, and insight in life and in academic. In the vastness of space and immensity of time, it is my joy to spend a planet and an epoch with you.

ABSTRACT

Introduced in Beijing in 2015, free-floating bicycle sharing (FFBS), or dockless bicycle-sharing has been spreading rapidly across the world with registered users exceeded 0.4 billion, thus making FFBS an unneglectable emerging new travel mode. As their name indicates, the main feature that distinguishes "free-floating" or "dockless" systems from traditional bike-share is that riders can pick up and drop off the bicycles anywhere on the street rather than at a fixed station. FFBS have been praised as a great new addition to the urban mobility landscape and it is seen by some as a key solution to urban mobility problems. However, FFBS is still an emerging technology with insufficient research and regulations.

This research focuses on the access to a randomly located bicycle from a person's origin and it has three main objectives. Firstly, it aims to develop a mode choice and bicycle flow model for a typical case such as morning commute scenarios, when the number of available bicycles is reducing over time. In that case the access time depends on the competition for available bicycles as well as the distribution of demand and bicycles. Secondly, it aims to quantify the access distance to free-floating services considering the density and distribution of travellers and bicycles. A focus is the effect of different information seeking and reservation strategies of travellers. Thirdly, a survey methodology is developed to obtain the required simulation parameters. Such results now can be feed back into the simulation to construct more practical case study.

In the first part of this dissertation, the assignment problem for travellers who have the choice of walking, taking a shared free-floating bicycle, or taking public transport is modelled. The problem is solved by a network description where the expected costs of links are obtained according to order statistics. Cases when both origin and bicycle location are random (Random-to-random, RR distances) and when the origin or destination location is fixed but the bicycle location not (Central-Random, CR) are distinguished. It is shown that the CR distance can be obtained analytically, but that the RR distance needs to be adjusted from the one obtained with order statistics. These expected distances are embedded into an assignment approach and differences among incremental, DUE, SUE assignment, and a basic agent-based simulation are discussed. It is observed that multiple equilibria exist as a result of different loading orders. The assignments and simulation results show in general good correspondence, especially with larger traffic volume and bicycle supply.

In the second part of this dissertation, an advanced agent-based discrete-event simulation is built to further understand the assumptions adopted in the assignment research. Those who use their smartphone actively during traveling to find the best available bicycle are distinguished from those who only check the availability before the journey. The simulation focuses on building a platform with high scalability as the main consideration in theoretical development. In the theoretical case study different input levels are tested. The role of reservation, traveller activeness and bicycle supply and distribution are tested as the first attempt. Different spatial and temporal distributions for bicycles and travellers are also investigated that represent different land-use types.

In the third part of this dissertation, a novel revealed preference (RP) and stated preference (SP) survey is designed with many innovative features. Up to eight attributes are packed into the one bicycle icon locates on the map with discount and risky markers. The preference of these attributes over different class of travellers are studied. It is found that users become less sensitive when longer trips are made, female users prefer less risky choices although walk/cycle distance or cost can be higher. We also find that limited influence can be addressed on users with higher income.

Overall, this thesis contributes to the first try in unveiling of the fundamental changes of space perception of urban travellers. This thesis provides a fundamental study as the basis to improve software implementations of network flow models with free floating services. A complex pioneering study with methodology formulation, simulation verification and a complementary survey are the main contribution of this research. Most of the research and its findings are presented for the first time.

Keywords: *Free-floating Sharing, Traffic Assignment, Agent-based Simulation, Stated Preference Survey, Uncertain Availability*

PREFACE

Parts of this dissertation have been published in journals, presented in conferences or else submitted for review are as follows

Conference presentations

I. **Ziang, Y.**,Schmöcker, J.-D (2018). Network Assignment and Design with Free Floating Bicycle, Autumn Conference of Committee of Infrastructure Planning and Management, Oita, Japan. (**Chapter 3.1 and 3.2**)

II. **Ziang, Y.**,Schmöcker, J.-D (2019). Equilibrium assignment issues with free-floating bicycles, The 3rd International Symposium on Multimodal Transportation (ISMT), NUS, Singapore. (**Chapter 3.1, 3.2, 3.4 and Chapter 4**) – Recommended for Journal Publication

III. **Ziang, Y.**,Schmöcker, J.-D (2020). Variance in access distance to free-floating services. The 8th International Conference on Transport Network Reliability (INSTR), Stockholm, Sweden **(Chapter 5)** – Recommended for Journal Publication

Under review/ To be submitted

I. **Ziang, Y.**,Schmöcker, J.-D (2022). Assignment and simulation considering access time under competition for free-floating bicycles (under submission). **(Chapter 3 and 4)**

II. **Ziang, Y.**,Schmöcker, J.-D (2022). Access Distance to Free-floating Services Considering Uncertain Availability and Smartphone Activeness, *Transportmetrica B: Transport Dynamics* (under review, minor revision). **(Chapter 5)**

III. **Ziang, Y.**,Schmöcker, J.-D (2022). How APP users select a free-floating bicycle? A SP survey using generated screenshots, *Transportation Research Board (TRB) 102nd Annual Meeting* (under submission). **(Chapter 6)**

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. INTRODUCTION

1.1. Overview of Bicycle Sharing Development

Bike sharing systems have been in operation in various forms since more than half a century. Since the first bicycle-sharing system was introduced in Amsterdam in 1965, this service has evolved by now into its fourth generation with the help of incessantly technology advances and the attempts to make sharing bicycles both easier to access and more vulnerable against theft and vandalism.

The “zero generation” is conventional bicycle rental where bikes are hired from a staffed station or shop. In this system, a bicycle needs to return to the same station. Frequent users are required to be registered or deposit before renting.

The first generation, “free bikes”, is an unregulated bicycle-sharing. It is also known as “White Bike Plan” thanks to the fifty white painted bicycles placed unlocked in Amsterdam by the group PROVO in 1965. This type of system requires no locks, no user identification or security deposits, simply released bicycles into the city or service area for anyone to use, and users are expected to leave the bicycles unlocked in the public space after reaching their destination. Such a system will suffer from both loss rates because of theft and vandalism, and the imbalanced distribution problem because more bicycles may end up in flat streets rather than hills of the city. Many attempts of similar schemes have been made but abandoned after a few years, while others are based around volunteers and supported by local associations.

The second generation, also known as coin deposit stations or *Bycykel*, namesake of the first large-scale second-generation bike-sharing service launched in Copenhagen by Morten Sadolin and Ole Wessung (Bycyklen København, 2010). These bicycles, adopted with solid rubber tires, require a coin (usually 20 DKK or 2 EUR coin) to unlock it from the station and then can be borrowed for an unlimited time. The coin deposited can be reimbursed by returning the bicycle to any station. Since the deposit is only a small fraction of the bicycle value and the users are not required to register themselves, this system can be vulnerable to theft and vandalism.

The third generation adopted automated stations which are also known as station-based bicycle-sharing (SBBS) or membership bicycles. Systems of this generation are usually composed of automated stations and bicycles which can be borrowed or returned only at these automated stations or ‘docking stations’. The bicycles can be returned to another station as long as it is belonging to the same system. These stations are electronically-controlled bicycle racks that lock the bicycles and release these after user validation and/or payment. In most cases users of this system are required to register to the service provider and identify themselves with their membership card at any docking stations, to borrow a bicycle for a period of time. Users are charged usually by the period of time. Some sharing system also requires users to provide a deposit or to become a paid subscriber. The user is responsible for any damage or loss happened during usage. As of June 2014, the third-generation public bicycle-sharing systems were available in 50 countries on five continents, including 712 cities, operating approximately 806,200 bicycles at 37,500 stations (Shaheen et al., 2014). Systems of this generation save labour comparing to staffed stations and reduce theft and vandalism compared to the first and second generation. However, higher investment for docking stations is required.

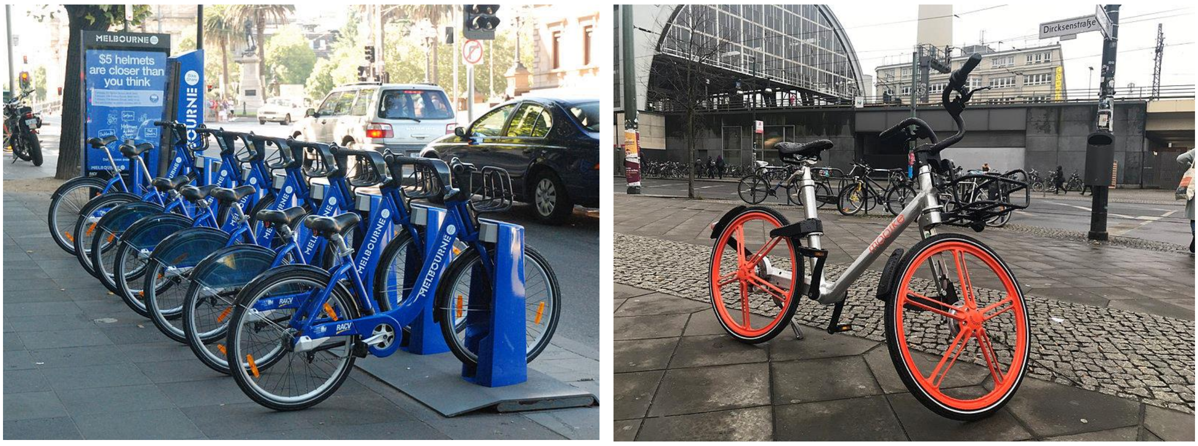


Figure 1.1 The station-based bicycles in Australia and a free-floating bicycle in Berlin in 2019
(Photos from Wikipedia, the free encyclopaedia at https://en.wikipedia.org/wiki/Bicycle-sharing_system)

The story of the fourth generation, free-floating bicycles sharing service (FFBS) or dockless bicycles, begins in China with the establishment of the start-up company OfO in 2014 and then Mobike in 2015. Unlike the self-service bicycle sharing modes such as station-based bicycle sharing which are often run by public or governmental companies with large investment on docking stations, the FFBS are usually run and owned by private companies. FFBS are therefore easier and less expensive to put into practice since it requires no infrastructure installation. Particularly, in China, Mobike once become the world's largest bike share operators with millions of bikes spread over 100 cities (Mobike Global, 2019a).

FFBS provides short-term rentals which allow you to rent a vehicle (in this case, bicycle) by paying only for the time or trip mileage of your rental. Because docking stations are no longer essential for FFBS, users can pick up and drop off the bicycle where they want as long as it is permissible to leave a bicycle at that place. Everything is done via a smartphone application, which locates the nearest vehicle and unlocks it, then, after the journey, locks it and applies the relevant charge. Therefore, it is a self-service way of renting without needing a docking station.

By getting rid of docking stations, free-floating has revolutionized short-term self-service rentals. Users are fully relieved from making roundtrips or one-leg routes, and in most cases, also relieved from finding docking stations with empty slot while returning the bicycle. These unique characteristics offer users more freedom and flexibility. FFBS contributes to the evolution of mobility and have been rapidly taking over cities especially in the last mile scenario, such as making door-to-door trips, and making intermodal trip with public transport. For example, in Kunming, the split rate of bicycles after introducing FFBS service into the urban area has doubled from 5.5% to 11.6%, with

89% of trips end within 4 kilometres. The bicycle usage to arrive at or depart from metro stations has changed from both less than 1% to 10.9% and 9.69% (Kunming Urban Transport Institute, 2019). Many may view FFBS as a complement to existing practices without jeopardizing the use of other services.

1.2. Impact on Urban Management

1.2.1. Impact on urban management

The users are more likely to use punctual travel mode in the morning peak comparing to evening peak, which will lead to more commuter's cycle toward and less away from public transport (PT) stations. This unbalanced flow will lead to an accumulation of bicycles around PT stations.

This accumulation effect will further dilute the density of available bicycles on the street, making it gradually more difficult to access available bicycles and reduce the profit of the service provider. Also, the bicycles accumulated around a station make it more inconvenient for other users to access to or depart from stations.

Figure 1.2 The street view of bicycles accumulated around PT stations in Hangzhou, China.
(Photos from Hangzhou Daily at http://www.hbspcar.com/2004.html)

Most of the FFBS service providers hire labours to transport bicycles from stations to the surrounding areas, such as residential or commercial space, where users always complain that it is difficult to find available bicycles. This rebalancing cost has become the main expenditure component for FFBS service providers in daily operations. However, the rebalancing amount and destinations are decided mostly by the experience of maintainers instead of other analytical approaches.

Figure 1.3 A bird's eye view of wrecked bicycle disposed of in Tong'an District, Xiamen
(Photos from the Guardian at http://photographyofchina.com/blog/feature-chinese-bike-share-graveyard)

1.2.2. Bicycles flooding pavement space

Currently, many free-floating bicycle-sharing service providers are competing for the monopolistic status in the market, which leads to an excess of investment of bicycles in the same city. Based on the discussion given by the chief secretary of Shanghai Bicycle Industry Association, the appropriate proportion should be around 1/50 of the resident population, but currently, this proportion is 1/9 in Beijing. On the other hand, the percentage of maintenance staff recommended by the Chinese municipal government is no less than 5‰ of fleet size, but currently, this percentage is below 2‰ (Jianrong, Guo, 2019).

The result of this excessive investment and lack of maintaining labour force have caused the pavement space flooded by the bicycles, and large amounts of wrecked bicycles mixed with the available bicycles. These inconveniences have already raised complaints among the citizens, and many cities have already prohibited service providers from investing any new bicycles in the urban area.

1.2.3. The infrastructure of the past

The infrastructure of current cities is unable to foresee the uprising of FFBS and worth rethinking. The combination of free-floating bicycle and public transport is promising since more bicycles are used to ingress and egress from public transport service. The percentage of bicycles activated within 300 meters around bus stations and 500 meters around metro stations are 81% and 44% in Beijing, and 90% and 51% in Shanghai, respectively.

With the help of FFBS services as a feeder mode, we can potentially expand catchment of PT stations, introduce more passengers to use PT services, integrate small stations into larger ones and provide faster PT services with fewer stops. On the other hand, by changing the amount and location of bicycles released around the station, one can better respond to the current public transport system and achieve higher penetration rates for the service provider and easier access for citizens.

1.3. Impact on User Behaviour

The impact on user behaviour is the focus of this thesis, and also the foundation toward better understanding the impact on urban management. When someone starts to use FFBS service, the following processes are followed:

1. The new user must have a smartphone installed with the corresponding application of the desired service provider. Obviously, the smartphone should be able to use internet service. The user also needs to be able to conduct online payment, which will be needed to pay for the charge of bicycle sharing service.
2. When a user decides to start the trip, the user firstly needs to launch the corresponding application on the smartphone and grant GPS access. The available bicycles around the current location will be shown on the map. Some service providers allow users to make a

reservation for up to 15 minutes on the desired bicycle, which will block the access from other users (Step 1 and 2 in Figure 1.4).

3. After selecting the desired bicycle, the user needs to walk to the bicycle. Once s/he reaches the location, the user needs to use the QR scanner in the application to scan the code on the wheel lock, and the smartphone will report an ‘occupied’ signal toward the operation system, which will block any access from other users. If the attached QR code on the bicycle is damaged or scribbled beyond recognition, the user still can connect his or her smartphone to the Bluetooth module on the bicycle, and the application will still report occupied for this designated bicycle. After receiving the ‘occupied’ signal, the operating system will send the unlock code to the designated bicycle, and then the wheel lock releases. The user can start cycling from now. During cycling, the user’s smartphone will continuously submit time stamp information and current GPS location to the operation centre (Step 3 in Figure 1.4).
4. After arriving at the user’s destination, he or she can park the bicycle anywhere near his destination, as long as agreed by the law, then manually lock the wheel lock. The cloud system will calculate the total fare of this trip. This fare will be charged through the online payment account of users (Step 4 in Figure 1.4).

These processes are also presented in Figure 1.4 below. We can further compare the differences between station-based bicycle sharing (SBBS) and FFBS to see the impacts of FFBS on each trip stage, as shown in (Photos from Pinterest at https://www.pinterest.pt/liuhaoxxy)

Table 1.1.

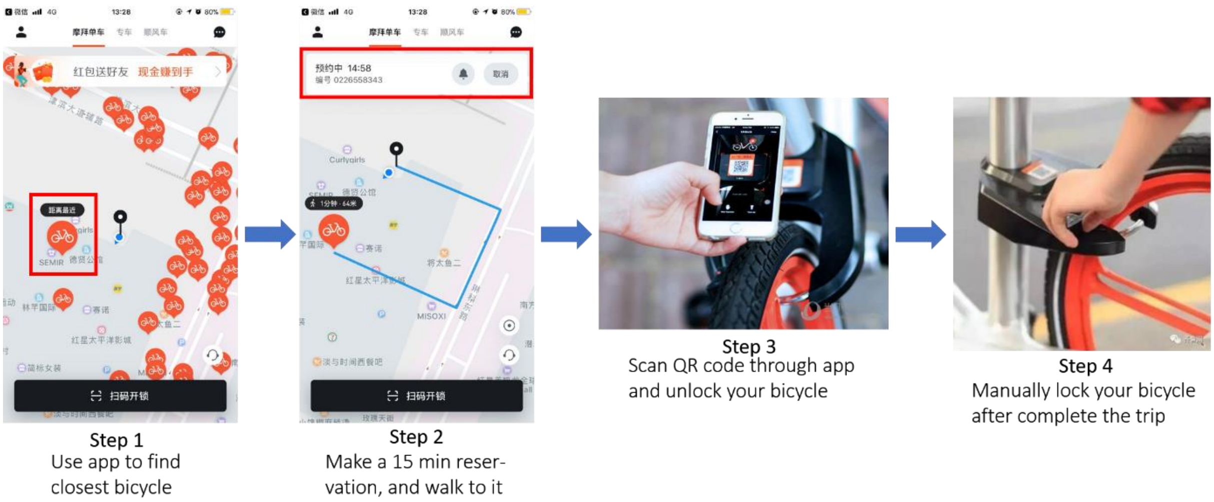


Figure 1.4 The steps for using free-floating bicycles (based on Mobike application)
(Photos from Pinterest at https://www.pinterest.pt/liuhaoxxy)

Table 1.1 Comparison between SBBS and FFBS on each trip stage

	Station-based bicycle sharing (SBBS)	Free-floating bicycle sharing (FFBS)
First time usage	Register and identify oneself mainly with issued IC card.	Download specific APP and register the online payment method.
Choosing cycling origin / destination	Docking station close to the trip origin with at least one available bicycle, and stations close to the trip destination with at least one empty slot, are considered.	Available free-floating bicycles close to origin, and any public location close to the trip destination as long as bicycle parking is allowed, are considered.
Before departure	Fix the cycling origin and cycling destination before departure.	Launch the APP and check the available bicycles around current location. Decide the cycling origin only before departure.
At origin	Tap the IC card on the reader at the docking station and start cycling.	Scan the QR code on the nameplate of the desired bicycle and start cycling.
Change destination during cycling	New destination must have docking station with empty slot.	Change destination easily as long as bicycle parking is allowed at new destination
At destination	Bicycles must be returned at the empty slot of docking station. Rental fee will be charged from the deposit after tapping the IC card on the reader to return the bicycle.	Bicycles can be returned anywhere as long as bicycle parking is allowed. Trip ends and the bicycle will be returned after user manually lock the bicycle. The rental fee will be charged through the registered online payment.
Impacts on user behaviour	Traveller's bicycle usages are heavily constrained by the temporal uncertainty of if bicycles/empty slot exists in the fixed docking station at current time.	Traveller now has to consider both the temporal uncertainty of whether available bicycle exist currently, and the spatial uncertainty of available bicycle location.

In SBBS, users only need to consider the temporal uncertainty of a fixed docking station: the desired bicycle may be occupied before users arrive at the station, or the empty slot been filled at the destination station by the other returned bicycles. Hence users only need to consider the risky period of time during which picking up and dropping off behaviour can frequently happen. In a system where reservation is not allowed, such frequent changes can easily accumulate into delay in the developed travel plan. Although FFBS users are relieved from finding suitable docking stations and offered more freedom and flexibility, the spatial uncertainty in bicycle usage should also be brought into consideration because the bicycles can be found not only at fixed locations. The spatial uncertainty is an important game changer that has brought many nonprecedential challenges into the academic discussion. Introducing spatial uncertainty not only bring the consideration from one-dimension (time) to three-dimension (time and plane position), but it also allows for a transfer of risk from one dimension into now “a continuous other dimension”. Traveller can replace the risk in time (wating for an available bicycle at desired place) into walking to a little further place where bicycles are expected to be continuously available.

1.4. FFBS Challenges to the Academic

1.4.1. Challenges to free-floating assignment research

In various countries around the world, dockless manual bicycles, e-bicycles, and e-scooters are both used together. These and other "little vehicles", as they are sometimes referred to, have led to reductions in the "last-mile-problem" and are seen by some as a key solution to urban mobility problems (Gu et al., 2019) . However, there are still a range of methodological difficulties to represent the dynamics of free-floating services. Although in this research free-floating bicycle becomes centrepiece, these problems are much broader for most of the free-floating modes. A more general approach should also be applicable to the other free-floating modes.

Firstly, the spatial uncertainty of free-floating bicycle locations can be understood in various ways. The access distances to bicycles can either be understood purely statistical, or more specifically the distance from one point to other randomly distributed bicycles. The former one may be less practical which in the end cannot provide much less guidance in the real-world planning, while the latter one is possibility more difficult in math and raise the barrier of real-world application. The different ways to interpret such bicycle-seeking process and how to integrate such “link cost” in the network assignment also distinguish the different attempts in solving this problem. The corresponding literatures will be reviewed in Chapter 2.

Secondly, the temporal uncertainty of bicycles should also be considered. The picking up and dropping off process of bicycles can be understood in different ways. During these processes, bicycles first get occupied become unavailable in the system. After the bicycles are released from occupation, such bicycle becomes available again. Although many methodologies are well-developed to solve such temporal uncertainty in different scenarios, such as the hyperpath or bottleneck model, whether it is applicable or suitable in solving this problem should be further investigated as a first attempt.

Thirdly, the fleet size is another unneglectable aspect in FFBS scenario. When bicycles become unavailable or if bicycles are accumulating at a different place, the fleet size should be changed correspondingly. How to understand the role of fleet size in the methodology construction, and how to construct a variant formulation to replicate such changes, should also be properly addressed as a first attempt.

1.4.2. Challenges to free-floating simulation research

The challenges to the simulation of FFBS behaviour raises because of the high flexibility in changing travel plans. FFBS users can easily change current choice on whether and which bicycle to use. Therefore, one must set both consistent standards for categorization of the FFBS users, and still be able to tolerate the ever-changing behaviour in traveller's choice making. Such standards are yet to be found. Another unneglectable aspect is the potential competition among bicycle-seeking process. A better simulation structure should be able to coordinate such competition and still able to replicate the behaviour patterns of different type of FFBS users.

Several hypotheses are expected to be answered in the simulation research. For example, the way smartphones are used may influences the access time. Active smartphone users may create "system instability" in that they update their path frequently depending on what bicycles are available.

Another important hypothesis is whether the ability to reserve bicycles is beneficial for the system and whether this simulation can help in finding the optimal reservation periods. The influence of spatial demand and supply distributions is also another aspect worth gaining insights on through the simulation research.

1.5. Research Objectives

As discussed in the previous section, understanding the behavioural impact of uncertain access to free-floating (bicycle) services is challenging. This dissertation explores a range of approaches to unveil the fundamental change space perception of urban travellers. The thesis does not lead to a "finished product" and does not include specific detailed case study of a specific location but is thought to be a fundamental study as the basis to improve software implementations of network flow models with free floating services. To achieve this, a complex pioneering study with methodology formulation, simulation verification and a complementary survey are the main contribution of this research. More specifically, the objectives are:

1) To develop a multi-modal assignment approach with FFBS

We aim to advance multi-modal assignment approaches that include a large-scale bicycle fleet. As we will study in the subsequent literature review, existing approaches assuming that the supply of bicycles in specific areas is constant during a time period. This is, however, only true if the number of incoming bicycles is equal to the number of outgoing bicycles and if the number of users finishing a trip is the same as the number of travellers starting a trip. Relaxing this assumption allows us to focus instead on the competition between travellers over limited bicycle resources. As the discussion will show an assignment approach needs to make, however, a number of important assumptions. Therefore, instead of continuing this line of research that can be a PhD thesis in itself, two further objectives are addressed.

2) To simulate various user behaviour in FFBS usage

Secondly this research aims to explore the separation of users and the simulation replication of different travel behaviour. The art of designing a robust simulation platform with high scalability is the main consideration in theoretical development. The investigation of different levels of input and their influences on the output statistics will be conducted, and some suggesting conclusions are expected. In detail, the following research question are expected to be answered:

3) To develop a survey methodology to obtain the required simulation parameters

Smartphones are deeply involved in FFBS usage, and the smartphone activeness becomes one of the classifiers in understanding the categorization of users as the simulation study will show. Therefore, a need for a survey was perceived before any attempt of putting methodology or simulation into practice. Especially in this research, the behavioural separation of FFBS users, their preference over several attributes, and the influence of sociodemographic on FFBS choice making are expected to be answered only through survey. To obtain the parameters a novel RP-SP survey is designed and implemented. The conclusions of this research are expected to benefit both simulation and methodology research, together set the foundation for any further research. In detail, the following questions will be addressed:

1.6. Outline and Structure of the Dissertation

This dissertation is organized into seven chapters. This introduction chapter explains FFBS development and its behaviour impact on both users and the academic as research motivation. The objectives of the study and research outline of the dissertation is also explained.

In Chapter 2, the development of various literature on bikesharing, assignment methodology, simulation structure and survey are fully reviewed.

Chapter 3 provides a table of notations and basic assumptions for the subsequent sections. The general formation of the link-cost function is deducted first and followed by a step-by-step deduction of the access distance as the innovative link cost functions. The key concepts for FFBS are modelling the uncertain distances. To achieve this, the random-random (RR) and centroid-random (CR) distance are deducted gradually from (1, 1) scenario to $(1, n)$ and finally (h, n) scenario where n stands for the number of users and h for the number of available bicycles. The RR distance describes access costs from an individual's activity place to bicycles; the latter describes access costs from a central point, such as a public transport station, to bicycles. The functionality of the formulations is heavily discussed, together with the explanation of other assignment approach used for comparison.

In Chapter 4 the basic simulation structure is firstly explained. The results of both simulation and previous mentioned assignment are intensive compared in this chapter. Small scale case studies comparing the two approaches under different OD matrix and bicycle supply patterns are conducted as examples. Finally, contributions and limitations are discussed

In Chapter 5 the basic simulation structure is extended. This is followed by an introduction of our own simulation framework, including an explanation of the types of travellers distinguished in this study. Travellers with different levels of activeness in smartphone usage during the vehicle-seeking process are categorized. In “Event Separations” the decision-making process of different types of travellers are separated into events in order to reproduce these in the agent-based model (ABM) with discrete-event simulation (DES). Simulation settings and evaluation criteria are explained thereafter, and results are discussed in the following section before conclusions are derived in the final section of this chapter.

In Chapter 6 the survey is introduced. The object of this survey and the art of designing corresponding questionnaire are explained. Eight random generated map figures are presented to the respondent. In such figure, six alternatives are presented and in each alternative, seven or eight attributes can be packed into one bicycle location with discount and risky markers. The other efforts are also made in order to guarantee no obviously better alternative is generated in each figure.

The correspondents are firstly categorized through a latent class analysis. The progressive analysis on the questionnaire data is conducted firstly through MNL and later moves to Nested Logit to study the relationship and preferences of each attribute. This is followed by a study of the interaction of scenario attributes and socio-demographic attributions. Conclusions from the survey are derived in the final section of this chapter.

Chapter 7 concludes this study by summarizing and converging the central findings of this study. Implication for policy and planning are derived, shortcomings of the study, recommendations for future work, as well as an assessment of the overall contribution of this study.

CHAPTER 2. LITERATU REREVIEW

2.1. Review on Bikesharing Systems

2.1.1. General literature on bikesharing system

The academic researches related to free-floating bicycle-sharing (or dockless bicycle sharing) have grown rapidly in recent years. Some general reviews of bicycle sharing system have been widely accepted (DeMaio (2009); Shaheen et al. (2010); Fishman et al. (2013); Fishman (2015)). Zhang et al. (2014) concluded the bicycle evolution in China which serves as a good background reading. Similarly, Shaheen et al. (2014) and Schoner et al. (2018) concluded the development of bikesharing systems in America. Some NGO reports also focusing on this topic such as the National Association of City Transportation Officials (2017) and Bicycle Transit Systems (2017).

2.1.2. Obstacles and promoters of bikesharing

FFBS schemes have experienced waves of increasing and decreasing popularity. Often hailed as the solution to the first and last mile problem, at the same time they have been abandoned in many cities due to above discussed issues as well as theft and vandalism (Van Lierop et al. 2015). Chen et al. (2020) identified the obstacles and promoters of bikesharing. Issues of vandalism and irregular parking occur with the expansion of shared bicycles remain key obstacles to the more rapid spread. As the initial bubble of the bicycle sharing industry collapsed in 2017 in China, the future business model and the sustainability of bicycle sharing industry raise deeper concern. Parkes et al. (2013) identified the obstacles and promoters of bikesharing spread by surveying 19 systems, 12 decision-makers in Europe and 14 in North America. The expensive or capricious policies remain key obstacles to the more rapid spread.

Choi and Choi (2020) identified factors for sustainable industry and called for the elimination of ‘over-supply issues’ through appropriate policies such as competition structure based on the licensing system and promoting regulations.

2.1.3. Reviews on the usage patterns of bikesharing

With respect to studies analysing usage patterns, we mention Shaheen et al. (2011) conducted an intercept survey in Hangzhou questioning bicycle sharing members and non-members to identify key differences. Bicycle sharing captures modal share from bus transit, walking, autos, and taxi: approximately 30% of members had incorporated bicycle sharing into their most common commute, and 80% of their users indicated that the most frequently used bicycle sharing station was one close to their home or work. Buck et al. (2013) examined usage patterns in Washington D.C., and suggested that users tend to be female, younger, have a lower household income, own fewer cars and bicycles and are more likely to ride for utilitarian trips. Shen et al. (2018) specifically focused on the usage of FFBS in Singapore by analysing GPS data of dockless bicycles. The influence of fleet size, the built environment, access to public transport, bicycle infrastructure, and weather conditions are explored. Generally, a larger bicycle fleet is associated with higher usage but with a diminishing marginal impact. Du and Cheng (2018) explore the characteristics and influential factors of different FFBS travel patterns, including occupation, travel distance, fare, accessibility to FFBS, etc. In particular, FFBS used for access/egress to public transport prevail when travelling beyond 4 km or during rush hours. Buck et al. (2013) compared the user property differences between bike share users and regular cyclists; Fishman et al. (2014b) and Efthymiou et al. (2013) further discussed the factors influencing the user's choice of bikesharing modes.

2.1.4. Reviews on the impact of bikesharing

The impact of bikesharing is also discussed. Fishman et al. (2014a) discussed the impact on car usage, Martin and Shaheen (2014) discussed the mode shift of public transport and Fishman et al. (2015) discussed the impact on active travel. Shaheen et al. (2011), Parkes et al. (2013) and Schoner et al. (2018) provide different methods on the research of the user's acceptance and its diffusion. Shen et al. (2018) adopted spatial autoregressive models to analyse the spatiotemporal patterns of bike usage, considering the impact of bike fleet size, surrounding built environment, access to public transportation, bicycle infrastructure, and weather conditions.

Although the station-based bicycles and its mechanism is well discussed, these researches cover the same topic as free-floating bicycle sharing. In station-based research, more attention was on optimizing the station locations and the dock size in each station. However, in free-floating scenarios, the object of these researches should be the predicting of bicycle distribution in each zone. Here we would like to focus on the following literature.

2.2. Review on Bikesharing Methodology Literature

Different from the rich literature on user preferences for shared bicycles, there is limited research aiming to analytically describe the evolving spatial fleet distribution of a sharing system. Related studies have mostly focused on station-based assignment, deep learning or microsimulation approaches for free-floating vehicle sharing.

We would like to specifically focus on the following literature.

Nair and Miller-Hooks (2014) provided a notable research in equilibrium network design with station-based vehicle-sharing under a bilevel model. The upper level maximizes the operator's revenue by varying station locations, fleet size, and initial vehicle distribution, and the lower level calculates the assignment of the fixed demand to the combined network. Within the context of free-floating carsharing, Li et al. (2018) proposed a dynamic user equilibrium model that embeds the choice of carsharing into daily trip chains by extending a multi-state supernetwork representation. In their research, a deterministic representation of the urban system was used where free-floating cars can be parked and picked up in designated areas. Thus, users are assumed to have a certain waiting time following the first-in-first-out principle when waiting for free-floating cars to become available.

Friedrich and Noekel (2017) discussed the traffic assignment of intermodal networks with public transport and vehicle sharing systems. They propose an approach to integrate FFBS into the macroscopic VISUM assignment. They model the access time of the free-floating vehicle sharing system by looking into the probability of finding an available vehicle within a surface area. An average safety margin of this probability is thus fixed in their research for connection search and utility calculation. In contrast to their approach, we point out differences to our work that will be elaborated further in the following sections: Firstly, they assumed users have a fixed origin as all trips begin at the centroid of an origin zone and end in the corresponding centroid of the destination zone. Secondly, in the capacity-constrained scenario, they suggest that 'check-outs can occur anywhere in the network', thus they assumed that the free-floating bicycles (or cars) are perfectly re-positioned between uses. Thirdly, the walk distance towards free-floating bicycles is defined by the total number of bicycles supplied in the zone, and a pre-defined probability of finding an available bicycle in the zone. It hence does not consider competition for the available bicycles which we suggest should not be ignored. In conclusion, we suggest that there is a gap in the existing literature with respect to modelling the details in access costs to free-floating services, especially for large fleet sizes and in the case of asymmetric patterns, where one might not want to rely on simulation. In case when incoming and outgoing bicycles in a zone are fairly balanced, one might presume a fixed walking distance, but this will not be the case if the available fleet tends to deplete during a period of time.

Another important literature is Wu et al. (2018). This research discussed a closest-bicycle-seeking process based on square lattice network and Manhattan distance. This approach tried to approximate the free-floating scenario by the station-based system with the densely distributed station on every vertex of the square lattice network. Although this approximation is reasonable on a certain level, we believe it does not capture the 'randomness' essence of the 'free-floating' characteristic. Moreover, such assumption of bicycles distributed on every vertex of the square lattice network is only suitable for static analysis. When considering bicycles' relocation after each interval, this assumption may raise concerns.

2.3. Review on Bikesharing Simulation

Free-floating sharing services have been the topic of research from various angles including operational strategies, its integration and role in a city with other modes and their impacts on behaviour. We focus in the following on the latter.

The main interest of our simulation study is the role of smartphones in dealing with the uncertainty of where to find free-floating vehicles and whether these are available. Smartphones are involved both during travelling (scanning the QR code of free-floating vehicle after arriving at the spot) and possibly during trip planning (using smartphones to find or reserve a vehicle). There is a wide range of literature dealing with traveller's choice behaviour under uncertainty but relatively less with specific reference to the availability of free-floating services, the willingness to wait, and the role of smartphone during this process.

Smartphone usage on travel is mainly discussed in terms of making travel less stressful (Tan and Lu, 2020; Raveau et al., 2016; Dickinson et al., 2014), changing activity patterns and inducing demand (Shaheen et al., 2016; Fan et al., 2012). Khan et al. (2020) explored the effects of individuals' smartphone application usage on mobility choices in terms of their attitudes. Tech savvy auto commuters are prone to decrease their vehicle kilometres travelled due to smartphone application usage while non-tech savvy auto commuters demonstrated an opposite behaviour. Tech savvy urban area dwellers also showed less willingness to increase their mobility. Liu et al. (2022) find that smartphones can encourage the re-examination and re-arrangement of pre-trip plans by making physical and social contexts explicit and by enabling decision-making in much closer proximity to the time and location of the activity. Smartphones not only change the contexts but also afford new interaction possibilities and new opportunities for optimizing trip experiences.

Jamal and Habib (2020) show that activeness in smartphone usage has profound influences for both trip planning and travel outcomes. However, to the best of our knowledge, there is few literatures as to how often and when people use mobile phones during walking to update their route choice - and in particular to look for available free-floating vehicles. The most closely related study we find is Kwon et al. (2020) who report that more than 90% of young travellers use smartphones at least 'sometimes' while walking or waiting at a red signal.

Reservation of services will reduce anxiety but also creates costs, either directly or indirectly by the need to spend time for reservation and reduced flexibility as to one's route choice. Not only for parking problems, behavioural aspects and system efficiency connected to reservation systems have been discussed for other transportation modes. Liu et al. (2015) analysed the efficiency of a highway use reservation system under which reservation is required in advance and can be rejected when using a highway bottleneck. They find that queuing and congestion are relieved, the efficiency loss in a practical system is bounded, and furthermore, the reservation system approaches the same efficiency as the first-best time-varying toll in the ideal case. The transaction behaviour of tradable permits is often viewed as a type of reservation behaviour under uncertainty which allocate infrastructure capacity efficiently. Hara and Hato (2017) discuss the scenario that shared vehicles are auctioned and find that the reservation system does not necessarily lead to an efficient allocation because users postpone their decision-making and changed their schedule without prior warning. They empirically showed that this behaviour is one of the causes that the tradable permit system does not work. Kaspi et al. (2014) studied the effectiveness of parking reservation policy in one-way vehicle sharing. Their research reports that a complete parking reservation policy (CPR) reduces both the excess time spent in the system and the uncertainty related to the usage of vehicle sharing systems. Their further study (Kaspi et al., 2016) reinforces such conclusion by comparison to several partial reservation policies.

Their study suggests CPR to be the most effective in terms of reducing the total excess time while all partial parking reservation policies can save time compared to a no-reservation policy. Most of the free-floating carsharing services offer highly restrictive reservations to avoid vehicle idling instead of being used by other users. Molnar and Correia (2019) studied the drawbacks of providing long-term reservation and proposed a flexible relocation-based reservation (R-BR) method which locks vehicles only a short time before the trip departure. The R-BR method is proved to outperform conventional long reservation in all problem instances except for the scenarios with very low number of trips. Wu et al. (2019) conducted a stated-choice survey to identify the carsharing users' preference for reservation mechanisms. Respondents show positive willingness-to-pay (£0.54 per journey) for guaranteed advance reservation while negative willingness-to-pay for virtual queueing. They also find that socio-demographics and personality characteristics correlate with carsharing usage and reservation behaviour. They further proposed a choice-based optimisation approach to evaluate dynamic pricing with consideration of users' preferences to uncertainty (Wu et al., 2021). The dynamic pricing shows the potential for large gains in revenue relative to the currently prevailing flat-rate pricing structure.

To model such uncertainties associated with free-floating services and user responses we will develop an agent-based simulation approach to fit our needs. Such models have been a main tool to model transportation systems with free-floating vehicle sharing. The multi-agent transport simulation project, MATSim, is an activity-based, extendable, multi-agent, dynamic traffic assignment model which has been attracting extensive attention worldwide. For example, Ciari et al. (2014) simulated three different scenarios to evaluate different carsharing scenarios for the city of Berlin. The early scenarios are station-based services, and these are then combined with free-floating services. Bischoff et al. (2017) integrated shared taxi services into dynamic simulation based on insertion heuristics in MATSim. Using a taxi data set from Berlin, their simulation suggests that the overall vehicle kilometres travelled may be reduced by 15–20% , while travel time increases can be kept at a relatively low level. Balac et al. (2019) developed a first implementation of a carsharing relocation interface for MATSim. They investigated the interaction of two competing free-floating carsharing operators in the city. They reported that relocations are unprofitable in a competitive carsharing market. Even if every relocation would be turned into a rental, relocations at best leads to a marginal increase in revenue. Similarly, Heilig et al. (2018) proposed the first one-week simulation considering station-based and free-floating carsharing with the help of a modular agent-based travel demand modelling framework, mobiTopp. Both pieces of research provide an activity-based, multi-modal approach, and are seeking user equilibrium under a microsimulation-based framework. They presume that users can make infinite long reservations and do not estimate suitable timespans of reservation. Moreover, the traveller's attitude toward smartphone usage in seeking available vehicles is not modelled, which we suggest is significant in understanding the competition for reserving and using of free-floating vehicles as well as resulting distributions of the vehicles.

In summary, both traveller's choice behaviour under uncertainty and the impact of smartphone usage for travel patterns are widely acknowledged. With respect to free-floating services, the smartphone is the key information source of travellers but how it is used on a microlevel for such as booking services and how this then impacts the system performance appears to be understand. To analyse this, our agent-based simulation approach described in the following is hence with respect to some details of the agents' decisions "nano-scope" whereas a range of network and multi-modal aspects are simplified.

2.4. Reviews of the Survey of Bikesharing

Yang et al. (2018) studied the real data of the public bicycle-sharing systems of Hangzhou and Ningbo in China and find that both systems can decrease the average trip time of passengers and increase the efficiency of an urban public transport network, as well as effectively improve the uneven level of traffic flow spatial distribution of an urban public transport network and will be helpful to smoothening the traffic flow and alleviating traffic congestion. Reck et al. (2021) provides a comprehensive data-driven study of choice among docked and dockless micromobility modes. They observe a "plateau effect" between increasing fleet densities and decreasing marginal utility gains. However, they did not further investigate the heterogeneity among travellers, which we will include in the following section. The connection to additional modes such as walking and public transport are also not investigated in their research.

de Luca and Di Pace (2015) who presented a stated preference survey on drivers' parking location choice under uncertain parking availability and search time. The majority of drivers are willing to seek a parking spot for up to 8-13 minutes as they approach or arrive at their destination. Uncertain parking availabilities rank as second (for availability after 8 minutes) and fourth (for availability upon arrival) most important factors in determining parking location decision, where parking costs is ranked first, and walking distance to destination is ranked third. Whether such values and rankings are transferable to the problem of searching for available free-floating services is, however, not clear.

CHAPTER 3. ASSIGNMENT WITH FREE-FLOATING

This chapter is an advance of Master thesis. In this chapter our focus is on the effect of access cost to the nearest available bicycle from a person's origin considering cases when the number of available bicycles is reducing over time. In that case the access time depends on the competition for available bicycles as well as the distribution of demand and bicycles. We solve the problem by a network description that includes 'random-to-random' and 'centroid-to-random' links. The former describes access costs from an individual's activity place to bicycles; the latter describes access costs from a central point, such as a public transport station, to bicycles. Expected costs of these links according to order statistics are obtained. We embed this into an assignment approach and point out that asymmetric link cost functions arise due to the competition for the same bicycles on different links.

3.1. Notation and Main Assumption

The notations used in this paper are summarized in Table 3.1We split our area of analysis into a number of square zones with links and nodes. The general topology of a zone i is shown in Figure 3.1. Each zone generates and attracts trips. The demand node (D_i, black) is the abstraction of all trip origins and destinations located in this zone. Therefore, though it is illustrated in Figure 3.1 as a fixed node, it has to be thought of as a node with an unknown and varying location within the zone. We further presume that each zone initially has a given number of free-floating bicycles φ_i distributed randomly (according to a known distribution) throughout the zone. We indicate bicycle nodes in Figure 3.1 but emphasize that these are also nodes with an unknown, randomly varying location. The internal bicycle node (B_i^I, blue) indicates the bicycles used to access D_i from T_i. Finally, the outbound bicycle node (B_i^O, blue) is used to model the abstraction of the bicycles used to depart from D_i. Furthermore, one PT station (node T_i, red) is presumed to exist at the centroid of each zone. We note that the case of no public transport service for a zone is covered by assuming no service from this node.

The walking distance from the (random) origin to the bicycle is our main variable of interest in this paper. The distance from D_i to B_i^O is the distance between two random points, which we mark in the green shade as RR (Random-to-Random) distance. Instead, travellers aiming to use bicycles when arriving with a public transport service at the central PT node have two alternatives: If there are bicycles left at the PT node, then travellers can access these with little effort (walk with a fixed, short distance) before cycling. Otherwise, the travellers must walk from the centroid (T_i) to a random point (B_i^I). We refer to this distance as CR (Centroid-to-Random) in Figure 3.1.

Table 3.1 Notations

Network topology variables	
$i \in Z$	Element and set of zones
$k \in K$	Element and set of travellers
$l \in L$	Element and set of links
$m \in \{w,\ c,\ t\}$	Element and set of link-specific modes (walking, cycling, transit)
$p \in \{w,\ c,\ t,\ ct,\ tc,\ ctc\}$	Element and set of path-specific modes (walking, cycling, transit, cycling + transit, transit + cycling, cycling + transit + cycling)
D_i, T_i	Demand node and transit node in zone i
B_i^I, B_i^O	Internal and outbound bicycle node in zone i
$c_{ij}^p(k),\ \tilde{c}_{ij}^p(k)$	Deterministic and stochastic travel cost of the k^{th} traveller from zone i to j on path p.
l_{rs}^m	Link from node r to s by mode m
v_{rs}^m	Volume on link l_{rs}^m
q_{ij}^p	Volume from zone i to j on path p
V_m	The velocity of traveling by mode m
$2r$	The side length of the square zone
Network inputs	
φ_i^T	Number of bicycles distributed at the PT (transit) station in zone i
φ_i^Φ	Number of bicycles free-floatingly distributed in zone i
φ_i	Number of bicycles distributed in zone i ($\varphi_i = \varphi_i^T + \varphi_i^\Phi$)
g_{ij}	The OD from zone i to zone j
θ	The positive sensitivity parameter for SUE assignment
Bicycle-seeking related variables	
$x_1,\ \ldots,\ x_n$ and $X_1,\ \ldots,\ X_n$	Statistically IID random observations and variates
$X_{(k),n}$	The k^{th} order statistic of sample size n
$E_{(k),n}$	The expectation of $X_{(k),n}$
u	The walking distance toward free-floating bicycles
$f^{CR}(u),\ F^{CR}(u)$	The ‘Centroid-to-Random’ (CR) pdf and cdf of walking distance
$f^{RR}(u),\ F^{RR}(u)$	The ‘Random-to-Random’ (RR) pdf and cdf of walking distance
$f_{(k),n}^{CR}, E_{(k),n}^{CR}$	The pdf and expectation of $X_{(k),n}$ in a CR scenario
$f_{(k),n}^{RR}, E_{(k),n}^{RR}$	The pdf and expectation of $X_{(k),n}$ in a RR scenario
$G_{rs}^{CR}(k,h,n), \mathrm{G}_{rs}^{RR}(k,h,n)$	The expected distance of the k^{th} among h traveller with leet size n from node r to s in the CR and RR scenarios
$S_{rs}^m(k,h,n)$	Link cost of the k^{th} among h traveller with fleet size n on link l_{rs}^m ($k \le h$ and $k \le n$)

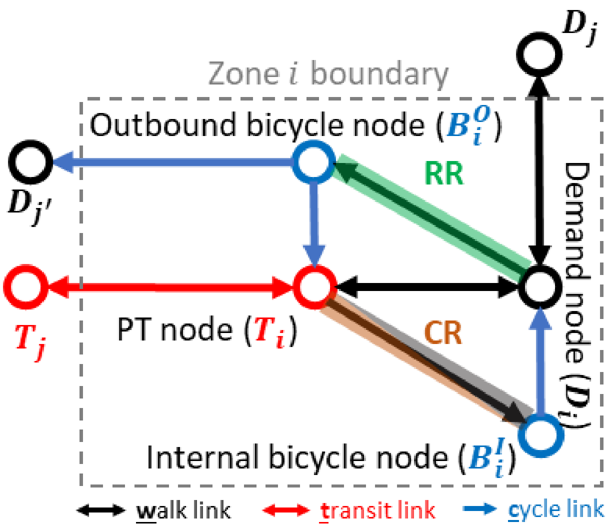


Figure 3.1 The general topology of zones with node abbreviations ($j \in Z$), the locations of the black and blue nodes are unknown and represent distributed demand bicycles. The cost of shaded links is influenced by competition.

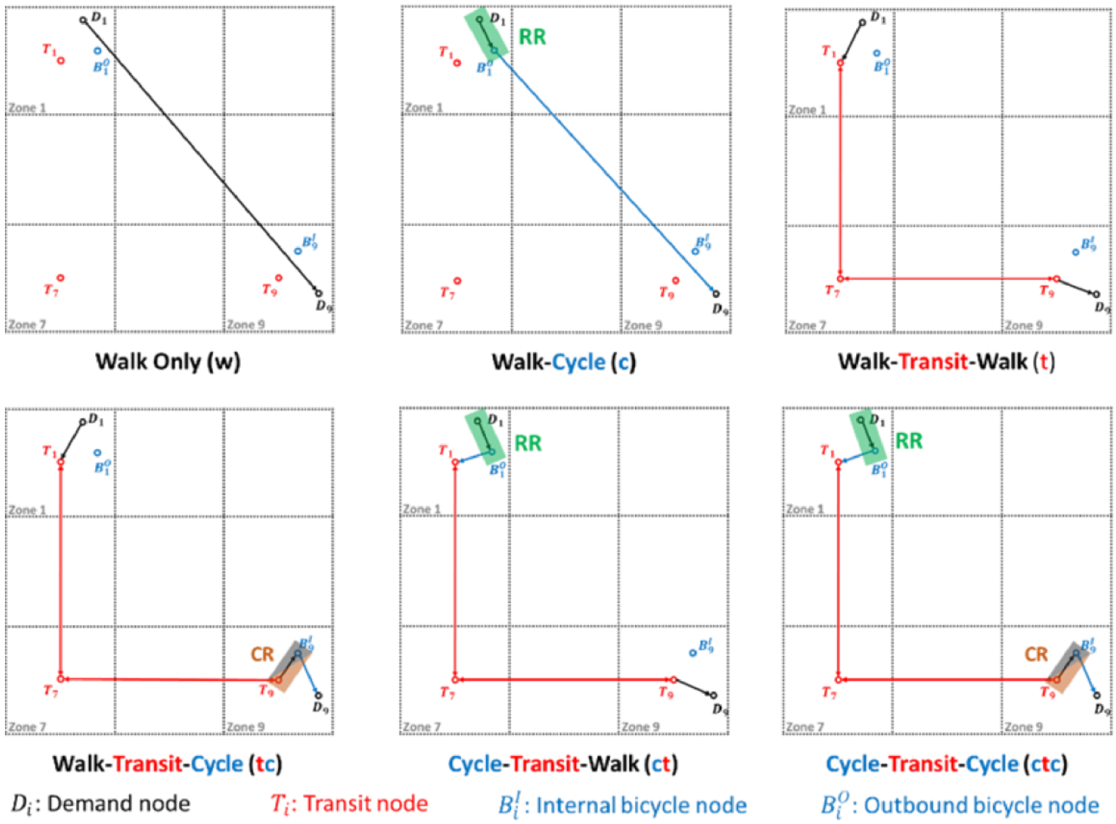


Figure 3.2 Six feasible paths and corresponding abbreviations

Combining several zones will generate the study area. It also leads to the definition of six feasible mode combinations that we describe as paths. We illustrate the options for travellers from Zone 1 to Zone 9 in Figure 3.2. In the example there is only one public transport connection and travellers must transfer at T_7 when using this service. Additional transport options can be added to our model but are not our focus and omitted for simplicity. We assume there are following 6 feasible travel modes between demand nodes as shown in Figure 3.2 (take trips from upper left zone to lower right zone as an example). The utility of each mode is calculated as:

$$U_{p\,\in\,\{w,\,c,\,t,\,ct,\,tc,\,ctc\}} = \sum_{m\,\in\,\{w,t,c\}} \beta_m t_m \sum_{l\in L} \delta_{l,p}^m dis_l^m + \varepsilon_p \tag{3.1}$$

where β_m is the corresponding marginal utility of time travelling by using walking, transiting and cycling; t_m is the corresponding standardized time unit which is defined as the reciprocal of walking speed, PT operation speed and cycling speed; $\delta_{l,p}^m$ equals to 1 if link l is a part of mode m travelling by walking, transiting or cycling; dis_l^m is the travel distance of travelling by walking, transiting and cycling on link l. ε_p is the residual of all unobserved factors that affect the traveller's choice of mode p.

For better formalization, we would like to use the following abbreviations in the discussion of six feasible travel modes.

1. Walk-Only (w): Walk-Only scenario represents travellers walking from a demand node to another demand node directly. The trip distance is the Euclidean distance between origin and destination. The corresponding random utility function can be shown as:

$$U_w = \beta_w t_w dis_{D_1 D_9} + \varepsilon_w \tag{3.2}$$

   where $\mathrm{dis}_{D_1 D_9}$ is the expected distance from origin (node D_1) to destination (node D_9) of this trip, ε_w is the residual of all unobserved factors that affect the traveller's choice of Walk-Only mode.

2. Walk-Cycle (c): Walk-Cycle scenario represents travellers walking from a demand node to the closest bicycle with unknown location, and cycling directly to another demand node, which is the destination of the trip. The corresponding random utility function is:

$$U_c = \beta_w t_w \mathrm{dis}_{D_1 B_1^O} + \beta_c t_c \mathrm{dis}_{B_1^O D_9} + \varepsilon_c \tag{3.3}$$

   where ε_c is the residual of all unobserved factors that affect the traveller's choice of Walk-Cycle mode.

3. Walk-Transit-Walk (t): Walk-Transit-Walk scenario represents travellers walking from a demand node to the closest PT station and board. Alighting at the closest PT station to the destination and then walking to another demand node, which is the destination of the trip. The walking distance from one demand node to the PT station (or reversely) is the expected distance between one random point to the centroid in a square. Thus, the random utility function of transiting mode is:

$$U_t = \beta_w t_w (\mathrm{dis}_{D_1 T_1} + \mathrm{dis}_{T_9 D_9}) + \beta_t t_t (\mathrm{dis}_{T_1 T_7} + \mathrm{dis}_{T_7 T_9}) + \varepsilon_t \tag{3.4}$$

where ε_t is the residual of all unobserved factors that affect the traveller's choice of Walk-Transit-Walk mode.

4. Walk-Transit-Cycle (tc): Walk-Transit-Cycle represents travellers walking from a demand node to the closest PT station and board. Travellers then alight at the closest PT station to the destination and walk to the closest bicycle (location unknown), and finally cycle to another demand node, which is the destination of the trip.

$$U_{tc} = \beta_w t_w \left(\mathrm{dis}_{D_1 T_1} + \mathrm{dis}_{T_9 B_9^I}\right) + \beta_c t_c \mathrm{dis}_{B_9^I D_9} + \beta_t t_t \left(\mathrm{dis}_{T_1 T_7} + \mathrm{dis}_{T_7 T_9}\right) + \varepsilon_{tc} \tag{3.5}$$

which ε_{tc} is the residual of all unobserved factors that affect the traveller's choice of 'Walk-Transit-Cycle' mode.

5. Cycle-Transit-Walk (ct): Cycle-Transit-Walk represents travellers walking from a demand node to the closest bicycle, and cycle to the closest PT station then board. Travellers alight at the closest PT station to the destination and then walking to another demand node, which is the destination of the trip.

$$U_{ct} = \beta_w t_w \left(\mathrm{dis}_{D_1 B_1^O} + \mathrm{dis}_{T_9 D_9}\right) + \beta_c t_c \mathrm{dis}_{B_1^O T_1} + \beta_t t_t \left(\mathrm{dis}_{T_1 T_7} + \mathrm{dis}_{T_7 T_9}\right) + \varepsilon_{ct} \tag{3.6}$$

where ε_{ct} is the residual of all unobserved factors that affect the traveller's choice of 'Cycle-Transit-Walk' mode.

6. Cycle-Transit-Cycle (ctc): Cycle-Transit-Cycle represents travellers walking from a demand node to the closest bicycle, cycling to the closest PT station and boarding. Travellers then alight at the closest PT station and walk to the closest bicycle, and cycle to another demand node, which is the destination of the trip.

$$U_{ctc} = \beta_w t_w \left(\mathrm{dis}_{D_1 B_1^O} + \mathrm{dis}_{T_9 B_1^I}\right) + \beta_c t_c \left(\mathrm{dis}_{B_1^O T_1} + \mathrm{dis}_{B_1^I D_9}\right) + \beta_t t_t \left(dis_{T_1 T_7} + dis_{T_7 T_9}\right) + \varepsilon_{ctc} \tag{3.7}$$

which ε_{ctc} is the residual of all unobserved factors that affect the traveller's choice of 'Cycle-PT-Cycle' mode.

Following the above assumptions, we require an approach to determine the RR and CR distances of travellers to model the access cost to the bicycles. We consider cases where the available fleet size is gradually decreasing over a time period. This could be because a) of morning commute type problems where travel in a zone is unidirectional b) because the usage period is long, that is, once a bicycle is under usage it can be assumed that it will not be used by other users in the same period of analysis or c) because the booking system is 'discrete', i.e. a booking is made for fixed time intervals such as from a scroll down menu where say 30min time slots can be selected. In any of these cases, therefore the earlier the traveller departs (or books the service) the lower the access cost. In case the available fleet size remains constant the problem simplifies. In the following, we construct a link-cost function under these assumptions.

3.2. Deduction of the RR and CR Expected Distance in (1, 1) Case

We first assume the existence of only one traveller and only one bicycle and denote this as the (1, 1) case for which the CR and RR distributions are deducted as follows. Let $f^{CR}(u)$ denote the CR probability distribution function (pdf) of walking distance u from the zone centroid (the PT station) to one randomly, uniformly distributed bicycle. Similarly, we denote the RR probability distribution function as $f^{RR}(u)$, which stands for the pdf of the distance between a uniformly distributed origin and an also uniformly distributed bicycle.

3.2.1. Deduction of $\boldsymbol{f^{RR}(u)}$ and $\boldsymbol{F^{RR}(u)}$

Philip (2007) provided the logic of deducting the expected distance between two random points in a rectangle with edge lengths a and b. Following such logic, we complete and present the deduction of $f^{RR}(u)$ and $F^{RR}(u)$ for a simpler case with identical side length in this section.

Assume X_1, X_2 are two independent and identically distributed (IID) random variables (r.v.) obeying $U(0, a)$. We firstly construct $F_a(t)$ as the cdf of $(X_1 - X_2)^2 \leq t$:

$$F_a(t) = \text{Prob}\{t|(X_1 - X_2)^2 \leq t\} \tag{3.8}$$

Because X_1, X_2 are IID distributed uniform variables, we can easily expand the geometric distribution of Eq.(3.8) into two straight lines as shown in Eq.(3.9). For non-uniform distributions, an extra one-one mapping is needed.

$$X_1 - X_2 \leq \sqrt{t},\ X_1 - X_2 \geq -\sqrt{t} \tag{3.9}$$

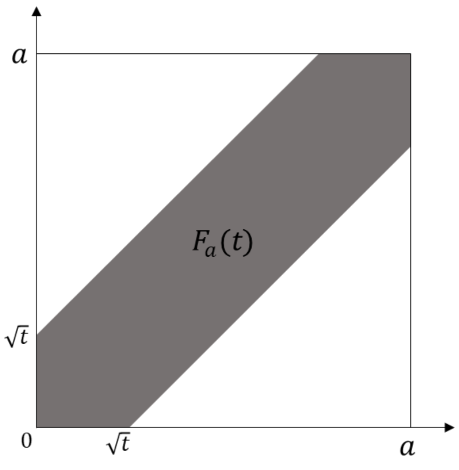


Figure 3.3 The area of $\boldsymbol{F_a(t)}$

These two lines can also be plotted, together generate a grey strip as shown in Figure 3.3. The $F_a(t)$ is proportional to the area of that. $F_a(t)$ can be easily presented as:

$$F_a(t) = \begin{cases} 1 - \left(1 - \sqrt{t}/a\right)^2, & 0 < t \le a^2 \\ 1 & a^2 < t \end{cases} \tag{3.10}$$

Since $F_a(t)$ is the cdf of $(X_1 - X_2)^2 \le t$, the pdf can also be acquired:

$$f_a(t) = \frac{1}{a\sqrt{t}} - \frac{1}{a^2},\ 0 < t \le a^2, \text{ when } X_1, X_2 \text{ obey } U(0, a) \tag{3.11}$$

Assume random variables X_1, X_2 obey $U(0, a)$ and Y_1, Y_2 obey $U(0, b)$. We can easily construct similar $f_b(t)$ from Eq.(3.27) for Y_1 and Y_2. We now construct $g_{ab}(s)$ as:

$$g_{ab}(s) = \text{Prob}\{s | (X_1 - X_2)^2 + (Y_1 - Y_2)^2 \le s\} \tag{3.12}$$

(X_1, Y_1) and (X_2, Y_2) can be viewed as a pair of uniformly distributed endpoints of one line. Obviously, $(X_1 - X_2)^2$ and $(Y_1 - Y_2)^2$ are also independent. The physical meaning of s is the square of Euclidean distance between (X_1, Y_1) and (X_2, Y_2). $g_{ab}(s)$ is then the convolution of f_a and f_b ("$*$" is the convolution operator):

$$g_{ab}(s) = f_a * f_b = \int f_a(s - \tau) f_b(\tau)\, d\tau \tag{3.13}$$

After substituting f_a and f_b into Eq.(3.29) and assuming $a = b$, we can obtain the following piecewise function:

$$g_{ab}(s) = \begin{cases} \int_0^s f_a(s - \tau) f_b(\tau)\, d\tau & 0 < s \le a^2 \\ \int_{s-a^2}^s f_a(s - \tau) f_b(\tau)\, d\tau & a^2 < s \le b^2 \\ \int_{s-a^2}^{b^2} f_a(s - \tau) f_b(\tau)\, d\tau & b^2 < s \le a^2 + b^2 \end{cases} \tag{3.14}$$

In a simpler case we can assume $a = b$. Therefore, Eq.(3.14) is then simplified as:

$$g(s) = \begin{cases} \int_0^s f_a(s - \tau) f_a(\tau)\, d\tau = \int_0^s \frac{1}{a^2}\left(\frac{1}{\sqrt{s\tau - \tau^2}} - \frac{1}{a\sqrt{\tau}} - \frac{1}{a\sqrt{s - \tau}} + \frac{1}{a^2}\right) d\tau & 0 < s \le a^2 \\ \int_{s-a^2}^{a^2} f_a(s - \tau) f_a(\tau)\, d\tau = \int_0^s \frac{1}{a^2}\left(\frac{1}{\sqrt{s\tau - \tau^2}} - \frac{1}{a\sqrt{\tau}} - \frac{1}{a\sqrt{s - \tau}} + \frac{1}{a^2}\right) d\tau & a^2 < s \le 2a^2 \end{cases} \tag{3.15}$$

Further substituting will finally give us the formulation as shown in Eq.(3.16), a piecewise $g(s)$ is then obtained.

$$g(s) = \begin{cases} -\frac{4\sqrt{s}}{a^3} + \frac{\pi}{a^2} + \frac{s}{a^4} & 0 < s \le a^2 \\ \frac{4 \sin^{-1}\frac{a}{\sqrt{s}}}{a^2} + \frac{4\sqrt{s - a^2}}{a^3} - \frac{2}{a^2} - \frac{s}{a^4} - \frac{\pi}{a^2} & a^2 < s \le 2a^2 \end{cases} \tag{3.16}$$

Further assume $s = u^2$ which gives u the physical meaning as the Euclidean distance, we can get the density for the distance $g_u(u)$ as Eq.(3.17). After substituting s with u^2 and a with side length $2r$, we get the pdf and cdf of the distance between two random points in the $2r \times 2r$ square in Eqs. (3.18) and (3.19).

$$g_u(u)du = g_s(u^2)\frac{du^2}{du} = 2ug_s(u^2) \tag{3.17}$$

$$f^{RR}(u) = \begin{cases} -\frac{u^2}{r^3} + \frac{\pi u}{2r^2} + \frac{u^3}{8r^4} & 0 < u \le 2r \\ \frac{2u\,sin^{-1}\left(\frac{2r}{u}\right)}{r^2} + \frac{u\sqrt{u^2-4r^2}}{r^3} - \frac{u}{r^2} - \frac{u^3}{8r^4} - \frac{\pi u}{2r^2} & 2r < u \le 2\sqrt{2}r \end{cases} \tag{3.18}$$

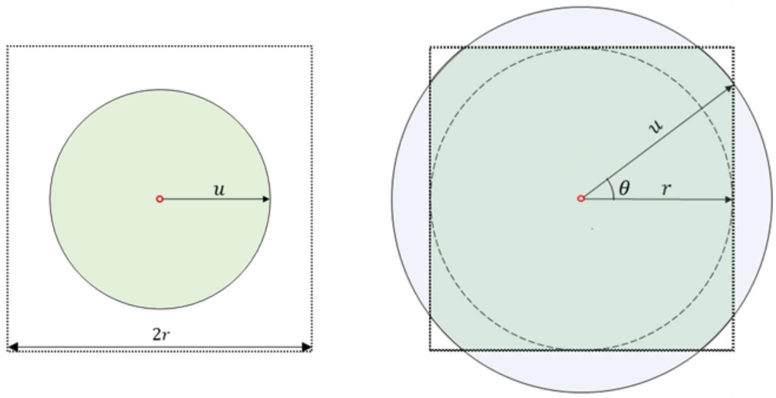
$$F^{RR}(d) = \begin{cases} \frac{\pi u^2}{r^2} - \frac{8u^3}{3r^3} + \frac{u^4}{2r^4} & 0 < u \le 2r \\ \frac{8u^2\sqrt{u^2-r^2}}{3r^3} - \frac{u^2\left[-4sin^{-1}\left(\frac{r}{u}\right)+\pi+2\right]}{r^2} - \frac{4\sqrt{u^2-r^2}}{3r} - \frac{u^4}{2r^4} + \frac{1}{3} & 2r < u \le 2\sqrt{2}r \end{cases} \tag{3.19}$$

3.2.2. Deduction of $f^{CR}(u)$ and $F^{CR}(u)$

The $f^{CR}(u)$ and $F^{CR}(u)$ can be calculated through a geometric way. This cdf can be viewed as the round catchment area in a square zone with $2r$ side length. With the walking distance u increases, it ranges between 0 and r, and further u can ranges between r and $\sqrt{2}r$. The square with dotted line has the $2r$ side length. When $0 \le u < r$, $F^{CR}(u)$ is the geometric probability of the specific bicycle falls within a round catchment with radius u which centred at the centroid. Therefore $F^{CR}(u)$ and further $f^{CR}(u)$ can be derived after taking derivate. Catchment (green circle within the square) under such scenario is shown in Figure 3.4 (a).

$$F^{CR}(u) = \frac{\pi u^2}{4r^2}, 0 \le u < r \tag{3.20}$$

$$f^{CR}(u) = \frac{\pi u}{2r^2}, 0 \le u < r \tag{3.21}$$



(a) $0 < u \le r$ (b) $r < u \le \sqrt{2}r$

Figure 3.4 The catchment of $F^{CR}(u)$ when $0 \le u < r$ (a) or $r \le u \le \sqrt{2}r$ (b)

When u further extend from r to $\sqrt{2}r$, the catchment is no longer fully captured by the square research area. The overlapping area can be considered as a full circle except four identical (the blue parts outside the square), as shown in Figure 3.4 (b). The overlapping part can then be calculated as the area of round catchment minus four identical segments with central angle θ. Therefore, the area of green catchment can be formulated in Eq.(3.22). After expanding and taking derivates, $F^{CR}(u)$ and $f^{CR}(u)$ with $r \le u \le \sqrt{2}r$ can be obtained, as shown in Eqs. (3.23) and (3.24).

$$S_{\text{green}} = \pi u^2 - 4\frac{\theta - \sin\theta}{2}u^2,\ where\ \theta = 2\cos^{-1}\frac{r}{u} \tag{3.22}$$

$$F^{CR}(u) = \frac{\pi d^2 - 2(\theta - \sin\theta)d^2}{4r^2}, r \le \mathrm{u} \le \sqrt{2}r \tag{3.23}$$

$$f^{CR}(u) = \frac{u}{2r^2}\left[\pi + \frac{2r}{\sqrt{u^2-r^2}} - \frac{2u^2}{u^2-r^2}\sqrt{\frac{(u^2-r^2)r^2}{u^4}} - 2\,cos^{-1}\left(\frac{2r^2}{u^2} - 1\right)\right],\ r \le u \le \sqrt{2}r \tag{3.24}$$

In conclusion, the $f^{CR}(u)$ is obtained in Eq.(3.25):

$$f^{CR}(u) = \begin{cases} \frac{\pi u}{2r^2}, & 0 < u \le r \\ \frac{u}{2r^2}\left[\pi + \frac{2r}{\sqrt{u^2-r^2}} - \frac{2u^2}{u^2-r^2}\sqrt{\frac{(u^2-r^2)r^2}{u^4}} - 2\,cos^{-1}\left(\frac{2r^2}{u^2} - 1\right)\right], & r < u \le \sqrt{2}r \end{cases} \tag{3.25}$$

The$f^{CR}(u)$ can also be obtained by add more simplification to Eq.(3.12). Instead of assuming X_1, X_2 obey $U(0,a)$ and Y_1, Y_2 obey $U(0,b)$, now we assume $X_2 = \frac{a}{2}$ and $Y_2 = \frac{b}{2}$. Therefore Eq.(3.25) is then derived by assuming $a = b = 2r$, and fixing one of the points at the centroid.

3.3. The Solution to (1, n) and (h, n) Cases

We now expand the choice sets for a single traveller from one to n bicycles in both CR and RR scenarios, denoting these as (1, n) cases. The walking distance then is the distance from the origin to the closest among n independent and uniformly distributed bicycles, which is the smallest distance value among n IID (Independent and Identically Distributed) samples. This pdf of the walking distance can be obtained with the help of order statistics.

We follow the simple definition of order statistic given by David and Nagaraja (2004):

> "If the statistically IID random variables $X_1,\ \dots,\ X_n$ are arranged in order of magnitude and then written as $X_{(1),\,n} \le \cdots \le X_{(n),\,n}$, we call $X_{(k),\,n}$ the k^{th} order statistic ($k = 1,\ \dots,\ n$)."

Correspondingly, the first order statistic, $X_{(1),\,n}$, is the minimum value of the sample and the n^{th} order statistic, $X_{(n),\,n}$ is the maximum value when the sample size is n. Let $X_1, \dots, X_n$ be random variables, and order statistics $X_{(1),n} = h_1(X_1, \dots, X_n)$, ..., $X_{(k),n} = h_k(X_1, \dots, X_n)$ be an 1-1 mapping. The general form of the joint pdf of $X_{(1),n}$ to $X_{(k),n}$ is shown in Eq.(3.26)

$$f_{(1,\dots,k)}\big(x_{(1),n},\ \dots, x_{(k),n}\big) = n!\ \prod_{k=1}^{k=n} f\big(x_{(k),n}\big),\quad if\ a < x_{(1),n} < \cdots < x_{(k),n} < b \tag{3.26}$$

In this research we assume X_1, ..., X_n has identical pdf $f_X(x)$ and cdf $F_X(x)$. Therefore, the general form of the joint pdf of $X_{(1),\,n}$ to $X_{(n),\,n}$ can be simplified as:

$$f_{X_{(1),n},\dots,X_{(n),n}}(x_1, \dots, x_n) = n!\, f_X(x_1)\cdots f_X(x_n),\ LB < x_1 < \cdots < x_n < UB \tag{3.27}$$

The marginal pdf of $X_{(k),\,n}$ with sample size n is then:

$$f_{X_{(k),n}}(x) = \frac{n!}{(k-1)!(n-k)!}[F_X(x)]^{k-1}[1-F_X(x)]^{n-k}f_X(x),\ LB < x < UB \tag{3.28}$$

where LB and UB are the corresponding lower and upper boundaries. The pdf and cdf for the CR and RR scenarios can be substituted into Eq.(3.28) so that $f^{CR}_{X_{(k),n}}(u)$ and $f^{RR}_{X_{(k),n}}(u)$, and furthermore $E^{CR}_{X_{(k),n}}$ and $E^{RR}_{X_{(k),n}}$ can be obtained, which denote the probability (expected distance) of finding the k^{th} closest bicycle at distance u (in the zone) in the CR and RR scenarios respectively.

3.3.1. Transform (h, n) case into link-cost function with capacity constraint

We continue to study the case when the k^{th} out of h $(1 \le k \le h)$ travellers is seeking a bicycle in a zone with fleet size n, which further extends the $(1, n)$ case into (h, n) scenarios. To represent the randomized characteristics of free-floating bicycle-sharing in the form of link cost, we define the link from node r to node s by mode m as l^m_{rs}. In this section we derive the expected distance of the next, the k^{th} among h traveller with fleet size n, on the RR and CR links.

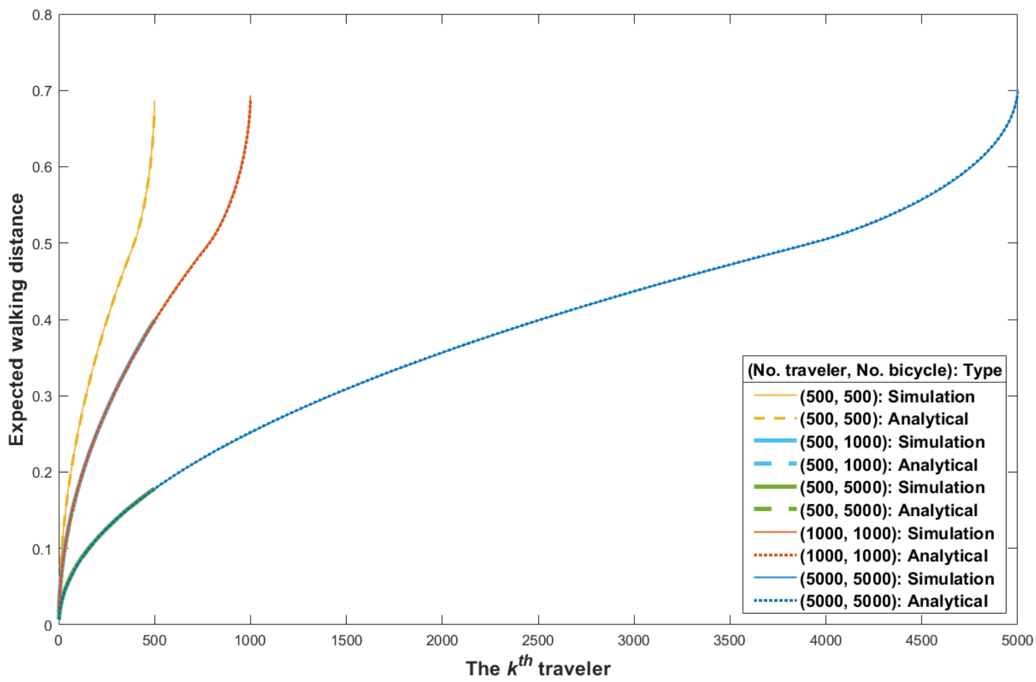


Figure 3.5 CR scenario: Results of analytical and Monte-Carlo simulation results in the unit zone for the k^{th} traveller for different h and n

In the CR scenario, travellers are homogenous since all travellers start seeking bicycles at the same location, and all travellers are assumed to choose the closest-available bicycle. Therefore, a total of n traveller-bicycle combinations remain feasible, and the distance for the k^{th} traveller $G^{CR}_{T_iB_i^I}(k,h,n)$ is equivalent to the k^{th} smallest value among n IID samples when $k \le n$. Following the deductions in the previous section, this distance can be calculated as:

$$G^{CR}_{T_iB_i^I}(k,h,n) = E^{CR}_{(k),n} = \begin{cases} \int_0^{\sqrt{2}r} f^{CR}_{X_{(k),n}}(u)\,du\,, & 1 \le k \le h \text{ and } 1 \le k \le n \\ \infty, & n < k \le h \end{cases} \tag{3.29}$$

Both analytical results following Eq.(3.29) and the results of a Monte-Carlo simulation are plotted in Figure 3.5. The Monte Carlo simulation randomly creates the bicycle location and the traveller order. The mean values of 100 simulations for the k^{th} traveller is shown in the Figure 3.5. The figure illustrates the increase in expected access cost for the later traveller and it also illustrates that the analytical result fits the Monte-Carlo simulation well as the corresponding curves are hardly distinguishable.

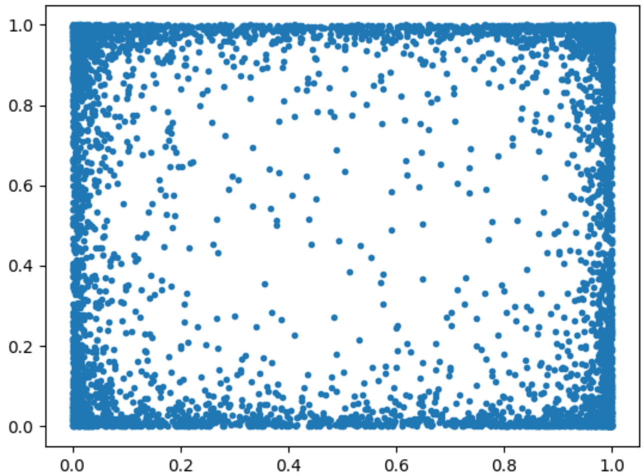


Figure 3.6 The distribution of the last available bicycle in 5000 trials ($\boldsymbol{h = 1000, n = 1000}$)

We now turn to the RR scenario. Different from the CR scenario, travellers are no longer homogenous when deriving $G^{RR}_{D_i B_i^O}(k, h, n)$. Since we assume that the bicycles are not redistributed during the selection process, this means that the IID assumption is violated. To illustrate this, we conduct 5000 Monte Carlo simulations for the ($h = 1000, n = 1000$) case and record the location of the last remaining bicycle. The results are shown in Figure 3.6. Before any bicycles are chosen, both travellers and bicycles obey a uniform distribution in the unit zone. Travellers pick the closest-available bicycle in random order and exclude it from the choice set of posterior travellers. As the bicycles gradually get occupied, the remaining bicycles are more likely to locate in the corners of the square. For the later travellers, their choice set has hence a different, biased distribution compared to those of the previous travellers.

After loading the k^{th} ($1 \le k \le h$, $1 \le k \le n$) traveller, now $(h-k)$ travellers are competing for $(n-k)$ remaining bicycles which leads to $(h-k)(n-k)$ combinations in the next assignment. The bicycle with the shortest distance will be chosen by the (randomly selected) next traveller, with endpoints determining the identity of the $(k+1)^{\text{th}}$ traveller and the $(k+1)^{\text{th}}$ bicycle to be occupied. If we ignore above illustrate problem simplify this case by assuming the distances of $(h-k)(n-k)$ possible lines are IID, thus each obeying $f^{RR}(u)$, then the approximated distance expectation of the $(k+1)^{\text{th}}$ traveller, $\tilde{G}^{RR}_{D_i B_i^O}(k+1,\ h,\ n)$, can be formulated:

$$\tilde{G}^{RR}_{D_i B_i^O}(k+1,\ h,\ n) = E^{RR}_{(1),\,(h-k)(n-k)} \tag{3.30}$$

$$E^{RR}_{(1),\,(h-k)(n-k)} = \begin{cases} \int_0^{2\sqrt{2}r} f^{RR}_{X_{(1),hn-nk-hk+k^2}}(u)du\,, & 1 \le k \le h \text{ and } 1 \le k \le n \\ \infty, & n < k \le h \end{cases} \tag{3.31}$$

We note that the exact mathematical deduction further depends on the assumption as to whether bicycles are reserve-able. If not, then the effect of the access time spread needs to be considered. We denote this spread as $0 \ldots T_{\max}$. A short spread means that users might head to the same bicycle but find it is occupied at the time when they arrive. If bicycles are reserve-able this is equivalent to $T_{\max} \to \infty$.

In order to reflect such causality, and to improve the accuracy of $\tilde{G}_{D_iB_i^O}$ adjustments are made to Eq.(3.30). To do so a log-linear curve-fitting with constant parameters $(\alpha,\ \beta)$ following Eq.(3.32) is conducted. The parameters $(\alpha,\ \beta)$ can be found after solving Eq.(3.33) where G^{obs} stands for observed, in our case simulated, data as will be discussed in Chapter 6.2. We note that alternative formulations with more parameters are feasible, but we found that, unless the parameter number is largely increased, the impact on the adjustment accuracy is low.

$$\log G^{RR}_{D_iB_i^O}(k+1,\ h,\ n) = \beta \log\left(\alpha E^{RR}_{(1),\,(h-k)(n-k)}\right) \tag{3.32}$$

$$\underset{\alpha,\beta}{\operatorname{argmin}}\ \ Z(\alpha,\beta) = \sum_{T_{\max}} \sum_{(h,n)\,\in\,\text{training set}} \sum_k \left[G^{RR}_{D_iB_i^O} - G^{\text{obs}}\right]^2 \tag{3.33}$$

In conclusion, the link-cost function for link l^m_{rs} with link volume v^m_{rs} can be acquired as shown in Eq.(3.34) where $h = \sum_p\left(\sum_j q^p_{ij} + \sum_j q^p_{ji}\right)$, and $n = \varphi_i$. The constants for the non-access links shown in Figure 3.1 are derived in the subsequent section.

$$S^m_{rs}(k,\ h,n) = \begin{cases} \frac{1}{V_m} G^{RR}_{\text{rs}}(k,h,n), & \text{for RR links } l^w_{D_iB_i^O} \\ \frac{1}{V_m} G^{CR}_{\text{rs}}(k,h,n), & \text{for CR links } l^w_{T_iB_i^I} \\ \text{constant}, & \text{for other links} \end{cases} \tag{3.34}$$

3.4. Assignment

3.4.1. Link costs

The volumes on the bicycle access walking links with variable travel times are composed of different path flows as in Eqs. (3.35) for RR links and in (3.36) for CR links:

$$v^w_{D_iB_i^O} = \sum_j\left(q^{ctc}_{ij} + q^{ct}_{ij} + q^{c}_{ij}\right)\ i,\, j \in \boldsymbol{Z},\ i \neq j \tag{3.35}$$

$$v^w_{T_iB_i^I} = \sum_j\left(q^{ctc}_{ji} + q^{tc}_{ji}\right)\ i,\, j \in \boldsymbol{Z},\ i \neq j \tag{3.36}$$

Bicycles are shared independently as to whether they are used for access or egress so that the link-cost function of the RR links can be written as:

$$S^w_{D_iB_i^O}(k,h,n) = \frac{1}{V_w} G^{RR}_{D_iB_i^O}\left(\left\lfloor\left(v^w_{D_iB_i^O} + v^w_{T_iB_i^I}\right) + \frac{1}{2}\right\rfloor, \sum_p\left(\sum_j q^p_{ij} + \sum_j q^p_{ji}\right), \varphi_i\right), i \in \boldsymbol{Z} \tag{3.37}$$

where $\left\lfloor (\cdot) + \frac{1}{2} \right\rfloor$ stands for rounding off to the closest integer. The travel cost for CR links, $S^{w}_{T_iB_i^I}$ is obtained analogously by replacing $G^{RR}_{D_iB_i^O}$ with $G^{CR}_{T_iB_i^I}$. φ_i is assumed constant in this research but can also depend on flows from other zones as well as the expected trip duration.

The travel time of internal walking links $l^{w}_{D_iT_i}$ and $l^{w}_{T_iD_i}$ to and from the PT node as well as the internal cycling links $l^{c}_{B_i^OD_i}$ and $l^{c}_{B_i^IT_i}$ are assumed to have a constant travel time. The travel time for walking links is calculated using the Euclidean distance as in Eq.(3.38). The travel time for cycling links $S^{c}_{B_i^OD_i}$ and $S^{c}_{B_i^IT_i}$ is assumed to be $\frac{V_W}{V_C}$ times of $S^{w}_{T_iD_i}$ and $S^{w}_{D_iT_i}$.

$$S^{w}_{D_iT_i} = S^{w}_{T_iD_i} = \frac{1}{V_w} \int_{x_{T_i}-\mathrm{r}}^{x_{T_i}+\mathrm{r}} \int_{y_{T_i}-\mathrm{r}}^{y_{T_i}+\mathrm{r}} \sqrt{\left(x - x_{T_i}\right)^2 + \left(y - y_{T_i}\right)^2}\, dxdy \tag{3.38}$$

Further, the cross-boundary travel time for 'walking all the way' links $l^{w}_{D_iD_j}$ and 'cycling-all the way' links $l^{c}_{B_i^OD_j}$ can be obtained by substituting the corresponding integration limits into Eq.(3.38). The costs of transit links $l^{t}_{T_iT_j}$ links are obtained assuming a fixed cost for the public transport service that we presume includes waiting, travel, and fare.

3.4.2. Equilibrium with link interactions

The independency of link-cost functions formulated in conventional network assignment is not always valid as discussed in, for example, Sheffi (1985). Traffic related cases where flow interactions cannot be ignored include unsignalized interactions or left-turning movement at signalized interactions. Similarly, with our network definition, competition for bicycles between travellers on $l^{w}_{D_iB_i^O}$ links and on $l^{w}_{T_iB_i^I}$ links within each zone constitute such a case.

When the link interactions are asymmetric as in this research, there is no known equivalent minimization program that can be used to find the equilibrium flow pattern analytically. Moreover, specific conditions need to be met in order to guarantee a unique solution in the link flow pattern. Smith (1979) proved the uniqueness of traffic equilibria when the Jacobian matrix of the link-travel time function is positive definite. Considering one RR link always pairs one CR link in each zone for our cases, the uniqueness conditions can be rewritten with Eqs. (3.39), (3.40) and (3.41). For actual link performance functions, Eq.(3.39) is naturally met. The strict inequality constraints in Eqs. (3.40) and (3.41), however, cannot be fulfilled as the LHS and RHS of (3.40) and (3.41) are the reverse of each other. The impact of flows on links $l^{w}_{D_iB_i^O}$ and $l^{w}_{T_iB_i^I}$ are equivalent. In words, an additional person seeking a bicycle increases the cost equally from wherever s/he starts his/her journey, be it a random place of origin or the transit station. Therefore, in our study, multiple equilibria are expected as will be shown in our case study.

$$\frac{\partial S^{w}_{D_iB_i^O}\left(v^{w}_{D_iB_i^O}+v^{w}_{T_iB_i^I},\varphi_i(t)\right)}{\partial v^{w}_{D_iB_i^O}} > 0,\ \frac{\partial S^{w}_{T_iB_i^I}\left(v^{w}_{D_iB_i^O}+v^{w}_{T_iB_i^I},\varphi_i(t)\right)}{\partial v^{w}_{T_iB_i^I}} > 0 \tag{3.39}$$

$$\frac{\partial S^{w}_{D_iB_i^O}\left(v^{w}_{D_iB_i^O}+v^{w}_{T_iB_i^I},\varphi_i(t)\right)}{\partial v^{w}_{D_iB_i^O}} > \frac{\partial S^{w}_{T_iB_i^I}\left(v^{w}_{D_iB_i^O}+v^{w}_{T_iB_i^I},\varphi_i(t)\right)}{\partial v^{w}_{D_iB_i^O}} \tag{3.40}$$

$$\frac{\partial S^{w}_{T_iB_i^I}\left(v^{w}_{D_iB_i^O}+v^{w}_{T_iB_i^I},\varphi_i(t)\right)}{\partial v^{w}_{T_iB_i^I}} > \frac{\partial S^{w}_{D_iB_i^O}\left(v^{w}_{D_iB_i^O}+v^{w}_{T_iB_i^I},\varphi_i(t)\right)}{\partial v^{w}_{T_iB_i^I}} \tag{3.41}$$

3.4.3. DUE conditions

We remind that our objective is to obtain an assignment for this problem that avoids a simulation approach in order to be scale-able for large size problems. We therefore formulate firstly a deterministic user equilibrium (DUE) solution. This assumes that travellers have perfect information regarding travel time and are consistently making ‘correct’ decisions and all behave in identical fashion. The complementary equilibrium conditions of conventional DUE assignment can be written as:

$$\left(c_{ij}^{p} - c_{ij}^{*}\right)q_{ij}^{p} = 0\ \ \forall i,j \in Z\ \ \forall p \in \{w,\ c,\ t,\ ct,\ tc,\ ctc\} \tag{3.42}$$

with

$$q_{ij}^{p}\begin{cases} > 0 & \text{if } c_{ij}^{p} \le c_{ij}^{p'}\ \forall p, p' \neq p \\ 0 & \text{otherwise} \end{cases} \tag{3.43}$$

where c_{ij}^{p} is the travel cost that all travellers on path p experience and c_{ij}^{*} is the travel cost of the shortest path from zone i to zone j. The flow constraints are expressed in Eq.(3.44).

$$\sum_{p\in\{w,\,c,\,t,\,ct,\,tc,\,ctc\}} q_{ij}^{p} = g_{ij}\ \forall i,j \in Z \tag{3.44}$$

Importantly, in our problem not all travellers on the same path have the same costs since the access cost is increasing with each traveller. Therefore Eq.(3.42) only holds for the last traveller choosing path p and ‘forcing our problem to be static’ we obtain instead Eq.(3.45) where $c_{ij}^{p}(k)$ is the cost of the k^{th} traveller taking path p.

$$\begin{cases} \left(c_{ij}^{p}(k) - c_{ij}^{*}\right)q_{ij}^{p} \le 0 & \text{if } k \le q_{ij}^{p} \\ \left(c_{ij}^{p}(k) - c_{ij}^{*}\right)q_{ij}^{p} = 0 & \text{if } k = q_{ij}^{p} \end{cases} \tag{3.45}$$

To obtain the correct solution we therefore need to revert to incremental assignment, loading each traveller one by one. The incremental assignment also demonstrates the effect of priority rules or different random orders in which bicycles are taken. As the results will show, we obtain different path flows depending on the order that yield all the DUE conditions for the last traveller.

3.4.4. SUE conditions and solution approach

We also compare the results with a stochastic user equilibrium (SUE). We suggest an SUE is more appropriate than a DUE not only due to different user perceptions but also due to the discussed random distribution of the bicycles. For this, we define the stochastic cost for path p as:

$$\tilde{c}_{ij}^{p}(k) = -\theta c_{ij}^{p}(k) + \varepsilon_p \quad i, j \in \boldsymbol{Z}, k \in \boldsymbol{K} \tag{3.46}$$

where θ is the positive sensitivity parameter and ε_p is the residual of traveling on path p. This leads to the SUE conditions Eq.(3.47)

$$\left(\tilde{c}_{ij}^{p}(k) - c_{ij}^{*}\right)\left(q_{ij}^{p} - q_{ij}^{*}\right) \leq 0 \tag{3.47}$$

where q_{ij}^{*} is the non-negative flow volume on the shortest path from zone i to zone j. The regular network flow constraints Eq.(3.44) also hold.

3.4.5. Review of the discrete choice model

The discrete choice model hypothesis that when faced with a choice situation, an individual's preferences toward each option can be described by an 'attractiveness' or 'utility' measured with each alternative. The decision makers are assumed to be rational and always choose the alternative that yields the highest utility. However, not all of the alternatives influence individuals' utilities can be observed thus should be treated as random, thus the utilities are modelled as random, which will only give the chosen probability of each alternative, but the choice itself. The general form of the random utility function of an alternative is:

$$U_k(\boldsymbol{a}) = V_k(\boldsymbol{a}) + \xi_k(\boldsymbol{a}) \quad \forall k \in \boldsymbol{\mathcal{K}} \tag{3.48}$$

which $U_k(\boldsymbol{a})$ is the utility associates with a given set of alternatives $\boldsymbol{\mathcal{K}}$ with a denote the vector of variables which includes the characteristics of this choice. $V_k(\boldsymbol{a})$ is the systematic component which stands for the utility of measured attributes, and $\xi_k(\boldsymbol{a})$ is the random component which stands for the unobserved utility of unobserved attributes. The random component satisfies $\mathrm{E}[\xi_k(\boldsymbol{a})] = 0$, meaning $\mathrm{E}[U_k(\boldsymbol{a})] = V_k(\boldsymbol{a})$. (Sheffi, 1985).

There are two kinds of models based on the different assumptions of the error term, the logit model, and the probit model.

3.4.5.1. **The multinomial probit (MNP) model**

One straight forward logical assumption is to view the error term as the summation of a large number of unobserved independent components. Based on the central limit theorem, the distribution of the error term should be approximated by the normal distribution. Thus, the joint density function of these error terms of the multivariate normal (MVN) function, which is the extension of the well-assumed normal density function. In the multivariate scenario, the choice probability cannot be expressed analytically since the cumulative normal distribution function cannot be evaluated in closed form (Ben-Akiva et al., 1985). Here we choose a two-variate scenario as a demonstration.

Assume that $\boldsymbol{U} = (U_1, U_2)$ where $U_1 = V_1 + \xi_1$ and $U_2 = V_2 + \xi_2$, the distribution of the error term vector is given by:

$$\xi \sim \text{MVN}\left(0, \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2 \\ \sigma_2\sigma_1 & \sigma_2^2 \end{pmatrix}\right) \tag{3.49}$$

Thus, the probability of choosing the first alternative can be defined as:

$$P_1 = \Pr[(U_1 \geq U_2)] = \Pr[(V_1 + \xi_1) \geq (V_2 + \xi_2)] = \Pr[(\xi_2 - \xi_1) \leq (V_1 - V_2)] \tag{3.50}$$

which $(\xi_2 - \xi_1)$ is a normally distributed random variable with zero mean and variance $\sigma^2 = \sigma_1^2 + \sigma_2^2 - \sigma_1\sigma_2$. By accepting the standard normal distribution, Eq.(3.50) implies that

$$P_1 = \Phi\left(\frac{V_1 - V_2}{\sqrt{\sigma^2}}\right) \tag{3.51}$$

which $\Phi(\cdot)$ is the standard cumulative normal curve.

The computation of MNP choice probability can be acquired a Monte Carlo simulation or several analytical approximations. Several outstanding pieces of research have been done on the Monte Carlo simulation approach, such as Daganzo et al. (1977) and Sheffi and Powell (1981). A well-accepted analytical approach known as Clark's method can be checked in Clark (1961). We omit the detailed solution approach here for simplicity.

3.4.5.2. **The multinomial logit (MNL) model**

Differ from the straight-forward normal distribution assumption of the error term, the logit model is derived by assuming that the error term of each utility function is independently and identically distributed obeying Gumbel distribution, which is also known as 'extreme value' distribution. It views the error terms as the maximum of a large number of unobserved independent components, which obeying the following pdf and cdf

$$f(\xi) = \mu e^{-\mu(\xi - \eta)} e^{\left(-e^{-\mu(\xi - \eta)}\right)} \tag{3.52}$$

$$F(\xi) = e^{\left(-e^{-\mu(\xi - \eta)}\right)} \tag{3.53}$$

with location parameter η and scale parameter $\mu > 0$, denoted as $\xi \sim EV(\eta, \mu)$.

Two critical property of Gumbel distribution are:

1. If $\xi_i \sim EV(\eta_i, \mu)$ for $\mathrm{i} = 1, \dots, \mathrm{J}$, and ξ_i are independent, then:

$$\xi = \max_{i=1,\dots,J} \xi_i \sim \text{EV}\left(\frac{1}{\mu} \ln \sum_{i=1}^{J} e^{\,\mu\eta_i}, \mu\right) \tag{3.54}$$

2. If $\xi_a \sim EV(\eta_a, \mu)$ and $\xi_b \sim EV(\eta_b, \mu)$ are independent, then:

$$\xi = \xi_a - \xi_b \sim \text{Logistic}(\eta_a - \eta_b, \mu) \tag{3.55}$$

Thus, similarly to Eq.(3.50), the probability of choosing the first alternative under two-variate scenario is given as:

$$P_1 = \Pr(\xi \leq V_1 - V_2) = F(V_1 - V_2) = \frac{1}{1+e^{-\mu(V_1-V_2)}} = \frac{e^{\mu V_1}}{e^{\mu V_1}+e^{\mu V_2}} \tag{3.56}$$

Comparing to the computation of MNP choice probability discussed in previous section, the general analytical formulation of MNP choice probability can be easily given by $(\mu = 1)$

$$P_k = \frac{e^{\mu V_k}}{\sum_{i=1}^{K} e^{\mu V_i}} = \frac{1}{1+\sum_{i\neq k} e^{V_i - V_k}}, \forall \mathrm{k} \in \boldsymbol{\mathcal{K}} \tag{3.57}$$

Here we choose to apply MNL as the choice model in current research. In the next section, a well-accepted logit-based loading algorithm will be introduced.

3.4.6. Review of logit-based network assignment algorithm

3.4.6.1. **Formalizing the problem**

Consider a population of travellers between a given origin and a given destination. Each OD pair is connected by many alternative paths and assumed with some travel time. Because of the different perceptions and preferences of each traveller, the path travel time are perceived differently by each traveller. Each traveller is assumed to choose the shortest travel time path from origin to destination. Based on these assumptions, we would like to find out the flow pattern at equilibrium.

Let C_k^{rs} be the perceived travel time on route k between origin r and destination s, where $k \in \mathcal{K}_{rs}$. let c_k^{rs} be the measured travel time on route k between origin r and destination s. We can give the following equation:

$$C_k^{rs} = c_k^{rs} + \xi_k^{rs} \quad \forall k, r, s \tag{3.58}$$

where ξ_k^{rs} is a random error term of the corresponding route. We assume $E(\xi_k^{rs}) = 0$ which means we assume the average travel time is the measured travel time. If this population between origin r and destination s is large, the share of travellers choosing path k, P_k^{rs} can be obtained by:

$$P_k^{rs} = \Pr(C_k^{rs} \leq C_l^{rs}, \forall l \in \mathcal{K}_{rs}) \quad \forall k, r, s \tag{3.59}$$

The path flow pattern should be:

$$f_k^{rs} = q_{rs} P_k^{rs} \quad \forall k, r, s \tag{3.60}$$

The differences of various stochastic network loading approaches are the assumed distribution of the perceived travel times. In this research, we would like to follow the MNL assumption discussed in section 3.4.5.2, thus the route-choice probability P_k^{rs} is given by Eq.(3.57). The link flows can be calculated as:

$$x_a = \sum_{rs} \sum_k f_k^{rs} \delta_{a,k}^{rs} \quad \forall a \tag{3.61}$$

where $\delta_{a,k}^{rs}$ equals to 1 if link a is a part of path k connecting OD pair rs.

3.4.6.2. **Solution method**

The algorithm introduced here is well known as the STOCH method or Dial's algorithm, which is firstly proposed by Dial (1971). This algorithm can effectively generate a logit-based flow pattern on the network level with a given OD matrix and network structure. However, it does assume the existence of flows on all paths connecting origin and destination (OD) pair, it will reject 'unreasonable' travel choices that are not assumed to be reasonable in practice. This characteristic is rooted from the preliminary step which generates the set of 'reasonable' paths connection each OD pair. This 'reasonable-path-only' assumption can be mathematically defined in different criteria, which also raises many concerns.

Here we provide a 'double-pass' algorithm comparing to the more efficient but less strict 'single-pass' algorithm, which defines path 'reasonable' if it not only takes travellers further away from the origin but also closer to the destination. Such criteria can be identified with the help of these two labels of each node i:

r_i: the travel time from origin node r to node i along the minimum travel time path

s_i: the travel time from node i to destination node s along the minimum travel time path

Thus, each reasonable path should only include links l_{ij} that $r_i < r_j$ and $s_i > s_j$. The following steps demonstrate this algorithm for one OD pair, which should be repeated for each OD pair in the network in order to generate a network level flow pattern. Here we follow the demonstration provided by Sheffi (1985).

Step 0: Preliminaries

1. Compute the minimum travel time from node r to all other nodes. Determine r_i for each node i.
2. Compute the minimum travel time from each node i to node s. Determine s_i for each node i.
3. Define $\mathcal{O}_i$ as the set of downstream nodes of all links leaving node i.
4. Define $\mathcal{F}_i$ as the set of upstream nodes of all links arriving at node i.
5. For each link l_{ij}, compute the 'link likelihood', L_{ij}, where t_{ij} is the measured travel time on link l_{ij}:

$$L_{ij} = \begin{cases} e^{\theta[r_j - r_i - t_{ij}]} & \text{if } r_i < r_j \text{ and } s_i > s_j \\ 0 & \text{otherwise} \end{cases} \tag{3.62}$$

Step 1: Forward pass

Considering nodes in ascending order of r_i staring with the origin r. For each node, i, calculate the 'link weight', w_{ij} for each $j \in \mathcal{O}_i$ until the destination node, s, is reached.

$$w_{ij} = \begin{cases} L_{ij} & \text{if } i = r \\ L_{ij} \sum_{m \in \mathcal{F}_i} w_{mj} & \text{otherwise} \end{cases} \tag{3.63}$$

Step 2: Backward pass

Considering nodes in ascending values of s_j starting with the destination, s. When each node j is considered, computing the link flow x_{ij} for each $i \in \mathcal{F}_j$ until the origin node, i, is reached, by following the assignment:

$$x_{ij} = \begin{cases} q_{rs} \frac{w_{ij}}{\sum_{m \in \mathcal{F}_i} w_{mj}} & \text{for } j = s \\ \left[\sum_{m \in O_j} x_{jm}\right] \frac{w_{ij}}{\sum_{m \in \mathcal{F}_j} w_{mj}} & \text{for all other links } l_{ij} \end{cases} \tag{3.64}$$

where q_{rs} is the OD volume from the origin node r to destination node s. The flow generated by this algorithm is equivalent to the logit-based network loading.

3.4.6.3. **Critiques of STOCH algorithm**

Although the STOCH algorithm does not require path enumeration, it does have some concerns.

Firstly, STOCH algorithm requires two minimum path calculation for each OD pair in the network, which would not be computationally acceptable in large networks. A more efficient algorithm can be modified by releasing the 'reasonable' criteria. A link is considered reasonable as long as it does not take travellers back toward the origin. In other word, a link l_{ij} is considered reasonable if and only if $r_i \leq r_j$. Since the second part of the original requirement, that these links take travellers closer toward the destination, is dropped, the calculation of s_i is no longer needed. Besides, the only change is in Step 2: for each link l_{ij}, the flow is assigned by following:

$$x_{ij} = \left[q_{rj} + \sum_{m \in O_j} x_{jm}\right] \frac{w_{ij}}{\sum_{m \in \mathcal{F}_j} w_{mj}} \tag{3.65}$$

This modified approach is known as the single-pass algorithm. It requires a modestly higher computation than those of the all-or-nothing assignment approach thus can be applied to a large real-world network. However, we accept the double-pass algorithm in this research.

The second concern is rooted in the basis of MNL's assumption: the error term of each choice is assumed to be independence from irrelevant alternatives, also known as IIA property. An appropriate explanation of IIA property is: the ratio of the choice probability of any two alternatives is entirely unaffected by the presence (or absence) of any other alternatives in the choice set, and by the systematic utilities of any other alternatives. This can be shown to hold in the following:

$$\frac{P_k}{P_m} = \frac{e^{\mu V_k} / \sum_{i=1}^{K} e^{\mu V_i}}{e^{\mu V_m} / \sum_{i=1}^{K} e^{\mu V_i}} = \frac{e^{\mu V_k}}{e^{\mu V_m}} = e^{\mu (V_k - V_m)} \tag{3.66}$$

The violation of this property can give rise to some anomalies. One of the most widely cited anomalies is the red bus/blue bus paradox. Further discussion of this paradox can be seen in the discussion proposed by McFadden in McFadden (1974).

3.4.7. Review of Method of Successive Averages

The stochastic user equilibrium (SUE) assumes that the route choice is based on the perceived travel time instead of the measured travel time. This travel time is assumed to be random variables. Comparing to the deterministic user equilibrium (DUE) which the measured travel time on all used paths will be equal, at SUE, no motorist can improve his or her perceived travel time by unilaterally changing routes. Instead, the travel time will be such when the following Eq.(3.67) is satisfied with the equilibrium flow pattern.

$$f_k^{rs} = q_{rs} P_k^{rs} \qquad \forall k, r, s \tag{3.67}$$

where f_k^{rs} is the flow on route k between r and s, P_k^{rs} is the probability that route k between r and s is chosen given a set of measured travel time. The corresponding minimization programming can be written as:

$$\min z(f) = -\sum_{r\epsilon R} \sum_{s\epsilon S} q_{rs} S^{rs}\big(c^{rs}(f)\big) + \sum_{a\epsilon A} v_a t_a(v_a) - \sum_{a\epsilon A} \int_0^{v_a} t_a(x)\, dx \tag{3.68}$$

where $c^{rs}(f)$ is the random variable representing the perceived travel time between r and s with given flow level, f, and the satisfaction function is:

$$S^{rs}\big(c^{rs}(f)\big) = E\left[\min_{k\epsilon K_{rs}} \{C_k^{rs}(c^{rs}(f))\}\right] \tag{3.69}$$

Such programming can be very much difficult to search for the minimum by analytical approaches, such as Convex Combination Method, because the direction vector is random, and the move size cannot be optimized since the objection function is difficult to calculate. Thus, we search the equilibrium flow pattern by following the method of successive average (MSA) based on the discussion from Almond (1967) and Fisk (1980).

3.4.7.1. **Solution method**

The general MSA algorithm can be demonstrated as follows:

Step 0: Initialization.

Perform a stochastic network loading based on a set of initial travel time $\{t_a^0\}$. This generates a set of link flows $\{x_a^1\}$. Set $n = 1$.

Step 1: Update.

Set $t_a^n = t_a^0(x_a^n), \forall\, a$.

Step 2: Direction finding.

Perform as stochastic network loading procedure based on the current set of link travel time, $\{t_a^n\}$. This yields an auxiliary link flow pattern $\{y_a^n\}$.

Step 3: Move

Find the new flow pattern by setting

$$x_a^{n+1} = x_a^n + \alpha_n (y_a^n - x_a^n) \tag{3.70}$$

Step 4: Convergence criterion.

If convergence is attained, stop. If not, set $n = n + 1$ and go to Step 1:.

In order to ensure this algorithm converging to a minimum, the search direction has to satisfy: 1. This sequence should be a decreasing sequence; 2. The move sizes have to satisfy (Powell and Sheffi, 1982):

$$\sum_{n=1}^{\infty} \alpha_n = \infty, \text{ and } \sum_{n=1}^{\infty} \alpha_n^2 = \infty \tag{3.71}$$

The general formation of α_n satisfying the requirements in Eq.(3.71) can be acquired by

$$\alpha_n = \frac{k_1}{k_2 + n} \tag{3.72}$$

where k_1 is a positive constant and k_2 is a nonnegative constant. In this research, we set $k_1 = 1$ and $k_2 = 0$. Thus, the move function in Step 3: is defined as

$$x_a^{n+1} = x_a^n + \frac{1}{n}(y_a^n - x_a^n) \tag{3.73}$$

By expanding Eq.(3.74) we can find:

$$\begin{aligned} x_a^{n+1} &= \frac{n-1}{n} x_a^n + \frac{1}{n} y_a^n = \frac{n-1}{n}\frac{n-2}{n-1} x_a^{n-1} + \frac{n-1}{n}\frac{1}{n-1} y_a^{n-1} + y_a^n \\ &= \frac{n-2}{n} x_a^{n-1} + \frac{1}{n}(y_a^{n-1} + x_a^n) = \frac{1}{n}\sum_{l=1}^{n} x_a^l \end{aligned} \tag{3.74}$$

which is the source of this method's name, the method of successive averages.

3.4.7.2. **Critiques of MSA algorithm**

The method of successive average (MSA) is based on a sequence of predetermined move size along the descent direction, $\alpha_1, \alpha_2, \ldots$ as a priori. Thus, some may argue that the flow pattern $\{x_a^n\}$ is 'forced' to converge due to the descending sequence of move size. However, this critique can be avoided by setting MSA to terminate after predetermined iterations.

Another critique is on the nonmonotonically convergence of the MSA. This critique can be relieved by considering a generally monotonically decreasing flow pattern generated by averaging the flow over the last few iterations, such as:

$$\bar{x}_a^n = \frac{1}{m}(x_a^n + x_a^{n-1} + \cdots + x_a^{n-m+1}) = \frac{1}{m}\sum_{l=0}^{m-1} x_a^{n-l} \tag{3.75}$$

In this research, we set $m = 3$. The corresponding convergence criteria can then be set as:

$$\frac{\sqrt{\sum_a (\bar{x}_a^{n+1} - \bar{x}_a^n)^2}}{\sum_a \bar{x}_a^n} \leq \kappa \tag{3.76}$$

CHAPTER 4. BASIC SIMULATION AND COMPARISON AGAINST ASSIGNMENT

As the order in which the travellers choose bicycles matters, we present a basic agent-based simulation structure and discuss differences among simulation incremental, DUE, and SUE assignment after adopting the link cost function deducted in previous chapter. We observe that multiple equilibria are observed because of different loading orders. We further conclude that the assignments and simulation results show in general good correspondence, especially with larger traffic volume and bicycle supply. Some discrepancies between assignment and simulation occur through boundary effects and neglecting that some travellers might walk against their travel direction to find a nearby bicycle. One application of our work is that the assignment results include an estimation of how many of the initially distributed bicycles will accumulate at stations which can inform the bicycle relocation problem.

4.1. Simplified Simulation and Parameter Adjustment for RR Distance

4.1.1. Simulation framework

Observed data are needed to verify the cost functions. However, various privacy sensitive data sources are needed and some of them may be considered as business confidential. Moreover, some data would need to be gathered through tracking traveller's decision-making for which permissions need to be obtained. Therefore, considering a lack in availability of observed data both the RR adjustment problem in Eq.(3.33) and a case study, an agent-based simulation approach is proposed as reference. We develop a simulation with the below assumptions.

1. Travelers are initialized with a random location and generation time between $0 \ldots T_{\max}$.
2. Travelers can make 15 minutes reservation for one bicycle at a time. Upon initialization, they evaluate and create a travel plan according to the shortest path at that point in time.
3. The access to any of the available bicycles is based on the Euclidean distance between his/her point of origin and these bicycles.
4. The trip plan includes which route to go, when, and which bicycle to take if using a bicycle is included. Plans are made based on real-time bicycle locations.
5. Bicycles will be occupied and blocked from further access during reservation or cycling and released from occupation and ready for next usage when reservation expires, or cycling is completed.

We note that despite the assumption of bicycles being reservable, for modelling realistic scenarios we still require not only an ordering of the travellers, but a specific generation time and we do not exclude the chance of some (though rare) failures to obtain a targeted bicycle. For one, in line with common schemes, we presume that the reservation time is limited to 15 minutes so that the walking time to a bicycle might be too long if even the nearest bicycle is located relatively far away. Further, and also in line with common practice, we assume that only one bicycle at a time is reservable. Therefore, a traveller aiming to take a bicycle before and after using public transport can plan his route according to the currently available bicycles in the origin and destination zone but must complete his access ride before he can reserve a bicycle for the egress part.

The resulting choice flow chart under these assumptions is shown in Figure 5.4. The interactions among travellers are coordinated by sharing the system-wide timeline set T. For better simulation, we separate related decision makings into four events: 'launch_app', 'use_bic[ycle]', 'release [the bicycle]', and 'complete [trip]'. The 'launch_app' event includes the trip plan creation where the user is assumed to compare the different paths, chooses the shortest (in terms of generalised cost), and books a bicycle if this is part of the chosen path. In 'use_bic' the behaviour when reaching a bicycle is included. If the arrival time is beyond the reservation period, the users check if the desired bicycle is both at the predetermined location and free of the occupation or reservation from other travellers. If both are the case the travellers start cycling. In 'release' the behaviour that is conducted when completing using a shared bicycle is simulated. Upon finishing the cycling trip, the used bicycle becomes available for new bookings. Further, if the remaining unfinished trip involves a second bicycle trip, the traveller aims to book this one. Finally, upon 'complete' the travellers will be marked as 'trip completed' and removed from further simulation. The pseudo code is provided in Algorithm 1. For brevity further details are omitted and we refer to Yao and Schmöcker (2021) instead where different information cases are modelled.

4.1.2. Obtaining the RR adjustment parameters

To create the data for solving Eq.(3.33) the simulation is limited to one zone, so travellers never use more than one bicycle. The data set is composed of 100 combinations with h, n each from500 to 5000 in steps of 500, and 70 of them are randomly marked as the training set. Each curve contains 100 data points, and each data point is obtained by averaging 100 trials. $T_{\max}$ is set to 15 minutes.

Parameters (α, β) are estimated as (0.63, 0.53) after solving Eq.(3.33). Simulation and adjusted analytical curves are plotted as the upper two plots of Figure 5.5; cases with $h = 500$ are on the left and cases with $h = n$ on the right.

Algorithm 1: Traveller simulation

Input: Number of travellers (M), number of bicycles (N) and random-access time spread $T_{\max}$
Output: Expected walking distance, bicycle distribution after assignment

BEGIN

```
Create timeline set $T = \{\emptyset\}$; Initialize $N$ random located bicycles ($q \in N$); Create $M$ random located travellers ($p \in M$) with initialization time $t_{\text{ini}}^{p} = \text{RAND}(0, T_{max})$
$T$ += {launch_app ($p$)} for each $p$ in $M$ at $t_{\text{launch}}^{p}$

while $T \neq \{\emptyset\}$:
    read next event $E$ with minimal timestamp in $T$
    if $E$ == launch_app ($p$):
        $T$ −= {launch_app ($p$)}
        update traveller's origin and find SP
        calculate ETA towards each node
        if SP include use bicycle:
            make reservation on bicycle $q$
            $T$ += {use_bic ($p$, $q$)} at $t_{\text{use}}^{p,q}$
        else:
            $T$ += {complete ($p$)} at $t_{\text{complete}}^{p}$
        end if

    else if $E$ == use_bic ($p$, $q$):
        $T$ −= {use_bic ($p$, $q$)}
        update user current location
        if pre-reserved bicycle $q$ still available:
            bicycle $q$ get occupied by traveller $p$
            $T$ += {release ($p$, $q$)} at $t_{\text{release}}^{p,q}$
        else:
            $T$ += {launch_app ($p$)} for each element in $M$ at $t_{\text{use}}^{p,q}$
        end if

    else if $E$ == release ($p$, $q$):
        $T$ −= {release ($p$, $q$)}
        update traveller $p$ and bicycle $q$ current location
        bicycle $p$ is free from occupation
        if no more bicycle usage in traveller $p$ unfinished SP
            $T$ += {complete ($p$)} at $t_{\text{complete}}^{p}$
        else:
            $T$ += {use_bic ($p$, q)} at $t_{\text{use}}^{p,q}$
        end if

    else if $E$ == complete ($p$):
        $T$ −= {complete ($p$)}
        update user current location
        exclude traveller $p$ from further consideration
    end if
end while

pack and save all data into CSV files
```

END

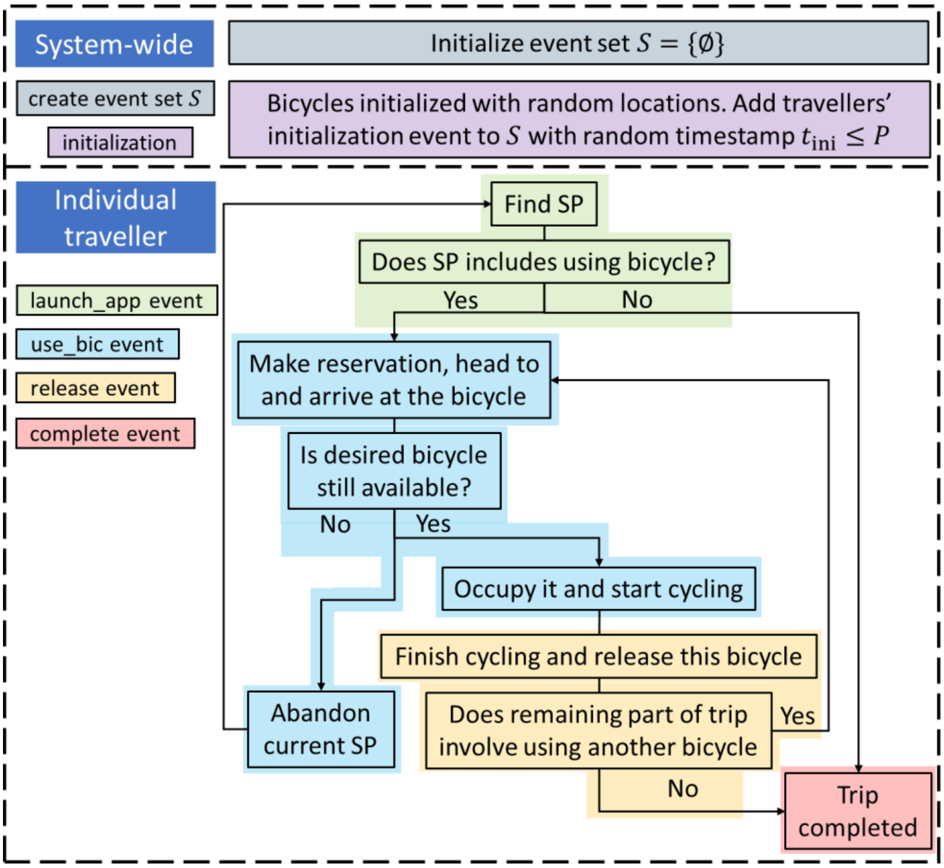


Figure 4.1 The flow chart of individual choice-making and event separation in the simulation approach

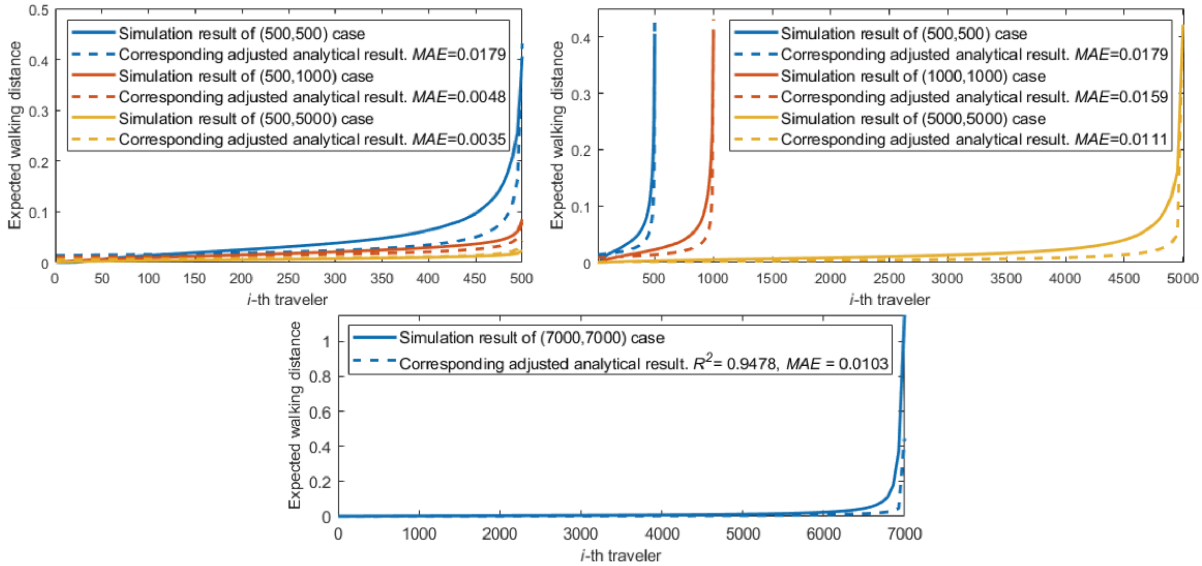


Figure 4.2 Comparisons between simulation and adjusted analytical curves for different cases. The upper figures show results for training curves. Lower figure application to an 'holdout' curve.

All simulation curves are plotted in solid lines. The curves are relatively flat except for the last 5% to 10%, suggesting relatively small differences in expected walking distances for most travellers except when the available fleet is significantly depleted. The 'adjusted analytical curves', resulting from finding the trip plans with the proposed assignment including the fitted parameters are plotted in dashed lines. From Figure 5.5 we observe that the adjusted curves fit the simulation well for the beginning parts, which reflects the majority of the travellers. Only for the last few travellers discrepancies arise though the general sharp increase in cost is also reflected. The MAE (Mean Average Error) remains small when considering the absolute costs of access. To show that our parameters remain valid for larger samples not included in the calibration set we add the bottom plot of Figure 5.5 where the case of $h = n = 7000$ is shown. The R^2 remains high (> 0.9) and the MAE remains low suggesting an acceptable fit.

4.2. Case Study

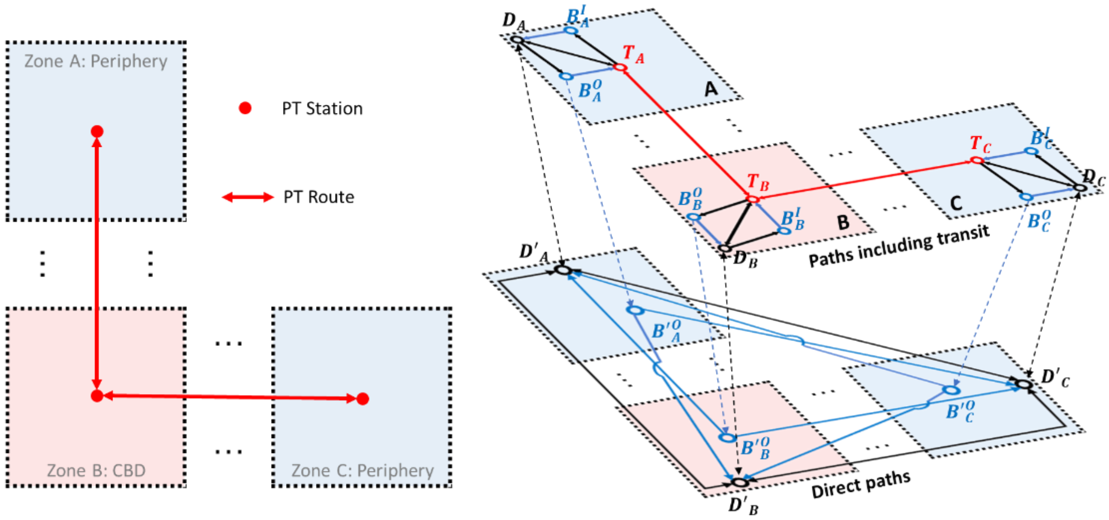
4.2.1. Symmetrical, low demand case study

We now compare the traditional assignment approaches and the simulation in order to derive insights into the validity of the traditional assignment with the above-described cost functions and link interaction. Even though our analytical approach is targeted at large demand cases, we compare here cases with relatively low demand and few bicycles being supplied. These cases highlight some differences that are less pronounced with large demand as will be shown in 7.2.

4.2.1.1. **Case settings**

We consider a simple three zone network as in Figure 4.3. Extension to more zones does not yield additional insights for the purposes of this study. For better visibility we show intrazonal links that are used when using transit as an 'upper level' and interzonal links for direct paths in the 'lower level'. No costs are associated with the dashed links. (One might use them to model fixed costs associated with unlocking or locking a bicycle).

We first assume that each zone has a side length of 1 km and that the distances between each zone are set to 2 km. Four demand and bicycle supply scenarios are shown in Table 4.1. In Cases 1 and 2 there are no outgoing trips from B so that these cases might be considered 'morning commute scenarios'. In Cases 1 and 3 initially there are no bicycles in Zone B.



(a) (b)

Figure 4.3 The layout of the three-zone network and its topology

Table 4.1 OD and bicycle supply adopted

Case 1		A	B	C
Origin	A	\	120	0
	B	0	\	0
	C	0	120	\
Bicycle supply		100	0	100

Case 2		A	B	C
Origin	A	\	120	0
	B	0	\	0
	C	0	120	\
Bicycle supply		100	100	100

Case 3		A	B	C
Origin	A	\	60	0
	B	60	\	60
	C	0	60	\
Bicycle supply		100	0	100

Case 4		A	B	C
Origin	A	\	60	0
	B	60	\	60
	C	0	60	\
Bicycle supply		100	100	100

We apply incremental, DUE and SUE assignment and simulation as defined. For the incremental assignment we set the increment to one traveller to strictly respect the order and therefore reflect the choice dynamics. In the first series of tests, the sequence of OD pairs in the incremental assignment is selected in random order ('Incre_1, rand') and the 95% confidence interval is provided by averaging 1000 trials. Furthermore, the extreme cases prioritizing particular zones ('Incre_1, A' and 'Incre_1, C') are also tested in Cases 1 and 2. In 'Incre_1, A' all travellers from A can choose a bicycle before travellers from C and only can persons from C choose the remaining available bicycles. The assignment 'Incre_1, C' is the reverse case.

4.2.1.2. **Comparisons and observations**

Results for Cases 1 and 2 are shown in Table 4.2 and Table 4.3. Table 4.2 shows the bicycle distribution and link volume on bicycle access and egress links for the different solution approaches. Brackets in the bicycle distributions show the number of bicycles accumulated at stations in zone i. In the random, incremental assignment we repeat the random drawing of users from zones A and C. In 'Incre_1, rand', the brackets in the link volume column show 95% confidence intervals obtained from 1000 trials. Table 4.3 shows the path volumes and path travel time for the last traveller under different solution approaches. Similarly, the 95% confidence intervals in path volume are also shown. Cases 3 and 4 are discussed with results shown in Table 4.4 and Table 4.5 with the same structure. Instead of unidirectional traveller flows as in Case 1 and 2 now there are bi-directional traveller flows.

We firstly consider Cases 1 and 2. In both cases in the assignment approach travellers aim to take a bicycle to the station as long as available. Compared to Case 1, path flows partially shift from the ct to the ctc path in Case 2. Now the fact that bicycles are also available for the last mile, i.e., from the station in B to the destination means that it becomes more attractive to use transit and hence around half of the travellers shift their egress mode. We note that in the SUE cases with higher dispersion parameters the paths with none or low flow now also attract some demand and accordingly this also impacts the bicycle distribution. As the bicycle supply is not sufficient some travellers are forced to walk to and from the station (path t).

Table 4.2 The bicycle distribution and critical link flows at equilibria for Case 1 (left) and Case 2 (right)

$\varphi_i^{\Phi}(\varphi_i^{T})$			Link volume						Case 1 ← / Case 2 →	Link volume						$\varphi_i^{\Phi}(\varphi_i^{T})$		
$i = C$	$i = B$	$i = A$	$T_C B_C^I$	$D_C B_C^O$	$T_B B_B^I$	$D_B B_B^O$	$T_A B_A^I$	$D_A B_A^O$		$D_A B_A^O$	$T_A B_A^I$	$D_B B_B^O$	$T_B B_B^I$	$D_C B_C^O$	$T_C B_C^I$	$i = A$	$i = B$	$i = C$
1	0	1	0	99	0	0	0	99	Incre_1, rand	99	0	0	100	99	0	1	100	1
(99)	(0)	(99)	(0, 0)	(99, 99)	(0, 0)	(0, 0)	(0, 0)	(99, 99)	CI ^{*_1}	(99, 99)	(0, 0)	(0, 0)	(100, 100)	(99, 99)	(0, 0)	(99)	(0)	(99)
1	0	1	0	99	0	0	0	99	Incre_1, A	99	0	0	100	99	0	1	100	1
(99)	(0)	(99)														(99)	(0)	(99)
1	0	1	0	99	0	0	0	99	Incre_1, C	99	0	0	100	99	0	1	100	1
(99)	(0)	(99)														(99)	(0)	(99)
1.30	0	1.30	0	98.70	0	0	0	98.70	DUE	98.74	0	0	99.79	98.74	0	1.26	100	1.26
(98.70)	(0)	(98.70)														(98.74)	(0)	(98.74)
4.72	0	4.72	0	95.28	0	0	0	95.28	SUE, $\theta = 20$	95.32	0	0	99.89	95.32	0	4.68	100	4.68
(95.27)	(0)	(95.27)														(95.32)	(0)	(95.32)
26.19	54.53	26.19	0	73.81	0	0	0	73.81	SUE, $\theta = 1$	69.75	0	0	99.90	69.75	0	30.25	131.87	30.25
(46.54)	(0)	(46.54)														(53.82)	(0)	(53.82)
6.39	20.42	6.46							Simulation							6.51	111.67	6.50
(83.41)	(0)	(83.32)														(87.71)	(0)	(87.61)

Table 4.3. The paths from zones A to B: flow patterns and travel time for Case 1 (left) and Case 2 (right)

Path index						Case 1 ←		Case 2 →	Path volume					
w	tc	t	ct	ctc	c				c	ctc	ct	t	tc	w
0	0	21	99	0	0	v^{*_2}	Incre_1, rand	v	0	49.97	49.03	21	0	0
(0, 0)	(0, 0)	(21, 21)	(99, 99)	(0, 0)	(0, 0)	CI		CI	(0, 0)	(49.74, 50.21)	(48.79, 49.26)	(21, 21)	(0, 0)	(0, 0)
3.418	∞	1.365	1.372	∞	1.907	t^{*_3}		t	1.907	∞	1.372	1.365	∞	3.418
0	0	21	99	0	0	v	Incre_1, A	v	0	99	0	20	1	0
3.418	∞	1.365	1.372	∞	1.907	t		t	1.907	∞	1.372	1.365	∞	3.418
0	0	21	99	0	0	v	Incre_1, C	v	0	0	99	21	0	0
3.418	∞	1.365	1.372	∞	1.907	t		t	1.907	∞	1.372	1.365	∞	3.418
0	0	21.30	98.70	0	0	v	DUE	v	0	49.89	49.85	21.26	0	0
3.418	∞	1.365	1.367	∞	1.902	t		t	1.902	1.471	1.367	1.365	1.469	3.418
0	0	24.72	95.27	0	0	v	SUE, $\theta = 20$	v	0	95.32		24.68		0
3.418	∞	1.365	1.297	∞	1.832	t		t	1.832	1.241	1.298	1.365	1.309	3.418
5.26	0	40.94	46.54	0	27.26	v	SUE, $\theta = 1$	v	15.94	53.82		47.18		3.06
3.418	∞	1.365	1.237	∞	1.772	t		t	1.768	1.246	1.233	1.365	1.378	3.418
0	0	26.45	83.33	0	10.22	v	Simulation	v	5.78	22.00	65.72	20.18	6.32	0

$*_1$: The 95% confidence interval of volume on links/paths

$*_2$, $*_3$: The path volume (v) and path travel time (t) of the specific path after the assignment

Table 4.4. The bicycle distribution and critical link flows at equilibria for Case 3 (left) and Case 4 (right)

$\varphi_i^{\phi}(\varphi_i^{T})$			Link volume						Case 3 ← / Case 4 →	Link volume						$\varphi_i^{\phi}(\varphi_i^{T})$		
$i = C$	$i = B$	$i = A$	$T_C B_C^I$	$D_C B_C^O$	$T_B B_B^I$	$D_B B_B^O$	$T_A B_A^I$	$D_A B_A^O$		$D_A B_A^O$	$T_A B_A^I$	$D_B B_B^O$	$T_B B_B^I$	$D_C B_C^O$	$T_C B_C^I$	$i = A$	$i = B$	$i = C$
50.54	0	50.54	49.47	49.53	0	0	49.54	49.46	Incre_1, rand	49.53	49.47	50.06	49.94	49.59	49.41	50.47	50.03	50.47
(49.46)	(0)	(49.46)	(49.35, 49.60)	(49.40, 49.65)	(0, 0)	(0, 0)	(49.41, 49.67)	(49.33, 49.59)	CI	(49.40, 49.65)	(49.35, 49.60)	(49.82, 50.30)	(49.70, 50.18)	(49.46, 49.71)	(49.29, 49.54)	(49.53)	(49.97)	(49.53)
50.67 (49.33)	0 (0)	50.67 (49.33)	49.33	49.33	0	0	49.33	49.33	DUE	49.35	49.35	49.80	49.80	49.35	49.35	50.65 (49.35)	50.20 (49.80)	50.65 (49.35)
52.36 (47.64)	0 (0)	52.36 (47.64)	47.64	47.64	0	0	47.64	47.64	SUE, $\theta = 20$	47.66	47.66	49.88	49.88	47.66	47.66	52.34 (47.66)	50.13 (49.88)	52.34 (47.66)
63.01 (22.33)	27.33 (0)	63.01 (22.33)	30.20	36.99	0	0	30.20	36.99	SUE, $\theta = 1$	35.22	27.87	56.31	43.70	35.22	27.87	70.81 (26.52)	61.09 (44.24)	70.81 (26.52)
47.89 (46.26)	11.80 (0)	47.94 (46.20)							Simulation							74.01 (25.21)	67.17 (34.65)	74.38 (24.58)

Table 4.5. The paths from zone A to B: flow patterns and travel time for Case 3 (left) and Case 4 (right)

Path index						Case 3 ←		Case 4 →	Path volume					
w	tc	t	ct	ctc	c				c	ctc	ct	t	tc	w
0	0	10.54	49.46	0	0	v	Incre_1, rand	v	0	25.15	24.38	10.47	0	0
(0, 0)	(0, 0)	(10.41, 10.67)	(49.33, 49.59)	(0, 0)	(0, 0)	CI		CI	(0, 0)	(24.94, 25.35)	(24.17, 24.58)	(10.35, 10.60)	(0, 0)	(0, 0)
3.418	∞	1.365	1.372	∞	1.907	t		t	1.907	∞	1.372	1.365	∞	3.418
0	0	10.67	49.33	0	0	v	DUE	v	0	25.13	24.22	10.65	0	0
3.418	∞	1.365	1.370	∞	1.905	t		t	1.890	1.363	1.355	1.365	1.372	3.418
0	0	12.36	47.64	0	0	v	SUE, $\theta = 20$	v	0	47.66		12.34		0
3.418	∞	1.365	1.297	∞	1.832	t		t	1.832	1.333	1.298	1.365	1.399	3.418
2.62	0	20.39	23.33	0	13.66	v	SUE, $\theta = 1$	v	8.70	26.52		23.12		1.66
3.418	∞	1.365	1.231	∞	1.766	t		t	1.763	1.296	1.228	1.365	1.433	3.418
0	0	7.01	47.19	0	5.89	v	Simulation	v	3.22	27.68	23.23	3.06	2.81	0

We observe that in the assignment approaches the bicycles rarely relocate to B from A or C except for SUE with θ = 1 when travellers become insensitive to link costs. In Cases 1 and 2, almost all bicycles end up being located at the station as typical for morning commute problems.

We now discuss the differences between equilibria in the different assignment cases. In line with our expectation, multiple-equilibria can be observed in Case 2 and further in Cases 3 and 4. For incremental assignments with different loading sequences of OD pairs (‘Incre_1, rand’, ‘Incre_1, A’ and ‘Incre_1, C’) in Table 4.3, results of path travel time remain identical while path volumes differ. Furthermore, in Cases 3 and 4, the DUE assignment also reaches equilibrium, but link flow patterns further fall outside the confidence interval of that in the incremental assignment. In words, the DUE and incremental assignments each reach a network equilibrium but with different path or/and link flow patterns. In further tests not shown for brevity, we observe that the differences in equilibria can be larger when the cost of travel between zones reduces.

Focusing on the bicycle distribution of Cases 3 and 4, now less of the initially supplied bicycles end up being located at the station. The reason is that bicycles are not only used to access a PT station, but also for egressing from a PT station. We further observe that in Case 4, when demand and initial bicycle supply are all symmetric, zone B nevertheless can end up with slightly more bicycles than before the assignment, due to more cross-boundary trips to the central zone B than the peripheral zones A and C.

4.2.2. Application to larger demand and fleet sizes

We now apply the simulation and deterministic assignment to a problem with larger fleet sizes and zones with different characteristics inspired by commute patterns observed in Beijing which has an extremely large fleet of free-floating bicycles. Two residential zones and one CBD zone are considered for our exemplary study. Similar as we discussed previously, because of a lack of real-world data, this case study is only exemplary rather than realistic. The zone setting is shown in Table 4.6. The location of Tiantongyuan South station (A) and Wangjing station (C) are selected as examples of residential centroids, and Guomao station (B) as a CBD centroid. Both bicycles and travellers’ origins are randomly distributed in the zones. The speed of cycling and public transport is set to be twice and five times as fast as walking. Both simulation and analytical assignment are conducted based on the same assumptions and the resulting bicycle distribution and path flows are compared. One hundred simulations are conducted to achieve stable average results.

Figure 4.4 shows the simulation result of travellers’ average travel time for different demand and supply cases. Clearly average travel time is lower in cases with supply exceeding demand ($\varphi_i > g_{iB}$) and is increasing with more demand. In the figure we further plot the average travel time for two cases of $\varphi_i = g_{iB}$. The average travel time on this 'demand matches supply diagonal' is strictly decreasing when both φ_i and g_{iB} are increasing. This is in line with our discussion related to Figure 4.2 since increasing φ_i and g_{iB} can lead to lower expected distance to find a bicycle for all travellers. This illustrates a positive feedback loop in that more demand can lead to more bicycles being supplied, leading to higher service quality for all.

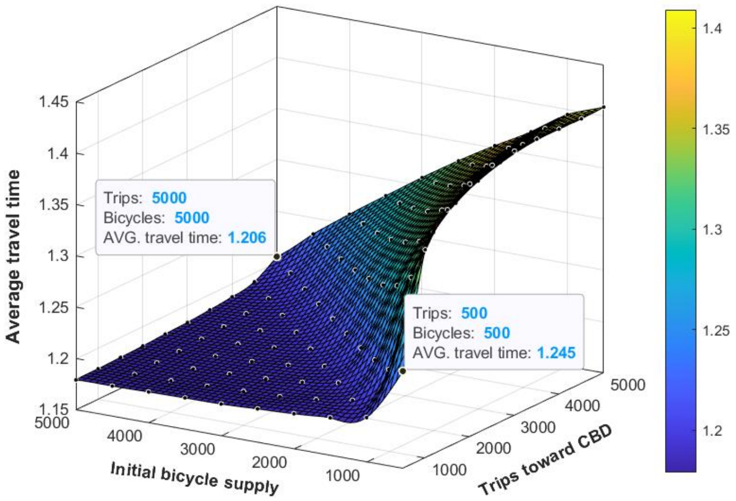


Figure 4.4 Traveller's average travel time in different cases

Table 4.6 Zone settings for larger case study

Zones		Tiantongyuan South	Wangjing	Guomao
Zone index (i)		A	C	B
Property		Residential	Residential	CBD
Centroid	Station	Tiantongyuan South Station (A station)	Wangjing West Station (C station)	Guomao Station (B station)
	Distance to CBD	17.97km	10.66km	
Side length		2 KM	2 KM	1 KM
Trips toward CBD zone (g_{iB})		250 ~ 5000		0
Initial bicycle supply (φ_i)		250 ~ 5000		0

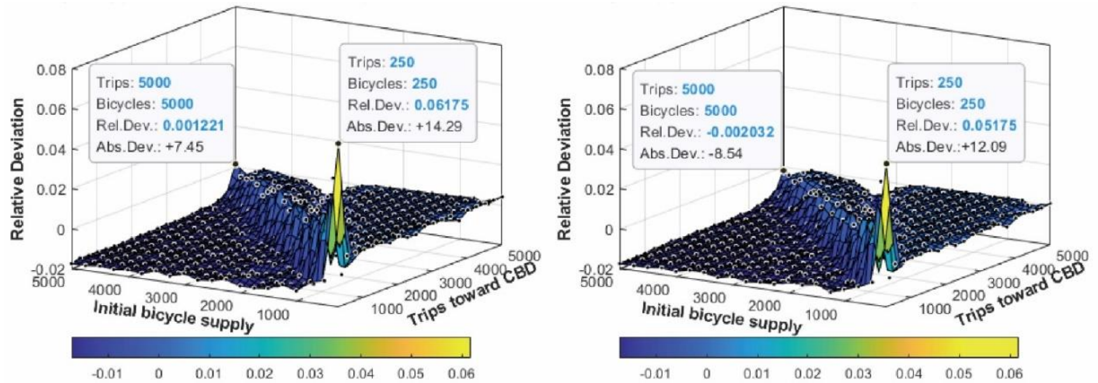


Figure 4.5 Differences analytical model versus simulation with $\boldsymbol{\varphi_A^T}$ on the left and $\boldsymbol{\varphi_C^T}$ on the right (positive values indicate overestimation in analytical results)

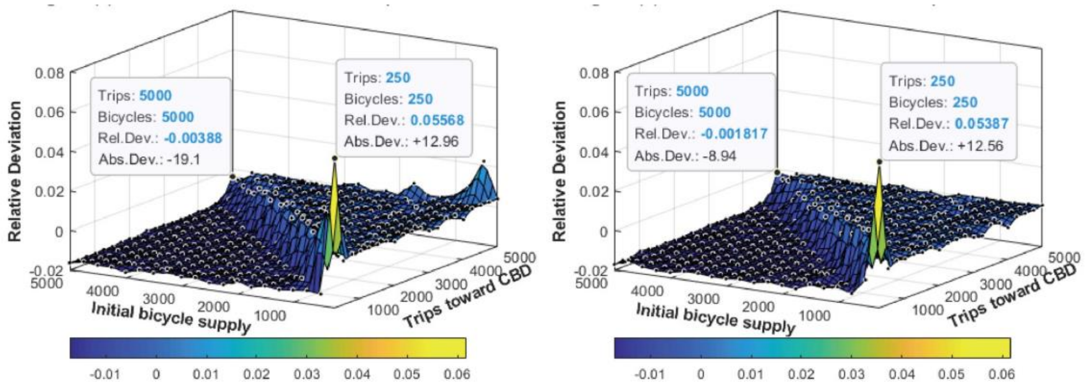


Figure 4.6 Differences analytical model versus simulation with $\boldsymbol{q_{AB}^{ct}}$ on the left and $\boldsymbol{q_{CB}^{ct}}$ on the right (positive values indicate overestimation in analytical results)

To further demonstrate the main objective of our paper, the feasibility of the proposed assignment approach, the deviation between simulation results and analytical assignment results are illustrated. Figure 4.5 shows the percentage of over/under-estimation of bicycles left at stations, compared to the simulation results. We model demand and bicycle supply from 250 to 5000 in steps of 250. The maximum relative deviation occurs for the case of $g_{iB} = \varphi_i = 250$ $(i \in A, C)$ when the assignment results overestimate the number of bicycles by 6.175%. However, the relative deviation shrinks with the increase of g_{iB} or φ_i. The relative deviation converges to -2% for the cases with $g_{iB} > \varphi_i$, and further converges to 0 when $g_{iB} < \varphi_i$. This tendency also applies to the bicycles left at the station in C. We also show the percentage of over/under-estimation for the path with the largest volume, path ct, in Figure 4.6 and observe a very similar tendency. Only for low demand and supply cases we observe notable link flow differences but even these are at the order of a maximum of 6%.

4.3. Conclusion and Discussion

We derive appropriate cost functions to reflect the access competition of persons aiming to reach free-floating bicycles. Our main idea is to abstract the distance between random origin and bicycle locations into single nodes with links connecting these that reflect the random-to-random and central-to-random distance between these. We obtain formulations that reflect the increasing costs with more demand and fewer bicycles. In particular, we model that the costs are increasing in case of a strictly depleting resource. This is in contrast to existing literature where (implicitly) during a given period a fixed number of available bicycles is assumed. We note that this case of constant supply can be modelled also with a simplified version of our approach. More difficult to model are intermediate cases where the bicycle supply is party replenished but gradually reducing. For such a case one might model this as a combination of the two extreme cases. Another approach is to again use the introduced order statistics, assume a fixed bicycle supply, but that travellers consider not the closest but the n-th bicycle as their expected cost.

We show that the central-to-random distance can be obtained analytically but that the random-to-random distance needs to be adjusted from the one obtained with order statistics. This is because, assuming that bicycles are not redistributed during a time interval, the remaining bicycles tend to be at the corner of a zone since the nearest, first choice bicycles are more likely found in the centre of a zone.

We then embed these bicycle access costs in a network assignment approach with walking, cycling, and alternative mode options. With this we obtain travel patterns, expected costs as well as the expected numbers left somewhere in a zone as well as at a transit station. We point out that asymmetric link cost functions arise in our assignment due to the network representation with competition for the same bicycles on different links. Due to this multiple equilibria are likely which we demonstrate with an incremental assignment where travellers are loaded with different priorities.

We further find that expected access distance is significantly influencing the modal share as the fleet size increase. The comparison between a simulation approach and the proposed approach shows in general good correspondence. Some errors occur through neglecting the possible angles in the walking trajectories, that is, if walking to a bicycle is not in line with the direction of the destination. This can lead to some underestimation in cross-zonal bicycle trips.

There are a range of research directions beyond those already mentioned that we aim to address in further work. For one, non-uniform distributions of bicycles inside a zone can be explored with more than one hotspot. Following the same logic of Chapter 3.2 and replacing f^{CR} and f^{RR} by correspondingly deducted functions, the access link costs for non-uniform distributions of bicycles can then be obtained. Secondly, φ_i can be defined according to flows from other zones as well as the expected trip duration. Then cost function can be adjusted accordingly to reflect that a) bicycles are available several times during a zone and that b) additional bicycles are becoming available from other zones. Thirdly, in this paper we have not embedded the assignment into a multi-time interval extension. The approach predicts the number of bicycles distributed “somewhere” in the zone and at a hotspot, such as a transit station. We suggest, together with information on the OD matrix during different time periods this can be the basis for a quasi-dynamic assignment where the resulting bicycle distribution becomes the input for the next time interval. This could then also be used for the optimization of the initial allocation of bicycles at the start of the day as well as efficient redistribution patterns during the day. We close by pointing out that clearly our approach could also be applied to multimodal assignments with free-floating cars or scooters instead of (or in addition to) free-floating bicycles.

CHAPTER 5. DISCRETE-EVENT SIMULATION

The aim of this chapter is to quantify the access distance to free-floating services considering the density and distribution of travellers and bicycles. A focus is the constructing of an agent-based discrete-event simulation (DES), and the study on the effect of different information seeking and reservation strategies of travellers. We distinguish those who use their smartphone actively during traveling to find the best available bicycle from those who only check the availability before the journey. We find that: 1. All travellers being active in seeking feasible bicycles does not necessarily lead to better system performance. 2. Enabling reservation can lead to longer average travel times, especially longer walking time. 3. When increasing the bicycle supply or reservation rate, the reliability of accessing desired bicycles will first increase then drop.

5.1. Simulation Assumptions

5.1.1. Basic assumptions

An illustration of the basic problem and of key notation used subsequently is shown in Figure 5.1. R_v is the ratio of vehicles over travellers. A total of M travellers and a fleet size of $M \times R_v$ vehicles are considered. The origin of traveller p, O_p, and initial location of vehicle q, V_q, are randomly located in the zone each obeying $\Theta_t(x,y)$ and $\Theta_v(x,y)$, where Θ_t and Θ_v are the distribution of travellers and the vehicles. Travellers can either take path W by walking from O_p to D, or take path C from O_p to V_q further to D. Travellers always choose the shortest path among all available paths.

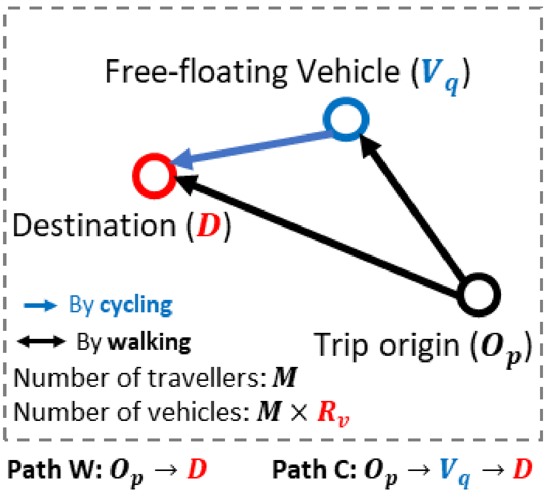


Figure 5.1 Illustration of traveller choice and notation

We further specify the following basic assumptions:

1. Free-floating vehicles are limited to be used by one traveller at a time.
2. Free-floating vehicles can be visually identified on the street. Their location information can be received through applications in smartphones.
3. Once a vehicle is occupied, it will be marked as ‘unavailable’ in the application. This means that access attempts from other travellers will be blocked until the vehicle is released from occupation.

5.1.2. The categorization of travellers

Travellers are categorized with respect to two decision dimensions: the ‘level of smartphone activeness’, and the ability and willingness to make a reservation. We introduce the concept of “smartphone activeness” to distinguish different levels of smartphone usage in seeking available vehicles. Though there clearly is a continuous scale in how active the users are in their smartphone usage we categorize travellers into discrete groups based on the activeness of smartphone usage during trip planning and when picking up free-floating vehicles.

As illustrated in Figure 5.2 we suggest that the end- and midpoints of the scale can be defined with the following three categories accordingly. We list “casual users” for completeness but note that we do not include them in the analysis in this paper.

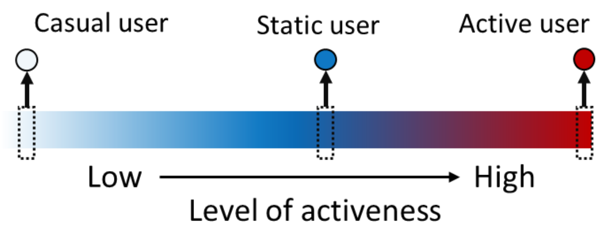


Figure 5.2 Illustration of the level of activeness

5.1.2.1. **Casual user: “Use smartphone only if really needed”**

This type of traveller does not utilize smartphone neither during trip planning nor when walking in order to pick up free-floating vehicles. These travellers tend to be less sensitive to travel costs or do not want to bother checking for the availability of vehicles. They are assumed to have a low motivation in seeking available vehicles and will walk toward one only if s/he spots a free-floating vehicle. In the simulation, casual users will hence not actively respond to any change in the fleet status. The challenge to model these travellers is that one needs to quantify “spotting a free-floating vehicle”, i.e., reflect the visibility of vehicles.

5.1.2.2. **Static user: "Use Smartphone at home, otherwise in pocket"**

This type of traveller utilizes a smartphone during trip planning but not the during the subsequent walking. In the simulation they constitute P_s $(0 \leq P_s \leq 1)$ percent of the total M travellers. The traveller will check their smartphone when s/he finishes his/her activity to make travel plans before they start their journey and possibly make a reservation. Only when the traveller finds the scheduled vehicle has been occupied/reserved by other travellers (because s/he did not make a reservation or because the reservation expired), the user will check her/his phone again and make a new plan. In the simulation, static users will only react when s/he finds the scheduled vehicle becomes unavailable for him/her.

5.1.2.3. **Active user: "Walk with the smartphone in hand"**

This type of traveller will utilize the smartphone both during trip planning and the afterwards picking up process. They constitute P_a $(0 \leq P_a \leq 1)$ percent of the total M travellers. This type of traveller is aiming to find the best alternative in response to changes in the availability of vehicles. They will continuously check their smartphone to pick up any update in fleet status while walking toward the current target. Once a better available alternative shows up, the travellers will shift toward the new target. This means that in the simulation, active users will immediately react and adjust his choice when a targeted vehicle becomes unavailable for him/her or any other, nearer vehicle becomes available.

5.1.2.4. **Reservation**

Another property of users, and considered independent to level of activeness, is their willingness to make a reservation of a specific vehicle. We define P_r $(0 \leq P_r \leq 1)$ as the percentage of the total M travellers who prefer to make a reservation and consider P_r to be independent of P_s and P_a. In line with common practice, one vehicle at a time can be reserved for up to 15 minutes, and a reserved vehicle will be marked as 'unavailable' until the reservation is expired, or the vehicle is released from usage. Policies such as additional or reduced prices for vehicles with prior reservation may be carried out in order to discourage or encourage reservation. Travellers may also choose not to make a reservation if 'staying flexible' is considered important. In general, we expect that in networks with large fleets and short usage duration the willingness to reserve is lower. For one, the overall likelihood that a vehicle is available is higher, and secondly the likelihood that a vehicle becomes available on one's walking path that was not available when the traveller started the journey is higher so that a reservation at the start of the journey would be sub-optimal.

5.2. Event Separations

Travellers are presumed to be only interested in their own travel. In a system where competition among travellers over limited vehicle resources is fully respected, chronologically earlier events will interrupt later ones. In order to capture such effect in a simulation, we merge discrete-event simulation (DES) with agent-based modelling (ABM) to represent the competition and time-varying behaviour of travellers. Because not every time slice has to be simulated, DES can typically run much faster than a corresponding fixed-increment time simulation.

The traveller's heterogeneous decision-making process is separated into several contextual events. Events are scheduled dynamically as the simulation proceeds. In the DES structure, events occur at the given instant in time and cause a change in the system state. Between consecutive events, no change in the system is assumed to occur. Events are executed and removed in strictly chronological order from the pending event set S regardless of the order in which they were added. Potential contextual events are added into the pending event set correspondingly. The pending event set S is generated and organized as a priority queue, sorted by event timestamp.

Initialization events of each traveller and vehicle need to be added into S before the simulation starts. In the 'initialization' event, the initial location of vehicles is fixed. The origin of each traveller is also fixed, together with destination, the type of this agent, and their random initialization timestamp $t_{\text{ini}} \leq T_{max}$, where T_{max} is the time limit of travellers joining the simulation. For modelling realistic scenarios, we further require not only an ordering of the travellers but a specific generation time.

5.2.1. Event separation of static travellers

If traveller p is initialized as a static user, we separate the related decisions into four events: 'launch_app', 'use_veh[icle]', 'release [the vehicle]', and 'complete [trip]'. We do not exclude the chance of some failures to obtain a targeted vehicle. For example, the scheduled vehicle in a user's travel plan may be reserved / occupied by other travellers before s/he can arrive at the vehicle location. Static users will only react to interruptions when s/he arrives at a scheduled vehicle location, but finds the desired vehicle is unavailable or no longer at that location.

The 'launch_app' event includes the trip plan creation where the user is assumed to compare the different paths, chooses the shortest path (in terms of generalised cost). If path W is chosen as desired travel plan, a 'complete' event is added into S with the timestamp of when the traveller arrives at the destination by walking; otherwise, a 'use_veh' event is added into S with the timestamp of when the traveller arrives at the desired vehicle q by walking. If reservation is enabled for static user p, extra reservations can be made on vehicle q if the travel plan includes using vehicle q.

In the 'use_veh' event, the behaviour when reaching vehicle q is included. If the desired vehicle q is unavailable, or no longer at the scheduled location, a 'launch_app' event is executed immediately as a new trip plan. Otherwise, q will be occupied by traveller p and marked as 'unavailable', and a 'release' event will be added into S with the timestamp of when the traveller arrives at the destination by the vehicle. If vehicle q is under reservation of traveller p, reservation is removed.

In the 'release' event, the behaviour conducted when completing using a free-floating vehicle is simulated. Upon finishing the vehicular trip, the occupied vehicle becomes available at the current location and ready for new bookings. If the remaining unfinished trip involves no more vehicle usage, a 'complete' event is added into S with the timestamp of when the traveller arrives at the destination by vehicle; otherwise, a 'use_veh' event is added into S with the timestamp of when the traveller arrives at the next desired vehicle.

Finally, upon 'complete' the travellers will be marked as 'trip completed' and removed from further simulation. The whole flow chart for Static travellers is shown in Figure 5.3.

5.2.2. Event separation of active travellers

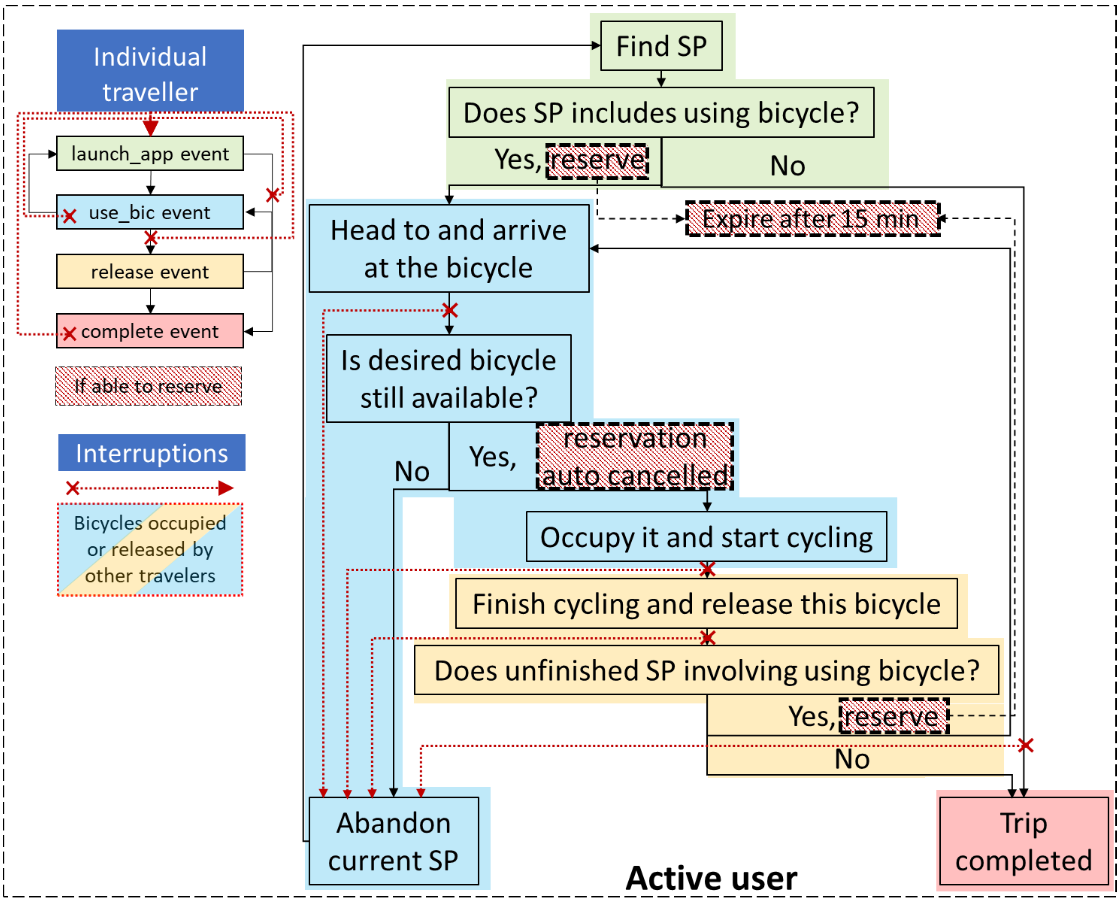


Figure 5.3 The flowchart of active users

The difference between active and static user is that an active user will respond to changes in the fleet size fast. In our simulation active users are at the extreme end of this scale and will react immediately whenever a vehicle in the fleet is released or reservation expired, and whenever a scheduled vehicle becomes unavailable. Therefore, from the aspect of simulation, an active user will inherit the same event separation from static users but 'launch_app' events are immediately executed when a new event occurs as shown in Figure 5.3.

5.3. Simulation Settings and Evaluation Criteria

5.3.1. Network specifications

Based on the simulation structure explained above, in this simulation we focus on the scenario when commuters are using free-floating services to access public transport (PT) stations in the morning. Following specifications are made correspondingly:

1. The research region is set to be a unit square with side length a. The destinations of all travellers are assumed to be the centroid of the research region. The centroid could be viewed as the central business district of the city or a major PT station which travellers want to access.
2. The free-floating vehicles are assumed to be bicycles. Significant differences exist between bicycle sharing and carsharing, for example, bicycle sharing services are less expensive and users tend to make shorter journeys with higher flexibility. We therefore suggest that our approach is primarily applicable for bicycle sharing scenarios, but the simulation framework can also be applied to carsharing studies.
3. Travellers are composed of static and active users, hence $P_a + P_s \equiv 1$.
4. We now discuss the input parameters. Firstly, the number of travellers M is not varied in the simulation but set to be 800. Instead, we vary the number of free-floating bicycles in the system. We note that it is mainly the ratio of vehicles to travellers that influences the result. Scenarios with higher spatial demand density and equal ratio of vehicles to travellers will lead to on average shorter access to bicycles and an increased usage of the bicycles. Tests with different M show though that these effects are not very significant unless the demand becomes very small.

We vary five parameters in the simulation with five levels for each of these independent input variables in this simulation as shown below in Table 5.1. The service level generally becomes better from level one to five. The first column in the table, $\boldsymbol{T_{max}}$, denotes the maximum time within which travellers are generated. The second column denotes the supply/demand ratio, $\boldsymbol{R_v}$, and the number of vehicles ($\boldsymbol{R_v} \times M$).

The ratio ranges from 0.25 to 4.0 so that the number of available vehicles ranges from 200 to 3200 in this simulation. Clearly in the low $\boldsymbol{R_v}$ scenarios there is intense and in the high $\boldsymbol{R_v}$ scenarios there is less competition for bicycles. To note is, however, that also in high $\boldsymbol{R_v}$ scenarios there is some competition as travellers might aim for the same bicycle. The third and fourth column show the percentage of static ($\boldsymbol{P_s}$), active ($1 - \boldsymbol{P_s}$) and reservation ($\boldsymbol{P_r}$) enabled travellers. Each range from 0% to 100% in order to cover the range of possible compositions. The distribution of travellers (Θ_t) and bicycles (Θ_v) are independent and identical except for the second type ("imbalanced"). The abbreviations used in Table 5.1, fifth column, are as follows:

1. "Uniform" (U / U): This is the base case in the following result discussion. Travellers and bicycles are uniformly distributed in the square zone. It is the basic scenario and serves as control level.
2. "Imbalanced" (U / N_{CTR}): This case is used to simulate the 'imbalanced scenario' where bicycles are mainly relocated around major public transport stations. Travellers are uniformly distributed but bicycles follow a two-dimensional normal distribution with peak at the centroid. The normal distribution is specified with ($X, Y \sim N(\mu_x, \mu_y, \sigma_x, \sigma_y, r)$ where $\mu_x = \mu_y = 0.5a$, $\sigma_x = \sigma_y = 1$ and $r = 0$).
3. "Centre" (N_{CTR} / N_{CTR}): This scenario is added to simulate the case of both travellers and bicycles tending to be accumulated around the city centre. Both travellers and bicycles follow two-dimensional normal distributions with a peak in the centre. The distribution is specified with ($X, Y \sim N(\mu_x, \mu_y, \sigma_x, \sigma_y, r)$ where $\mu_x = \mu_y = 0.5a$, $\sigma_x = \sigma_y = 1$ and $r = 0$).
4. "Corner" (N_{COR} / N_{COR}): This case is meant to simulate a scenario when a demand hotspot locates away from the destination, for example, travellers commute to the centre from a high-density residential area located around the corner with well-supplied free-floating bicycles. Both travellers and bicycles follow a two-dimensional normal distribution with peak near the corner. ($X, Y \sim N(\mu_x, \mu_y, \sigma_x, \sigma_y, r)$ where $\mu_x = \mu_y = 0.25a$, $\sigma_x = \sigma_y = 1$ and $r = 0$).
5. "CBD" (N_{COMP} / N_{COMP}): This case simulates one CBD in the centre while residential facilities locate in the surroundings. The bicycles are used to access their homes and no manual rebalancing was made. Both travellers and bicycles follow the complementary distribution of N_{CTR} where $F_{N_{COMP}} = 1 - F_{N_{\mathrm{CTR}}}$. This means that travellers are unlikely to live close to the centre.

To evaluate the simulation results the criteria shown in Table 5.2 are used. Three measures of travel time are used. Besides average travel time, we distinguish the time spent walking and cycling. For example, a lower walking time might not necessarily result in a significantly lower overall travel time for the traveller if the nearest bicycle is located not in the direction of the destination. To investigate this further also "cycle time per ride" is added. R_C is included as it relates to the overall attractiveness of the service as well as profit for the operator. $\bar{C}_{ST}^{F}$ describes the level of competition and potential frustration of users as their targeted bicycle is not available. We note that it is not useful for active users as these will have changed their path before reaching the bicycle. Instead, for active users, we include the count of how often they launch the app and how often they change their path. These two measures describe how dynamic the system is in terms of often new options appear and how often these are taken.

Table 5.1 Levels of the independent input variables.

	$\boldsymbol{T_{max}}$ (hour)	$\boldsymbol{R_v}$ $(\boldsymbol{R_v} \times M)$	$\boldsymbol{P_r}$ $(\boldsymbol{P_r} \times M)$	$\boldsymbol{P_s}$ $(\boldsymbol{P_s} \times M)$	$\boldsymbol{\Theta_t(x,y)}$ / $\boldsymbol{\Theta_v(x,y)}$
Level 1	0.0	0.25 (200)	0.0 (0)	0.0 (0)	"Uniform"
Level 2	0.25	0.5 (400)	0.25 (200)	0.25 (200)	"Imbalanced"
Level 3	0.5	1.0 (800)	0.50 (400)	0.50 (400)	"Centre"
Level 4	0.75	2.0 (1600)	0.75 (600)	0.75 (600)	"Corner"
Level 5	1.0	4.0 (3200)	1.0 (800)	1.0 (800)	"CBD"

Table 5.2 Evaluation criteria

Abbreviations	Definitions
$\bar{T}, \bar{T}_{\text{walk}}, \bar{T}_{\text{cycle}}$	The average travel time, average walk time and average cycle time per traveller
$\hat{T}_c$	Cycle time per ride. $\hat{T}_c = (\bar{T}_{\text{cycle}} \times M) / (R_C \times M) = \bar{T}_{\text{cycle}} / R_C$
R_C	Proportion of travellers using bicycles which equivalent to path C ratio in this simulation.
$\bar{C}_{ST}^{F}$	The average count of 'Fail to use desired bicycle' among static users
$\bar{C}_{AT}^{LCH}$	Average count of 'Launch app' event among active users.
$\bar{C}_{AT}^{CHG}$	Average count of changing to a new shortest path among active users.

5.4. Result Discussion

5.4.1. AVOVA analysis of all scenarios

Before discussing specific results, as an initial test whether we can expect the parameters to influence the evaluation criteria we utilise a selection of simulated scenarios for a univariate analysis of variance (ANOVA). We note that one simulation run requires several minutes, and the simulation time increases the larger the number of bicycles and the larger the percentage of active travellers as these induce more events. Therefore, we cannot run the 5^5 = 3125 possible combinations with sufficient trials. To avoid potential biases introduced from fragmental scenario selection and specific simulation scenarios, for the construction of Table 5.3, we select 25 simulation scenarios ($L_{25}(5^5)$) according to an orthogonal design for our five input variables with five levels. These 25 scenarios are selected as a representative of all 3125 possible combinations in order to generate results shown in Table 5.3. For each scenario

100 trials are run, and their average is taken as input. In Table 5.3 the evaluation criteria, which are taken as dependent variables, are listed in the first row. A constant and the five input variables listed as rows are taken as independent variables. Model fit (R^2) is also shown in the last row.

Table 5.3. The significance matrix of the univariate ANOVA test based on 2500 simulation runs (25 scenarios with 100 trials for each scenario)

	$\bar{T}$	$\bar{T}_{\text{walk}}$	$\bar{T}_{\text{cycle}}$	$\hat{T}_c$	R_C	$\bar{C}_{ST}^{F}$	$\bar{C}_{AT}^{LCH}$	$\bar{C}_{AT}^{CHG}$
$\boldsymbol{T_{max}}$	0.216	0.405	0.798	0.514	0.437	0.452	0.068	0.187
$\boldsymbol{R_v}$	0.011	0.008	0.008	0.498	0.000	0.152	0.419	0.470
$\boldsymbol{P_r}$	0.741	0.996	0.925	0.522	0.353	0.270	0.817	0.295
$\boldsymbol{P_s}$	0.316	0.618	0.900	0.555	0.444	0.213	0.250	0.191
$\boldsymbol{\Theta_t}$ / $\boldsymbol{\Theta_v}$	0.003	0.060	0.023	0.000	0.347	0.069	0.093	0.061
$\boldsymbol{R^2}$	0.980	0.963	0.967	0.993	1.000	0.929	0.930	0.932

We find that R^2 are generally strong suggesting that the majority of the variation is explained. The significance of input variables on the evaluation criteria varies, notably the significance of the spatial demand and supply distribution Θ_t / Θ_v are very strong on all criteria except for R_C, while R_v significantly influence R_C, $\bar{T}$, $\bar{T}_{\text{walk}}$ and $\bar{T}_{\text{cycle}}$. P_s and P_r have relatively less influence on $\bar{C}_{ST}^{F}$ and time-related criteria. Their influences will be discussed in more detail in the following sub-sections.

5.4.2. Impact of bicycle fleet size

In Figure 5.4, R_v on the x-axis varies from level one to five and Θ_t / Θ_v is fixed as uniform distribution. Three curves are shown where the other three parameters, $\boldsymbol{T_{max}}$, $\boldsymbol{P_r}$ and $\boldsymbol{P_s}$ are fixed to level one to five as defined in Table 5.1. Thus, the curves represent a change of multiple input parameters and hence are meant to show the range in variation of the evaluation measure for different scenarios. We remind that the service level generally improves from level one to five as a higher $\boldsymbol{T_{max}}$ means that demand is more distributed and hence there is less competition. The time-related statistics $\bar{T}$, $\bar{T}_{\text{walk}}$, $\bar{T}_{\text{cycle}}$, together with R_C are plotted in Figure 5.4. For $\bar{T}$ and $\bar{T}_{\text{walk}}$, we observe the spread of result gradually increases from zero bicycles to a critical point which in Figure 5.4 is around half of the potential demand. After that, the spread of results gradually converges when the number of bicycles increases thus showing that the temporal distribution, smart phone activeness and reservation behaviour have little influence when the bicycle fleet is large. However, for $\bar{T}_{\text{cycle}}$ and R_C we observe almost identical results independent of the three other input parameters. Such consistency suggests R_v is the main influencer of $\bar{T}_{\text{cycle}}$ and R_C. This conclusion can also be confirmed from the result in Table 5.3. The significance levels of R_v on $\bar{T}_{\text{cycle}}$ and R_C are high.

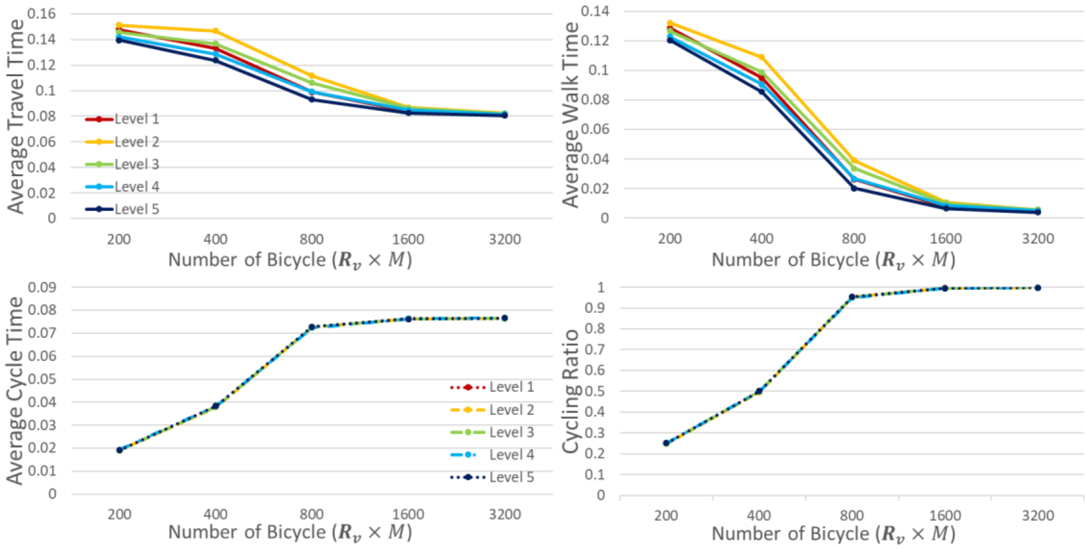


Figure 5.4 The influence of number of bicycles over different evaluation criteria

Following further noteworthy tendencies can be observed. An increasing fleet size R_v will lead to higher R_C, higher $\bar{T}_{\text{cycle}}$, but lower $\bar{T}$ and lower $\bar{T}_{\text{walk}}$. This result is expected as increasing the bicycle ratio leads to less competition in accessing the bicycles therefore R_C rises. To be noted is that there is a double effect with respect to the influence of fleet size on $\bar{T}_{\text{cycle}}$ and $\bar{T}_{\text{walk}}$. An increasing R_v not only leads to less competition in bicycles, but also shortens the expected walking distance to access a desired bicycle. Therefore, more walking is replaced by cycling therefore $\bar{T}_{\text{walk}}$ falls and $\bar{T}_{\text{cycle}}$ rises. The cycling speed is faster than walking so generally $\bar{T}$ falls to some extent. On further investigation we find that the average cycle time per ride in fact slightly decreases if the bicycle supply rises from 200 to 800 bicycles as some travellers will walk away from their destination to reach a bicycle. Only if the bicycle supply is large, more bicycles mean less cycle time per ride. We note, however, that the effects are minor.

5.4.3. Impact of reservation rate

We now vary the reservation rate $\boldsymbol{P_r}$ from level one to five. $\boldsymbol{\Theta_t}$ / $\boldsymbol{\Theta_v}$ remains fixed as uniform distribution. We again construct curves for three levels to illustrate changes with respect to the other three input parameters ($\boldsymbol{T_{max}, R_v, P_s}$). The time-related evaluation measures $\bar{T}$, $\bar{T}_{\text{walk}}$ and $\bar{T}_{\text{cycle}}$ are plotted in Figure 5.5. Counterintuitively, we find that with increasing reservation rate, the average walk time $\bar{T}_{\text{walk}}$ and average travel time $\bar{T}$ also increases. Reservation does not improve system performance in terms of travel time and higher reservation leads to longer walking. No clear influence with respect to $\bar{T}_{\text{cycle}}$ is observed.

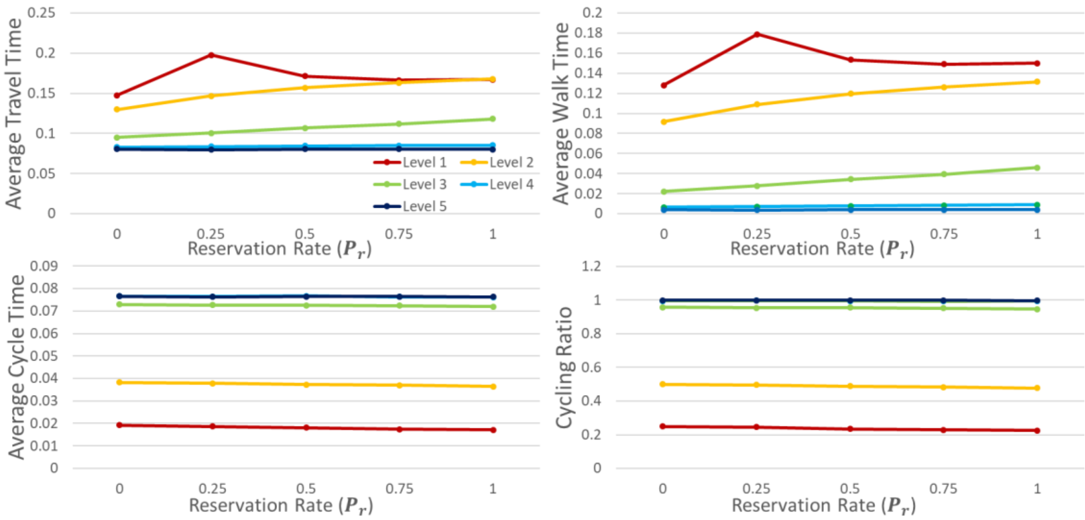


Figure 5.5 The influence of reservation rate over different evaluation criteria

We explain this effect as follows: In the case with competition among travellers, the traveller who uses the reservation system chronologically earlier will reserve the bicycle closest to him/her. This bicycle will be marked as 'reserved' and is removed from the choice set of the later travellers until expiration. However, from the viewpoint of later travellers, though s/he might in fact be closer to this bicycle, or s/he can actually arrive at the bicycle earlier, later travellers do not have a chance to use this bicycle anymore. The same effect can also be explained from the "perspective of bicycles": Higher reservation rate means bicycles are more easily reserved and occupied by reservation-enabled travellers who were randomly selected by the system, rather than occupied by the winner of the competition among reservation-disabled travellers. In other words, the pool of 'nearby competitors' shrinks with the increase of P_r therefore the access distance rises and $\bar{T}_{\text{walk}}$ and $\bar{T}$ increase accordingly.

5.4.4. Determinants of failure rate of using desired bicycle

In a system where reservation is not equally enabled for all travellers, or extra cost is claimed when making reservation, travellers may access desired bicycles without making a reservation. Under such circumstances, static users may find him/herself fail to use the desired bicycle that they have been walking towards because other travellers may arrive earlier. To quantify this effect $\bar{C}_{ST}^{F}$ is tracked during the simulation.

We firstly investigate how the reservation rate influence $\bar{C}_{ST}^{F}$. We again keep a uniform demand and supply distributions, vary the reservation rate, and plot the five levels of increasing service quality for the other three input variables on the left of Figure 5.6.

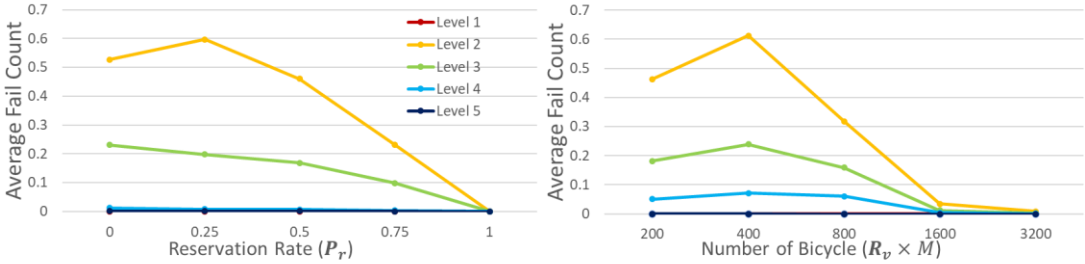


Figure 5.6 The influence of reservation rate (left) and number of bicycles (right) over average fail count

We observe that $\bar{C}_{ST}^{F}$ will generally reduce with higher reservation rate but that in some cases it first increases before than decreasing, exemplified in the figure with "Level 2 scenarios". Reservation-enabled traveller will face zero chance of failure, but at the same time this can lead to a higher chance of failure for those not reserving a bicycle as they compete for a smaller pool of bicycles, unless the lower number of available bicycles means that travellers prefer to walk. When the reservation rate is low, the majority are the travellers who do not make reservations. Hence, although some travellers have zero chance of failure, the failure rate of the majority is higher therefore the overall $\bar{C}_{ST}^{F}$ can increase as the figure shows. In case the reservation rate is high, obviously the majority will face zero chance of failure therefore few encounter a failure and hence $\bar{C}_{ST}^{F}$ falls. Clearly another influencing input for the failure rate is the bicycle supply R_v. Results are plotted on the right side of Figure 5.6. Similarly, $\bar{C}_{ST}^{F}$ first increases then falls close to zero. In this case we observe the effect is even more pronounced and occurs in more scenarios.

This effect can also be explained as a Markov process: Travellers can choose between two states: 'path C as SP' or 'path W as SP'. If 'path C as SP' is chosen, they will further be subject to an 'successfully occupy bicycle' or 'fail to access bicycle' event. Travellers experiencing 'fail to access bicycle' will continue their journey by choosing again between 'path C as SP' and 'path W as SP'. Therefore, $\bar{C}_{ST}^{F}$ is equivalent to the count of intermediate 'fail to access bicycle' states during the simulation process, which is proportional to the transition probability of 'path C as SP' times 'fail to access bicycle'. The absorbing states are 'path W as SP' (travellers complete with path C) and 'successfully occupy bicycle' (travellers complete with path W).

Further, when the number of bicycles is very high, the competition among travellers becomes less intense. Therefore, the transition probability of 'path C as SP' increases and the probability of 'fail to access bicycle' reduces. Therefore, the average count of 'fail to access bicycle' state will decrease and approach to zero when the number of bicycles is large enough. When the number of bicycles increases from a very low level, the transition probability of 'path C as SP' still increases while the probability of 'fail to access bicycle' remains high.

Therefore, as the number of bicycles increases from zero to a critical point, which in Figure 5.6 is around half the potential demand, the average count of 'fail to access bicycle' increases. After this critical point is exceeded it gradually decreases and approaches to zero.

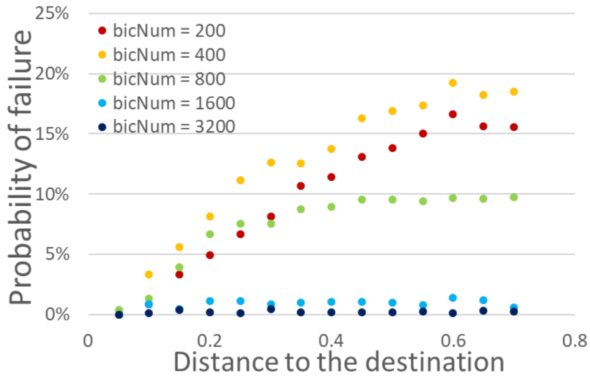


Figure 5.7 The probability of fail to pick up desired bicycle at different distance

Such phenomenon can also be observed from a different angle. In Figure 5.7 we plot the probability of failure versus traveller's origin-destination distance with a step length of 0.05 for static travellers. In contrast to $\bar{C}_{ST}^{F}$, the probability of failure only shows the percentage of static travellers and their "wasted walking distance". We remind that active travellers are likely to re-route before completing this unsuccessful trip. In Figure 5.7, all parameters are controlled except for the number of bicycles ($\boldsymbol{R_v} \times M$). We observed that for each curve, the probability of failure rises from 0% to 20% as the distance to the destination increases. We find that as the number of bicycles increases from 200 to 400 the probability of failure also increases only with further supply increases the failures also decrease. This hence supports our previous explanation. Overall, it shows again that a slight undersupply can be worse than a severe undersupply.

5.4.5. Impact of demand and supply distributions

Finally, the influence of different city layouts, in this research abstracted as distribution, is investigated. The time-related statistics and $\bar{C}_{ST}^{F}$ are plotted in Figure 5.7. The five types of Θ_t / Θ_v shown in Table 5.1 are distinguished on the x-axis and the variation between the other four input parameters is reflected with the Level 1 to 5 curves. In addition, the "no bicycle usage" scenario is added in the $\bar{T}$ figure, which serves as a benchmark when there are no bicycles in the city. It is not presented in the other three figures because failures can not be defined, $\bar{T}_{cycle}$ becomes zero and $\bar{T}_{cycle} \equiv \bar{T}$.

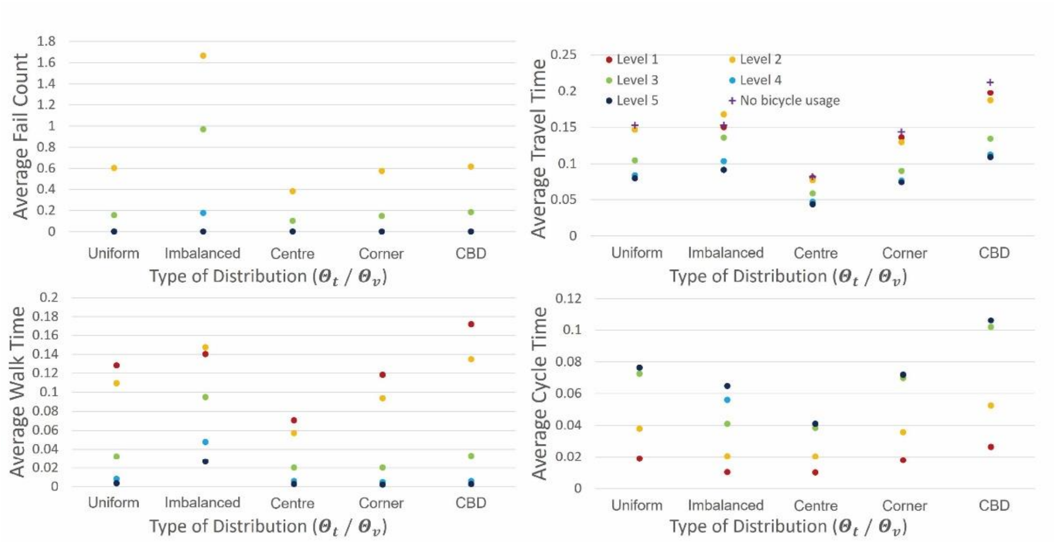


Figure 5.8 The influence of reservation rate over time-related statistics. Distributions as defined in Table 5.1.

We firstly investigate average fail count $\bar{C}_{ST}^{F}$ (top left in Figure 5.8). The "centre" scenario has the lowest $\bar{C}_{ST}^{F}$ whereas "imbalanced" has the highest $\bar{C}_{ST}^{F}$ as the distribution of traveller changes from N_{CTR} to U. We further find that under an "imbalanced" distribution when there is no bicycle, $\bar{T}$ is even lower than that under Level 2 input. In line with our previous discussion this means that the general travel quality can decrease when introducing a too low number of free-floating bicycles.

The low value in "centre" is because all travellers and bicycles are located around the centroid, which is also their destinations. Another noteworthy observation is made with respect to the remaining three travel time related subfigures in Figure 5.8. We find that "centre" is still the best scenario with lowest $\bar{T}$ while "CBD" is the highest. In the "CBD" scenario setting, both travellers and bicycles are more likely to start far from the centroid therefore the $\bar{T}$ and $\bar{T}_{cycle}$ are the highest. However, we observe that the "corner" scenario has the second lowest $\bar{T}$. Although distances in the "corner" case are long, the majority of the distance is travelled by cycling rather than walking as the bicycles are distributed closer to the travellers. Less walking is needed to access desired bicycles and start cycling. Therefore, from the viewpoint of travel time, this distribution still ranks high compared to other scenarios.

Finally, in Figure 5.9, we again construct failure probability curves as in Figure 5.7. We show figures for Level 2 to 4 to illustrate changes with respect to the other three input parameters ($\boldsymbol{T_{max}}, \boldsymbol{R_v}, \boldsymbol{P_s}$) for the five distributions. Static travellers face the highest probability that the desired bicycle becomes unavailable in the "imbalanced" scenario. Even if the overall service level raises, this phenomenon remains. We suggest this is because when more travellers are heading to the centroid from sub-urban areas rather than from downtown, an intense competition occurs for the bicycles in the periphery. The bicycles near the central part are not effective for travellers from the periphery, so that they contribute little in raising the overall service level. Such phenomenon can also be observed when services are limited to be used in certain areas, such as free-floating bicycles being limited within the tourist attraction areas.

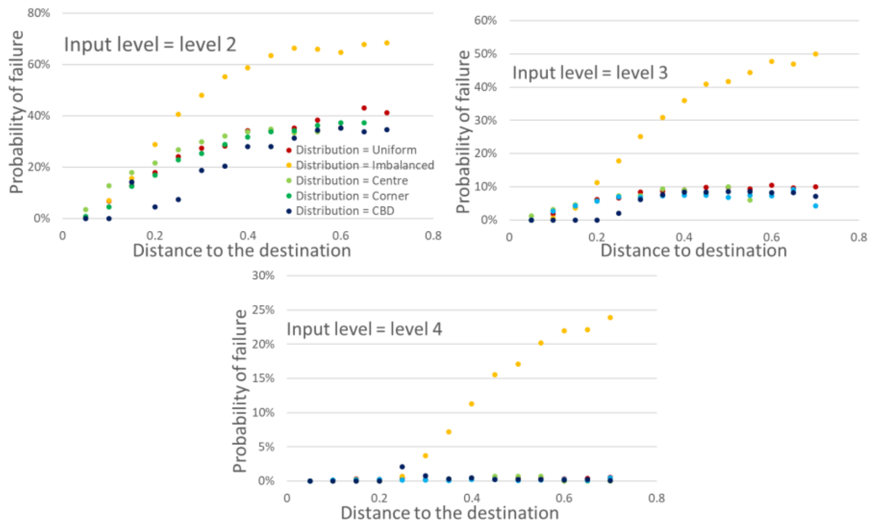


Figure 5.9 The probability of failure to pick up the desired bicycle in different input level

5.5. Conclusion

In this research, we construct an agent-based discrete-event simulation to investigate the influence of different information seeking and reservation strategies of travellers under uncertain availability, together with the density and distribution of travellers and vehicles. Travellers with different activeness in their smartphone usage in seeking available vehicles are distinguished. To the best of our knowledge, this is one of the first studies explicitly simulating different smartphone usage strategies and the impact on the performance of a transport system with shared vehicles.

We show that this activeness can indeed influence the performance of the system. We further quantify how increasing the bicycle ratio leads to less competition in accessing free-floating bicycle service. Increasing the bicycle to traveller ratio also leads to shorter average travel time. We show that this is not only due to on average less access time but also because travellers are more likely to walk in the direction of their destination to find a bicycle if more are available. The reservation rate is found to have a negative influence on average travel time. The reliability of accessing desired bicycles is also investigated through the average fail count $\bar{C}_{ST}^{F}$ and very non-linear effects are found and explained. Different spatial and temporal distributions for bicycles and travellers are also investigated that represent different land-use types.

We suggest our findings and the simulation tool developed as part of this research can support the understanding of the impacts of free-floating services. In particular we suggest following implications are important: Firstly, the value of reservation for free-floating services needs to be reconsidered. Adopting reservation benefits reservation-enabled travellers at the cost of reducing system performance, such as increases in the travel time and failures, and further worsen the service level of reservation-disabled travellers. In other words, enabling reservation is good for an individual, but a higher reservation rate will lead to less competition and therefore longer average travel time and especially longer walking time. Secondly, this cost is, however, depending on the overall percentage of travellers reserving a vehicle before they start walking towards it as well as their "smartphone activeness". Smartphone activeness cannot be controlled by an operator, but an operator should be aware that updating the fleet availability very frequently can lead to some negative effects in that those who prefer to not check information very often might encounter more failures to obtain a bicycle they thought would be available. We suggest reservation should be viewed and charged as a value-added service. Imposing uniformity on all travellers, neither allowing long reservation for all, nor disabling reservation for all, is not suggested. Thirdly, we demonstrate the benefit of the spatial bicycle distribution and the traveller distribution being similar. We also show that introducing free-floating bicycles will in many cases reduce the travel time in the network. There are however exceptions. In particular the travel time might increase if there are few bicycles but enough to trigger a steep competition among the traveller for these. Furthermore, if bicycle and demand distributions are not matched this effect can be larger. Therefore, our study can also be used as a basis to quantify the value of bicycle rebalancing schemes.

Lastly, although it cannot be controlled by an operator, we also demonstrate that the highly dynamic enroute decisions through smartphone usage can be important for understanding travel patterns.

There are a range of research issues that we suggest can be addressed in future work. For one, the manual redistribution, which becomes the main concern in daily operation, can be evaluated with the proposed discrete event simulation framework. New events reflecting the process of vehicles becoming unavailable, carried to certain location and re-available can be added. The redistribution strategy is then split into several events and a cost–benefit analysis can be made with respect to different redistribution strategies. Another interesting extension is to expand the work to multi-zone simulations and validate adjustments for analytically obtained access costs. Furthermore, we intend to obtain some of the input for this simulation from survey calibrations. We suggest that a better understanding of the 'level of activeness' and the 'willingness to make detour' to find available free-floating vehicles deserves further research. Beyond such direct model extensions, we believe further research is needed as to how negative experiences such as failure to obtain a bicycle will influence the system demand in the longer term. With appropriate parameters the framework presented here could also be extended in such a direction with varying day-to-day demand.

CHAPTER 6. SURVEY USING GENERATED SCREENSHOTS

6.1. The survey design overview

The centrepiece of this chapter is a) understand the choice preference of travellers; b) the possibility of deriving any policy for service provider and users; c) provides a foundation for further research. The usage of choice experience is necessary because the dimension of choices in our survey is not yet been seen in the market, and thus behavioural data can only be collected within the setting of a stated preference (SP) method. The experiment seeks from each respondent their circumstance and travel plan in the form of desired bicycle and whether to make reservation through a set of well-designed questions. Although a revealed preference (RP) is carried out in the first half of the survey while RP in the second half, these two parts are independent surveys and therefore should not be viewed as a SP-RP survey.

This survey comprised the following three major blocks, complemented by a short demo explaining how the map should be read and how the travel plan should be derived. The integrated anti-bot design in the third part is also an innovative point of this survey.

The first part seeks socio-demographic information with questions related to the respondent’s age group, gender, monthly income, education history, home city, occupation, employment status, gender and sharing service membership. The second part asks the respondents to evaluate their usage experiences in the following aspects: physical condition (frequency of exercise, daily walk steps, cycling frequency), bicycle and FFBS usage frequency, travel purpose, travel time period, attitudes toward FFBS usage (proficiency, satisfaction, willingness of continue usage), travel behaviour in FFBS usage, transfer frequency, reasons to use FFBS and smartphone usage behaviour. In our previous simulation research (CITE), we distinguished the different types of travellers based on their smartphone usage activeness and corresponding behaviour during the bicycle seeking process. In the second part of this survey, questions leading to the identification of traveller type are also added. This is another important aspect we would like to investigate in this survey. Data gathered in this part can be further adopted in the latent class analysis for identifying the type of traveller.

The third and the last part is a SP survey where the majority of consideration goes. It will be thoroughly discussed in the following section.

6.2. The RP part: Sociodemographic, attitudes towards FFBS usage

In this RP part, sociodemographic information of respondents are collected through answering a series of questions as shown in Table 6.2 and attitude questions shown in Table 2. Users under 12 are illegal to use free-floating service therefore the age group starts with 12 years old.

Table 6.1 The attribute level for attitudes towards cycling and FFBS

Part I: Exercise (in last three month)

Attribute	Attribute level
Exercise frequency	More than three times per week One to three times per week Once per week Once every two weeks Never
Daily steps	< 1000 1,000 – 3,000 3,000 – 6,000 6,000 – 10,000 10,000 – 15,000 15,000 – 20,000 > 20000
Cycling frequency	Almost everyday Five to six times per week Three to four times per week One to two times per week Less than once per week
FFBS usage frequency	Almost everyday Five to six times per week Three to four times per week One to two times per week Less than once per week Less than once per month

Part II: Attitudes towards FFBS usage

Attribute	Attribute level
Proficiency in FFBS usage	Scale 1 for not proficient at all to Scale 6 for very proficient
Proficiency in FFBS APP usage	Scale 1 for not proficient at all to Scale 6 for very proficient
Satisfaction in FFBS usage	Scale 1 for completely unsatisfied to Scale 6 for completely satisfied
Willingness in keep using FFBS	Scale 1 for completely unwilling to Scale 6 for completely willing
Willingness in recommending to others	Scale 1 for completely unwilling to Scale 6 for completely willing

Part III: Purpose in using FFBS

Attribute	Attribute level
The main purpose for FFBS trips:	For commuting For shopping For entertainment
I want to do more exercise	Scale 1 for completely disagree to Scale 6 for completely agree
FFBS trips are low carbon	Scale 1 for completely disagree to Scale 6 for completely agree
FFBS is easy to find and use	Scale 1 for completely disagree to Scale 6 for completely agree
FFBS trips are controllable	Scale 1 for completely disagree to Scale 6 for completely agree
FFBS trips are cheap in cost	Scale 1 for completely disagree to Scale 6 for completely agree
I simply enjoy cycling	Scale 1 for completely disagree to Scale 6 for completely agree

Part IV: The other attributes

Attribute	Attribute level
Type of behaviour when currently no bicycle available	Wait in suit for new available bicycles to pop-up Keep checking for newly pop-up available bicycle while walking to destination Quickly abandon using FFBS
Time period of FFBS usage	Peak hour Off-peak hour
Frequency in making reservation	Scale 1 for never make reservation to Scale 6 for always make reservation
Frequency in using APP for trip planning	Scale 1 for never use FFBS for transfer to Scale 6 for always use FFBS for transfer
Frequency in using FFBS for transfer	Scale 1 for never use FFBS for transfer to Scale 6 for always use FFBS for transfer
Smartphone daily usage time	< 1 hour 1 ~ 5 hours 5 ~ 9 hours > 9 hours
FFBS membership ownership	Yes No
How epidemic influence the frequency of FFBS usage	Increased after epidemic Remain unchanged Decreased after epidemic

In Table 6.1, questions are organized in the following four parts: exercise in the last three months, attitudes towards FFBS usage, purposes in using FFBS, and the other aspects. For example, nested questions are presented in identifying the type of behaviour when currently no bicycle is available. In the previous simulation research, we assume a categorization of active, static, and casual users based on their different behaviour. In this survey, we require respondents to revel themselves the type they belong to. Further questions are also asked, such as the transfer frequency, the usage of smartphones in trip planning and the influence of epidemic in FFBS usage. We hope these questions can give us a more comprehensive understanding in the FFBS usage.

Table 6.2 The attribute level for sociodemographic

Attribute	Attribute level	Attribute	Attribute level
Age	12 ~ 19	Occupation	Student
	20 ~ 34		White-collar employee
	35 ~ 49		Blue-collar worker
	50 ~ 64		Freelancer
	65 ~ 74		Professional
	> 75 ~		Public servant
Gender	Male		Company manager
	Female		Service worker
Monthly income	0-500		Contractor
	500-1500		No occupation
	1501-3000		
	3001-5000	Education level	Middle school
	5001-8000		High school
	8001-10000		College
	1001-20000		Undergraduate
	20000 and above		Graduate and above

6.3. SP part: The designs of map-reading questions

The third part, or the map-reading part, is the core of this research. The aim is to understand the attributes influencing traveller's willingness in bicycle seeking process. We provide travellers with screenshots of what they usually see after launching the APP. On such screenshots, a map of the street layout is provided, together with the traveller's current location, the location of feasible bicycles, and the discount information. By carefully control the location of bicycles and the show/hide of other information, such screenshots can help us both in excluding bot/impatient respondents and in acquiring more choices made by following instinct.

We firstly assume the following seven preferences are essential when travellers are deciding whether and which bicycle to use. Preference one and two are scenario-specific while preference three to seven are bicycle-specific.

1. Distance to the destination: longer distance may lead to higher tolerance in making a detour. Such distance will be given as a short scenario description in the beginning of each question.

Figure 6.1 The instructions for the map-reading figures given to respondents (translation from Chinese

2. Reservation time: travellers may have higher preference in bicycle usage when longer reservation is allowed. In this research, travellers can make 0 minute, 5 minutes, or 10 minutes reservation. Such information will be given in the short scenario description together with distance to destination. This reservation time remains the same for all bicycle alternatives in this scenario.
3. Direction: bicycles locate along the same direction toward destination are assumed to be favourable. Travellers may prefer bicycles with less detour when heading towards destination. The 'angle' is calculated as the angle of origin-bicycle vector minus origin-destination vector. Such angle ranges from $180°$ to $-180°$.
4. Distance to the bicycle: bicycles located closer to the traveller are assumed to be favourable. The distance will be calculated as the total sum of the blue arrows in Fig 6.1. It is calculated based on the actual path instead of crow-flay distance.
5. Number of intersections: bicycles are more favourable if no or less intersections are crossed on the way to pick up.
6. Risk: picking up bicycles without making reservation can be risky and may leads to potential failure, especially when the desired bicycle locates in popular area. Therefore, bicycles with lower risk are assumed to be favourable. In the presented screenshots, bicycles locate in 'popular spots' are marked as red flame in the legend. Scenario descriptions will also suggest that bicycles locate in the popular spot can be taken away in five minutes.
7. Cost: service providers frequently use discount as one way to intervein traveller's choice behaviour. Bicycles with higher discount or less cost are assumed to be more favourable. In the previous simulation research, we find reservation can worsen the overall performance of the system. Therefore, we add a 'cost-reservation balance' in which discount is valid only if a traveller chooses not to use reservation. In this study, the regular cost is two Chinese yuan (¥ 2), which is equivalent to about US$0.3 and a common price for FFBS in China, while no discount, 50% discount (−¥1) and 100% discount (-¥2) are potentially provided.

In this research, before presenting the map-reading questions to the respondent, a short demo is firstly presented as shown in Figure 6.1. Respondents are oriented in order to understand the map and legend, and the attributes need to consider

The map figures are specifically designed 'screenshots' mimicking what travellers will see when they launch the FFBS APP and preparing to find a desired bicycle. All the 'screenshots' have the identical street map, traveller's origin and heading direction. Regarding "heading direction", since the destination is presumed to be outside the very local map, it is presented with an arrow see top, middle figure in Fig. 6.1 as well as Fig. 6.2. A legend is also provided for each figure. A short message describing the distance to the destination and the reservation time allowed in this scenario is presented together with each map figure. In the series of figures provided to the respondents, six bicycle locations are randomly generated with different locations and discounts attributes.

Similarly, several precautions are taken in order to minimize the patience demanded and at the same time to maintain high explanatory power. In each scenario, a set of six bicycles are generated in such fashion:

1. The lanes for motorized vehicles are surrounded by pavements. Bicycles only locate along the streets,
2. Six bicycles are randomly generated with location only.
3. The locations of bicycles are tested to see if each bicycle fulfils only one of the comparative criteria. If not, then their locations will be regenerated.
4. If the locations fulfil the above-mentioned requirement, The discount and the risk markers are randomly assigned to each bicycle. The map figure and corresponding detailed information will be added into the question pool.

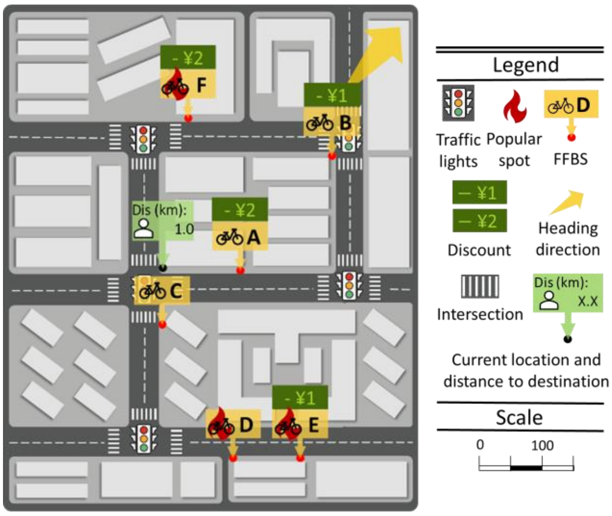


Figure 6.2 The example of anti-bot questions and the example of demo

Each respondent is presented with 10 scenarios, with two anti-bot scenarios and eight data-gathering scenarios. Respondents are required to decide if they would like to use a bicycle or not and if they choose one, and if the reservation is allowed in this scenario, if they would like to reserve it or not. Travellers can choose not to use any free-floating bicycle, choose and reserve a specific bicycle, or choose a specific bicycle but make no reservation. Therefore together 13 alternatives are available in each scenario. To better organize these choices, respondents are firstly asked to choose whether and which bicycle to choose, and then whether to reserve that bicycle.

Efforts are made to maximise the explanatory power from a limited number of scenarios that can be posed to respondents considering survey fatigue. In particular, we aim to prevent scenarios where one dominant alternative makes the remaining five bicycles trivial to the result. Therefore, we assume one bicycle will become competitive if any of the following criteria were met:

1. The bicycle is among the closest two alternatives among all six bicycles
2. The angle of such bicycle ranges within $60°$ to $-60°$, which suggests it locates in the direction towards the destination
3. No intersection is crossed during picking up such bicycle.

These criteria are used both in developing antibot question, and in excavating more explanatory power in data-gathering scenarios.

The antibot questions are designed following such logic. On one hand, if there is one bicycle that can meet all above three criteria at the same time while the other bicycles cannot, we have strong confidence that most of the conscience respondents will choose the dominant alternative, such as Bicycle A in Fig. 6.2. On the other hand, when there is one bicycle that cannot meet any of the criteria mentioned above while the other bicycles can, we have strong confidence that this inferior alternative is not favourable thus the conscience respondents are less likely to choose it. Examples are Bicycles D and E in Fig. 6.2. Therefore, with very little changes made on the location of bicycles, the data-gathering questions and anti-bot questions can be swiftly recomposed into each other. Distinguishing can be very difficult for respondents. The data-gathering and anti-bot questions together indistinguishably composed into a series of repeated questions. Such indistinguishability can not only help us in excluding the bots, but also able to help us removing questionnaires answered by impatient respondents (impatient respondents will not carefully compare different alternative therefore creating bias in follow-up analysis).

Each respondent randomly was assigned two anti-bot questions from the anti-bot question pool. In each question, a total of six bicycles are presented with one dominant and three inferior alternatives. Respondents unable to pick the dominant twice (Event A), or unable to avoid inferior alternative (Event B) are considered suspicious and are removed from the valid pool. A total of 10 figures are prepared in the anti-bot question pool. Table 6.3 is used to present the effectiveness of such criteria. We assume the row and column each stands for the alternatives of the first and second anti-bot question, and each alternative has an equal chance of been chosen. D_i, C_i and I_i stands for the dominant, the inferior and the conventional alternatives in the i-th antibot question. Table 6.3 shows all possible combinations of choices for respondents; therefore, each block has an equal chance of 1/36 to be chosen. Event A and B are the two reasons make respondent suspicions. We fill event A or B (or both) into the corresponding block to mark a suspicious combination. As one can read from the table, probabilistically speaking, $31/36$ (86.1%) of all randomly made choices can be identified by these two questions only. These respondents will be disqualified for receiving the incentives and their questionnaires rejected for entering the data set.

Table 6.3 The full combination of the first and second antibot questions

	D_1	C_1	C_1	I_1	I_1	I_1
C_2		A	A	A, B	A, B	A, B
D_2				B	B	B
I_2	B	A, B	A, B	A, B	A, B	A, B
I_2	B	A, B	A, B	A, B	A, B	A, B
I_2	B	A, B	A, B	A, B	A, B	A, B
C_2		A	A	A, B	A, B	A, B

For the remaining eight data-gathering scenarios, on the contrary to the anti-bot questions, all six alternative bicycles must fulfil only one of the three above-mentioned comparative criteria. In another word, no obviously better or worse choice is presented.

6.4. Sampling and sample profile

The online survey is carried out on a Chinese online survey platform called Tencent Questionnaire Platform. Questionnaires can be designed, edited, published, gathered, and analysed on such platform. The reason we choose such platform are: 1) this is a platform targeting at Chinese respondents, this platform is designed to cater the favour of Chinese users. 2) the dispatching of incentives can fully rely on the platform. Login of a social media account can be designed as mandatory, and the incentives can be sent to the login accounts of respondents, all through the questionnaire platform. This mandatory login can also help in reducing the potential access of bots. 3) their smart analysis system can help in identifying the questionnaire answered with the same IP address and questionnaires completed too fast. These respondents will be automatically disqualified in receiving the incentives and removed from the data set. The survey platform also protects the rights of respondents by setting a maximum rate of 40% in manual disqualifying one respondent and rejecting the issuing of one's incentive. However, we find such function is not 100% accurate in our following investigation. This online survey platform also shares the same problems of most online survey, the sample profile bias in gender and age remains strong as we will present later in this section.

In the small-scale testing we find such questionnaire can be completed within 10 to 15 minutes by most of the respondents, therefore an incentive of 7.5 CNY is guaranteed for all qualified respondents (equivalent to 30 to 45 CNY per hour). This amount is deemed appropriate as sufficient to motivate persons to complete the survey. A higher incentive would have increased the likelihood of the same individual repeatedly answering the survey with different accounts.

Table 6.4 The basic sample profile for this survey

Attribute	Attribute level	Percentage	Attribute	Attribute level	Percentage
Age	12 ~ 19	7.7%	Occupation	Student	20.5%
	20 ~ 34	72.3%		White-collar employee	25.2%
	35 ~ 49	18.7%		Blue-collar worker	11.1%
	50 ~ 64	1.2%		Freelancer	10.1%
	65 ~ 74	0.0%		Professional	7.3%
	> 75 ~	0.0%		Public servant	3.7%
Gender	Male	64.9%		Company manager	4.8%
	Female	35.1%		Service worker	6.3%
Monthly income	0-500	3.2%		Contractor	6.5%
	500-1500	10.7%		No occupation	4.5%
	1501-3000	15.6%			
	3001-5000	19.1%	Education level	Middle school	2.7%
	5001-8000	28.2%		High school	13.3%
	8001-10000	12.8%		College	24.9%
	1001-20000	7.9%		Undergraduate	53.2%
	20000 and above	2.6%		Graduate and above	5.9%

The link of such online questionnaire was accessed 3857 times and 52.74% of them complete the questionnaires (2034 questionnaire completed) with an average completion time of 542 seconds (9 min. 2 sec.). However, only 1189 were considered as valid (58.5% of 2034hh completed questionnaires). Among all 2034 respondents, 553 failed to pass the anti-bot test (27.3%). Another 292 respondents are excluded because of different reasons (14.4%). These reasons can be: too fast in completing the questionnaire, making identical choices no matter which question they pick, inconsistency in age, education level, and occupation, identical start-end timestamp among different users, etc.

The basic sample profiles of 1189 questionnaires are provided in Table 6.4. As a consequence of the distribution method only a very small percent of respondents ages 50 or more, and no respondent ages 65 or more. We expect a face-to-face survey can better address such problem. Similarly, the gender distribution and occupation distribution can be better addressed if an off-line survey is conducted.

The statistic of the questions regarding daily physical activity and in particular FFBS usage are presented in Table 6.5. Results in this part will be further used in the future latent class analysis. The answers generally show good distribution among the alternatives. Some interesting observations can be made. Firstly, respondents show generally positive attitude in different aspects towards FFBS usage. Median in most of the questions ranks 5 or even higher in a six-level scale question. Secondly, we find 66.4% of respondents use FFBS most frequently for commuting, while 17.9% for shopping and 15.6% for entertainment. As for the purpose of using FFBS, respondents generally hold a positive attitude towards the advantages of FFBS. Thirdly, the travel behaviour when there is no available bicycle is also investigated. In our survey, we find 69.5% of respondents will keep checking for newly available bicycles while walking towards destination.

Table 6.5 The attribute level for attitudes towards cycling and FFBS

Part I: Exercise (in last three month)		Sample size: 1189
Attribute	Attribute level	Percentages
Exercise frequency	More than three times per week	31.5%
	One to three times per week	32.6%
	Once per week	15%
	Once every two weeks	6.3%
	Never	14.6%
Daily steps	< 1000	5.2%
	1,000 – 3,000	11.4%
	3,000 – 6,000	27.6%
	6,000 – 10,000	38.1%
	10,000 – 15,000	13.3%
	15,000 – 20,000	2.8%
	> 20000	1.6%
Cycling frequency	Almost everyday	12.3%
	Five to six times per week	12.8%
	Three to four times per week	25.7%
	One to two times per week	26.1%
	Less than once per week	23.2%
FFBS usage frequency	Almost everyday	10.3%
	Five to six times per week	12.6%
	Three to four times per week	22.6%
	One to two times per week	29.7%
	Less than once per week	14.3%
	Less than once per month	10.4%

Part II: Attitudes towards FFBS usage		Sample size: 1189
Attribute	Attribute level	Results
Proficiency in FFBS usage	Scale 1 for not proficient at all to Scale 6 for very proficient	AVG: 5.14 Median: 5 Std. Dev.: 1.06
Proficiency in FFBS APP usage	Scale 1 for not proficient at all to Scale 6 for very proficient	AVG: 5.47 Median: 6 Std. Dev.: 0.78
Satisfaction in FFBS usage	Scale 1 for completely unsatisfied to Scale 6 for completely satisfied	AVG: 4.79 Median: 5 Std. Dev.: 1.10
Willingness in keep using FFBS	Scale 1 for completely unwilling to Scale 6 for completely willing	AVG: 5.05 Median: 5 Std. Dev.: 1.09
Willingness in recommending to others	Scale 1 for completely unwilling to Scale 6 for completely willing	AVG: 4.86 Median: 5 Std. Dev.: 1.21

Part III: Purpose in using FFBS		Sample size: 1189
Attribute	**Attribute level**	**Percentages/Results**
The most frequent purpose for FFBS trips:	For commuting For shopping For entertainment	66.4% 17.9% 15.6%
I want to do more exercise	Scale 1 for completely disagree to Scale 6 for completely agree	AVG: 4.42 Median: 5 Std. Dev.: 1.50
FFBS trips are low carbon	Scale 1 for completely disagree to Scale 6 for completely agree	AVG: 4.65 Median: 5 Std. Dev.: 1.46
FFBS is easy to find and use	Scale 1 for completely disagree to Scale 6 for completely agree	AVG: 4.83 Median: 5 Std. Dev.: 1.23
FFBS trips are controllable	Scale 1 for completely disagree to Scale 6 for completely agree	AVG: 4.76 Median: 5 Std. Dev.: 1.28
FFBS trips are cheap in cost	Scale 1 for completely disagree to Scale 6 for completely agree	AVG: 4.82 Median: 5 Std. Dev.: 1.29
I simply enjoy cycling	Scale 1 for completely disagree to Scale 6 for completely agree	AVG: 4.67 Median: 5 Std. Dev.: 1.39

Part IV: The other attributes		Sample size: 1189
Attribute	Attribute level	Percentages/Results
Type of behaviour when currently no bicycle available	Wait in suit for new available bicycles to pop-up Keep checking for newly pop-up available bicycle while walking to destination Quickly abandon using FFBS	14.7% 69.5% 15.8%
Time period of FFBS usage	Peak hour Off-peak hour	55.3% 44.7%
Frequency in making reservation	Scale 1 for never make reservation to Scale 6 for always make reservation	AVG: 3.21 Median: 3 Std. Dev.: 2.03
Frequency in using APP for trip planning	Scale 1 for never use FFBS for transfer to Scale 6 for always use FFBS for transfer	AVG: 5.20 Median: 6 Std. Dev.: 1.04
Frequency in using FFBS for transfer	Scale 1 for never use FFBS for transfer to Scale 6 for always use FFBS for transfer	AVG: 4.11 Median: 4 Std. Dev.: 1.56
Smartphone daily usage time	< 1 hour 1 ~ 5 hours 5 ~ 9 hours > 9 hours	1.7% 45.6% 40.9% 11.8%
FFBS membership ownership currently	Yes No	50.7% 49.3%
How epidemic influence the frequency of FFBS usage	Increased after epidemic Remain unchanged Decreased after epidemic	29.4% 47.2% 23.4%

We further gathered their frequency of checking. Only 22.7% of respondents report they will only check their smartphone when necessary or when waiting for traffic light, while 24.4% of respondents report they will stay on the same page of the APP and check anytime. Most of the respondents (37.3%) will check every few minutes while least of the respondents (15.6%) will check few times per minutes.

Aspects related to simulation are also investigated. For example, respondents very frequently use APP for trip planning and for finding available free-floating bicycle, which suggests our APP-mimicking simulation in Chapter 5 finds a reasonable starting point for building simulation scenarios. It also suggests the collaboration between FFBS and other navigation service providers should be reasonable. The respondents also report that they make reservation from time to time when using FFBS. This functionality is also captured and reappeared in our simulation. However, considering that many service providers have been or are planning to abandon the ability to reserve a bicycle, such result faces strong bias. More surveys should be done before any conclusion can be draw. The influence of the COVID epidemic is also asked. More respondents report to have increased frequency (29.4%) than decreased frequency (23.4%), while most of the respondents remain unchanged (47.2%). This result appears to confirm some of the findings from other literature that report increased usage of active modes during the COVID pandemic due to fear of using public transport.

6.5. Multinomial Choice model

Each respondent is presented with two anti-bot questions and eight data-gathering scenarios. Therefore, a panel data composed of 9512 observations (1189 × 8) is gathered and analysed. The multinomial logit (MNL) model with panel characteristics is firstly adopted to study the influences of different attributes. For better understanding, the distance to destination, distance to bicycle and angle are translated into walk distance (distance from origin to bicycle), cycle distance (distance from bicycle to destination) and angle.

Let 'j' indexes the alternative, 'i' indexes the individual and 't' index the particular choice occasion in a set of T_i ($T_i > 1$). The indirect utility of alternative j, U_{ijt}, consists of a random component ε_{ijt} and deterministic components.

$$U_{ijt} = \alpha_j + X_{ijt}\beta + \varepsilon_{ijt} \tag{6.1}$$

The deterministic component consists of a systematic part $X_{ijt}\beta$ (where X_{ijt} is a vector of characteristics confronting the individual i on alternative j during choice occasion t, and β is a vector of unknown parameters), and a fixed term α_j representing the choice-specific constant terms for alternative j. After assuming the error term ε_{ijt} is independently and identically distributed according to a type I extreme-value distribution, then the probability that individual i chooses alternative j is given by:

$$P_{ijt} = \frac{\exp\,(\alpha_j + X_{ijt}\beta)}{\sum_{k=1}^{J} \exp\,(\alpha_k + X_{ikt}\beta)} \tag{6.2}$$

However, unobserved individual heterogeneity is inevitable in this dataset. Moreover, the multinomial logit is based on a crucial assumption that observations for the same individual are independent. To account for correlated errors resulting from multiple observations for the same individual, it is necessary to allow some parameters to vary randomly across choices. This idea led to the multinomial logit model with random effects where choice probabilities for repeated observations on the same individual share the same unobserved random effects (Gonul & Srinivasan, 1993; Train, 2009). The random effects multinomial logit model is stated as：

$$U_{i,j,t} = (\alpha_j + u_{i,j}) + X_{i,j,t}\beta + \varepsilon_{i,j,t} \tag{6.3}$$

where, $u_{i,j}$ is the unobserved individual heterogeneity term representing the relevant regressor. This individual heterogeneity terms are omitted either because they cannot be measured, or because their existence is unknown. Therefore, the probability of an individual i choosing alternative j is:

$$P_{i,j,t}|u_i = \frac{\exp\left((\alpha_j+u_{i,j})+X_{i,j,t}\beta\right)}{\sum_{k=1}^{J}\exp\left((\alpha_k+u_{i,k})+X_{i,k,t}\beta\right)},\ j \in J \tag{6.4}$$

The Apollo choice modelling (version 0.2.7) is adopted for the estimation of our model (Hess, S. & Palma, D., 2019). We start with a simple multinominal logit (MNL) model without sociodemographic attributes. The result of MNL is reported in Table .

Table 6.6 Estimation results for MNL model without sociodemographic ($N = 9512$)

Independent Variables	Unit	Unstandardized Coef. (10^{-3})	Partially Standardized Coef. (10^{-3})	Std. Error (10^{-3})	t value
Walk distance	Meter	-1.38	-0.0032	0.043	-32.2*
Cycle distance	Meter	-0.55	-0.00095	0.032	-17.4*
No. intersection	Integer	-562.98	-1199.34	39.62	-14.2*
Reservation time	Minute	47.84	10.62	4.13	11.6*
Cost	CNY	-248.86	-214.19	16.01	-15.5*
Risk	Binary	-323.66	-486.83	27.97	-11.6*
Angle	Degree	0.62	0.015	0.44	1.41+
$\delta_{Not\ use}$	/	-847.72	-3646.14	80.00	-10.6*
Significant. codes: ‘*’: < 0.001; ‘+’: > 0.1				Adjusted R^2: 0.0766	

The partially standardized coefficients presented in this table is calculated by following the approach of SAS Institute (1995), which is still presented as the "Standardized Estimate" in SAS. The differences in standards for standardized logistic regression coefficients can be find in Menard (2011).

The estimation results are presented in Table . All attributes are significant except for angle. The reservation time is significant with positive estimation while other remain negative, which fits with common sense. These results suggest that when travellers are deciding which bicycle to pick up, they prefer to choose bicycles with shorter distance and less intersections to cross, and also prefer bicycles with lower cost and risk. Longer reservation time will lead to higher preference in using bicycles, while longer distance to destination have the opposite influence. The estimation of walking distance has larger absolute value than cycling distance, which suggests the walking distance is more influential when the distance is considered. We further find that as distance to destination becomes larger, the travellers become less sensitive to other attributes: angle, number of interactions, and cost.

As we can read from the unstandardized coefficient, each one-kilometre increase in the cycle distance is associated to -0.55 decrease in the log odds of specific bicycle being chosen, while each one-kilometre increase in walk distance provides about 2.5 times of the decrease comparing to cycle distance. We suggest this may related to the differences of physical fatigue in walking and in cycling. Travellers generally prefer to save a shorter walk distance even if it leads to a comparatively longer cycling distance, in order to avoid the stronger physical fatigue of walking. Another interesting observation can be made on the relation between reservation time and cost. Each one-minute increase of reservation time is associated with an increase of 0.0478 in the log odds of specific bicycle being chosen, while each one CNY discount of cost is associated with an increase of 0.249 in the log odds. Each one CNY discount is equivalent to about 5.2 minutes in reservation, whose 'value of reservation time' is equivalent to around 11.5 CNY per hour.

The dichotomous predictor, the risk of desired bicycle being taken by other travellers, can be studied by observing the (partially) standardized coefficients. We can find that the risk has the second largest absolute value among all predictor in standardized coefficients. This result suggests that the number of intersections (-1.199) has the strongest relationship with bicycle been chosen, followed by the risk (-0.487), then the cost (-0.214).

However, the angle does not appear to be significant. Even if we remove walk and cycle distance considering their potential correlations with angle, we do not obtain the expected result. To address this, we further tested if travellers prefer bicycles located in the section with smaller angle, as the red-shaded area shown in Figure 6.3. θ^+ and θ^- are proposed to mark the boundary of the preferred/un-preferred zone, their values stand for the angles between such boundary and the origin-destination line segment. We find that when $\theta^+ = 90°$ and $\theta^- = -30°$ or $-45°$, travellers will prefer bicycles locate in these red-shaded area with significance level < 0.001.

Table 6.5 Estimation results for angles in MNL ($N = 9512$)

Independent Angle Variables	Unstandardized Coef.	Partially Standardized Coef.	Std. Error	t value
$\theta^+ < \text{Angle} \leq 180°$	-0.061	-0.22	0.068	-0.9$^+$
$0 < \text{Angle} \leq \theta^+$	0.16	0.25	0.030	5.4*
$\theta^- < \text{Angle} \leq 0$	0.56	2.20	0.073	7.8*
$-180° < \text{Angle} \leq \theta^-$	0.093	0.56	0.112	-0.8$^+$
Significant. codes: '*': < 0.001; '$^+$': > 0.1			Adjusted R^2: 0.0797	

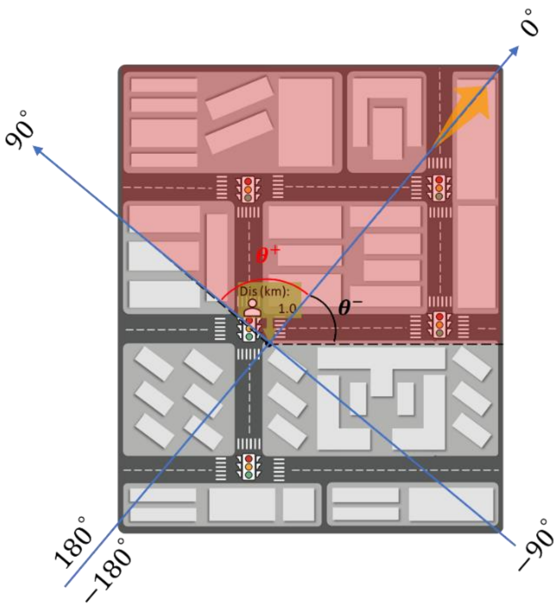


Figure 6.3 Illustration of sectors with smaller angle (red area)

If we take the traveller's current location as the origin point of a Cartesian coordinate system, and assume the axis are horizontally/vertically located, then we can find that the red-shaded areas cover almost all above-horizon space. We think it suggests that although the destination is pointed towards right-upper corner, travellers still prefer bicycles in the above-horizon space. A solid explanation should be deducted with more experiments with different heading directions. Here we only provide a potential explanation: travellers are more sensitive to the spatial upper-down relation rather than left-right relation: bicycles and heading direction remain in the same upper section become more important than belonging to the same right sector. Travellers may ignore the precise heading direction but choose with a vague idea in mind.

6.6. Nested logit model

In this section we further extend the MNL into a three-level nested logit (NL) model.

In the map-reading section, after respondents being presented with a screenshot and a short description, they are firstly asked if they willing to use bicycle. If travellers are allowed to make reservation and prefer to use any of the six available bicycles, they are then asked whether they prefer to make a reservation or not. Following the same logic, the structure of a three-level nested logit model can be organized, as shown in Figure 6.4.

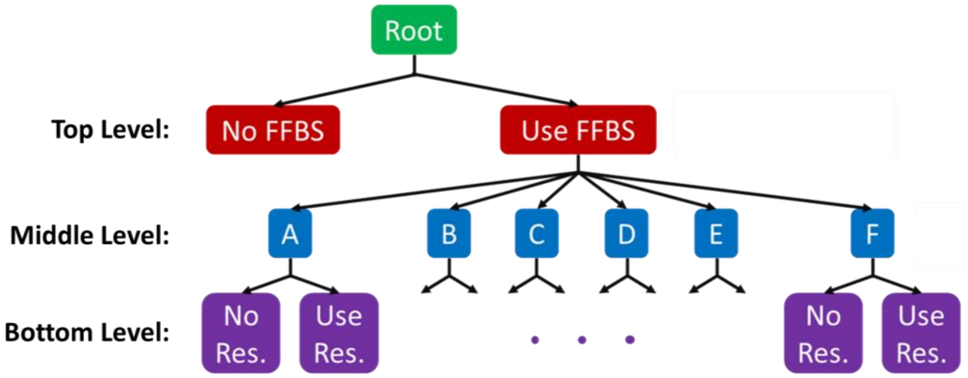


Figure 6.4 The structure of the three-level nested logit model

In the top level of this NL model, respondents are assumed to choose whether use or not to use free-floating bicycle. In the middle level, respondents choose among six available bicycles. Considering the index of bicycles holds no specific meaning (and they are randomly generated without systematic bias), the nesting parameters for the second level are assumed identical for alternative A to F. In the bottom level, respondents can choose whether they will make reservation or not.

In this research, we follow the formalization of Apollo choice modelling (Hess and Palma, 2019), which is the more commonly used version that divides the utilities by the nesting parameter in the within nest probabilities (see the discussions in Train 2009, chapter 4, and Koppelman and Wen, 1998). For normalisation, we set the nesting parameter of root equals to one. Lets assume a nesting structure with three levels and the alternative p falls into the nest O_q on the lowest level of nesting, which itself is a member of nest m on upper level of nesting, with m being in the root nest. The notations λ_m (also known as λ_{top}) and λ_{O_q} (a.k.a. $\lambda_{\text{mid.}}$) are adopted as the nesting parameter for the first two levels. Therefore, the probability of person i choosing alternative j in choice situation t is then given by:

$$P_{i,j,t} = P_{m,j,t} \times P_{(O_q|m),j,t} \times P_{(p|O_q),j,t} \tag{6.5}$$

where

$$P_{(p|O_q),j,t} = \frac{\exp\left(\frac{(\alpha_j + u_{i,j}) + X_{i,j,t}\beta}{\lambda_{O_q}}\right)}{\sum_{k \in O_q} \exp\left(\frac{(\alpha_j + u_{k,j}) + X_{k,j,t}\beta}{\lambda_{O_q}}\right)} \tag{6.6}$$

$$P_{(O_q|m),j,t} = \frac{\exp\left(\frac{\lambda_{O_q}}{\lambda_m} I_{O_{m,j,t}}\right)}{\sum_{l_m=1}^{M_m} \exp\left(\frac{\lambda_{l_m}}{\lambda_m} I_{l_{m,j,t}}\right)} \tag{6.7}$$

$$P_{m,j,t} = \frac{\exp(\lambda_m I_{m,j,t})}{\sum_{l=1}^{M} \exp(\lambda_l I_{l,j,t})} \tag{6.8}$$

with

$$I_{m,j,t} = \log \sum_{l_m=1}^{M_m} \exp \left(\frac{\lambda_{l_m}}{\lambda_m} I_{l_m,j,t}\right) \tag{6.9}$$

$$I_{O_m,j,t} == \log \sum_{k \in O_q} \exp \left(\frac{(\alpha_j + u_{k,j}) + X_{k,j,t}\beta}{\lambda_{O_q}}\right) \tag{6.10}$$

We would then expect that 0 < $\lambda_{\text{mid.}}$ (a.k.a. λ_{O_q}) ≤ λ_{top} (a.k.a. λ_m) ≤ 1. In this NL model, considering the alternatives in middle level are the index of bicycles which should not bear any preference, we further assume λ_{O_q} remain identical for all alternative O_q. The estimation results of such NL model are presented in Table .

Table 6.8 Estimation results for three-level NL model ($N = 9512$)

Independent Variables	Unit	Unstandardized Coef.	Partially Standardized Coef.	Std. Error	t value
λ_{top}: λ_m	/	0.245	/	0.0264	9.457*
$\lambda_{\text{mid.}}$: λ_{O_q}	/	0.462	/	0.0660	6.998*
Walk distance	Meter	-4.690E-4	-1.209E-06	4.793E-05	-9.786*
Cycle distance	Meter	-7.773E-5	-5.588E-08	1.337E-05	-5.814*
No. intersection	Integer	-0.117	-0.0874	0.0139	-8.386*
Reservation time	Minute	0.0203	0.00327	0.00300	6.795*
Cost	CNY	-0.0696	-0.0317	0.00846	-8.226*
Risk	Binary	-0.0870	-0.0561	0.0120	-7.237*
$\delta_{Not\ use}$	/	-1.792	-9.154	0.0950	-18.864*
Significant. codes: '*': < 0.001					Adjusted R^2: 0.0766

As we can see from the unstandardized coefficients in Table 6.8, we find that all estimates are negative except for the reservation time. Comparing to those in Table 6.6, most of the estimates of NL has shrink, while some ratios remain worth discussing. The ratio between walk distance and cycle distance increase from 2.5 times in MNL into 6.0 times in NL model, which suggests the influence of physical fatigue is further emphasized in NL mode. The ratio between cost and reservation time, on the contrary, has decreased from 5.2 times into 3.4 times in NL model. This can also be interpreted as an increase of 'value of reservation time' from 11.5 to 17.5 CNY per hour.

Observations on the partially standardized coefficients are also made. We find that although the absolute values shrink and the ratios between unstandardized coefficients may change, the ordering of the predictor's absolute value in partially standardized coefficients remains the same to that in MNL. Consistent ordering has been observed in the importance of the predictors to the probability of specific bicycle is observed.

The value of nesting parameters is estimated as $\lambda_{\text{top}} = 0.245$ and $\lambda_{\text{mid.}} = 0.462$. Both nesting parameters are estimated with significance level < 0.001. In some research, the dissimilarity parameter λ is also formulated with $\lambda = \lambda_{\text{mid.}}/\lambda_{\text{top}}$ and $0 < \lambda \leq 1$. In this research, although $\lambda = 1.886$ falls beyond the unit zone, we suggest it is not an error that needs to be reconsidered, but instead a meaningful and noteworthy result:

Firstly, to defend this finding, we note that the dissimilarity parameter λ can also be consistent with utility maximization theory. Börsch-Supan (1990) demonstrated local sufficiency conditions that permit values of $\lambda > 1$. The Daly-Zachary-McFadden condition of the validity of stochastic utility maximization in nested logit models is shown that can be unnecessarily strong therefore may too often reject NL models because of their large dissimilarity parameters. Kling and Herriges (1995) and Herriges and Kling (1996) provide tests of consistency of nested logit with utility maximization when $\lambda > 1$; Train et al. (1987) and Lee (1999) provide examples of how the self-selecting tariffs with basic and OCP (Optional Calling Plan) service options affect households' calling patterns and usage of interstate toll service. Their examples show thar $\lambda > 1$ can be observed in real-world scenarios.

Secondly, and more importantly, we can interpret the findings. The dissimilarity parameter measures relative substitutability within and among subsets. Conventionally λ should smaller than 1 which indicates that travellers would prefer to substitute within the bottom level, rather than make changes in the middle level. A value of $\lambda > 1$ suggests there is a greater substitution across the middle level (in this case, alternatives A ~ F) than between bottom level (Use / Not use reservation). In other words, $\lambda > 1$ suggests that if reservation is not allowed for a specific chosen bicycle, travellers are more willing to changes their choice made on the alternatives 'A ~ F' rather than make any changes on the decision of 'Use / No use reservation'. Such result confirms the importance of the reservation feature.

6.7. Choice Model with Sociodemographic

The conventional MNL or NL model can be extended in order to analysis the sociodemographic of respondents. The equation 6.1 can be extended as:

$$U_{ijt} = \alpha_j + X_{ijt}\beta + Z_i\gamma + \varepsilon_{ijt} \tag{6.11}$$

where Z_{ijt} stands for the sociodemographic of respondent while γ is the coefficients of sociodemographic. The data gathered in the second part of this survey can also be better utilized. For example, a latent class analysis can be conducted to conclude the potential classes in the respondents. This result will further serve as another input of the sociodemographic.

This part is now being explored further in collaboration with Prof. Zhang Dong and his students from Dalian Technology University.

CHAPTER 7. CONCLUSIONS AND FURTUER WORK

7.1. Summary of Research and specific findings

For better understanding of the free-floating mode, this thesis starts with an introduction to the development of FFBS in Chapter 1. FFBS impact on user behaviour and urban management is also introduced, with more focus on its challenges to the academic. This is the motivation and objectives of this thesis.

The overall objective of this thesis, i.e., explaining the behavioural impacts of uncertain access to free floating bicycle services (FFBS), have been broken down into three parts: a) to develop a multi-modal assignment approach with free-floating service; b) to develop user categorization standards and to simulate users with various behaviour during FFBS usage; c) to complement this with a SP-RP survey which then can bring the simulation approach closer to practical implementation.

To accomplish the first objective, this thesis first reviewed the weak points of current literature in Chapter 2.2 which led to the proposed assignment approach with free-floating in Chapter 3. The existing literature lacks the ability to model the details in access costs to free-floating services, especially for large fleet sizes and in the case of asymmetric patterns, where one might not want to rely on simulation. The replication of competition over deplete available fleet is also yet to be proposed.

In Chapter 3, a novel approach assignment approach is presented with the main idea of abstracting the distance between random origin and bicycle locations into single nodes with links connections. The random-random (RR) and central-random (CR) distance are formulated to reflect the increasing costs with more demand and fewer bicycles. In particular, the costs are increasing in case of a strictly depleting resource. We show that the CR distance can be obtained analytically but that the RR distance needs to be adjusted from the one obtained with order statistics. This is because, assuming that bicycles are not redistributed during a time interval, the remaining bicycles tend to be at the corner of a zone since the nearest, first choice bicycles are more likely found in the centre of a zone. In Chapter 4 these bicycle access costs were embedded in a network assignment approach with walking, cycling, and alternative mode options. With this the travel patterns, expected costs, the expected numbers left somewhere in a zone as well as at a transit station, can be obtained. This dissertation also finds that asymmetric link cost functions arise in the assignment due to the network representation with competition for the same bicycles on different links. Due to this multiple-equilibria are likely which we demonstrate with an incremental assignment where travellers are loaded with different priorities. The second objective is completed partially in Chapter 4 and mainly in Chapter 5. The simple structure of an agent-based discrete-event simulation is proposed in Chapter 4 to generate simulation results while the more complex, mix-type, dynamic simulation and corresponding analysis is presented in Chapter 5. We construct an agent-based discrete-event simulation to investigate the influence of different information seeking and reservation strategies of travellers under uncertain availability, together with the density and distribution of travellers and vehicles. Travellers with different activeness in their smartphone usage in seeking available vehicles are distinguished. To the best of our knowledge, this is one of the first studies explicitly simulating different smartphone usage strategies and the impact on the performance of a transport system with shared vehicles. We show that this activeness can indeed influence the performance of the system. We further quantify how increasing the bicycle ratio leads to less competition in accessing free-floating bicycle service. Increasing the bicycle to traveller ratio also leads to shorter average travel time. We show that this is not only due to on average less access time but also because travellers are more likely to walk in the direction of their destination to find a bicycle if more are available. The reservation rate is found to have a negative influence on average travel time. The reliability of accessing desired bicycles is also investigated through the average fail count and very non-linear effects are found and explained. Different spatial and temporal distributions for bicycles and travellers are also investigated that represent different land-use types.

The third and the last objective is completed in Chapter 6. This survey is an initial contribution towards understanding what attributes of FFBS choice might appeal to users. Using a SP and RP methods to reveal preferences of Chinese FFBS users, provides a baseline in understanding and designing of FFBS packages or policies. In each map figure, six available bicycles are generated with seven or eight attributes packed into each alternative. Considering the limited number of respondents, the limitation in respondents' patient, and the anti-bot preparations demanded by the online survey, several designs in a map figure generation are developed. Efforts are made in order to make sure no obviously better alternative is presented to the respondent. Such logic is also adopted in designing anti-bot questions: among all map-reading questions. Respondents failed twice in finding out the dominant, or failed twice in avoiding the obviously worse alternative, are considered as "impatient respondent" or "bots". There questionnaires will also be removed from the valid pool in order to maintain the purity of data. A total of 1189 valid responses and 9512 observations revealed and verified many suggestions for a first time. For example, users become less sensitive when longer trips are made, female users prefer less risky choices although walk/cycle distance or cost can be higher. We also find that limited influence can be addressed on users with higher income.

In connecting to the simulation research, this survey provides a first study in the composition of different type of users: the percentage of active, static, and casual travellers is obtained. The effect of walking direction against the direction of bicycles is also evaluated, suggesting travellers have a preference of choosing bicycles along such direction. Furthermore, the risk of a bicycle not being available can now be quantified.

7.2. Contribution to Knowledge and Potential for Practical Implementations

This dissertation provides various contributions to the transportation field.

Firstly, this dissertation provides a full picture of the FFBS impacts on urban management, on user behaviour and on the academic. The kernel of the difference between SBBS and FFBS and how would it influence the user behaviour is also defined in this research. This discussion is an initial and important contribution of this research.

Secondly, the statistical deduction of CR and RR link cost function, and the assignment approach proposed is another important contribution. It is advantageous in reflecting the increasing costs with more demand and fewer bicycles. In particular, we model that the costs are increasing in case of a strictly depleting resource. This is in contrast to existing literature where (implicitly) during a given period a fixed number of available bicycles is assumed. We then embed these bicycle access costs in a network assignment approach with walking, cycling, and alternative mode options. The asymmetric link cost functions arise during assignment due to the network representation with competition for the same bicycles on different links. Due to this, multiple equilibria are likely and then demonstrate with an incremental assignment where travellers are loaded with different priorities. The comparison between a simulation approach and the proposed approach shows in general good correspondence.

Thirdly, this dissertation provides a standard of user categorization, and further constructs an agent-based discrete-event simulation We find that: 1. All travellers being active in seeking feasible bicycles does not necessarily lead to better system performance. 2. Enabling reservation can lead to longer average travel times, especially longer walking time. 3. When increasing the bicycle supply or reservation rate, the reliability of accessing desired bicycles will first increase then drop. Some of the results are presented for the first time. To the best of our knowledge, this is one of the first studies explicitly simulating different smartphone usage strategies and the impact on the performance of a transport system with shared vehicles.

Last but not least, this dissertation is complemented with a RP and SP survey. There are many innovative features in this study, in particular the design of the choice experiment which tends to be more practical and complex than what would typically develop for a conventional mode alternative study. However, complexity must be aligned with the validity of potential choice making hence an extensive amount of work has been undertaken to ensure maximum explanatory power with limited respondents and before their patient running out. One way is through an investment in the survey design tailored to ensure all alternatives are comparable and no obviously better choice is generated.

7.3. Limitation of Study and Future Research Directions

For the assignment research presented in Chapter 3 and 4, there are a range of research directions we aim to address in further work.

For one, non-uniform distributions of bicycles inside a zone can be explored with more than one hotspot. By replacing corresponding uniform distribution functions, the access link costs for non-uniform distributions of bicycles can then be obtained follow the same logic.

Secondly, zonal fleet size can be defined according to flows from other zones as well as the expected trip duration. Then cost functions can be adjusted accordingly to reflect that a) bicycles are available several times during a zone and that b) additional bicycles are becoming available from other zones.

Thirdly, we have not embedded the assignment into a multi-time interval extension. The approach predicts the number of bicycles distributed “somewhere” in the zone and at a hotspot, such as a transit station. Together with information on the OD matrix during different time periods this can be the basis for a quasi-dynamic assignment where the resulting bicycle distribution becomes the input for the next time interval. This could then also be used for the optimization of the initial allocation of bicycles at the start of the day as well as efficient redistribution patterns during the day.

Fourthly, this approach could also be applied to multimodal assignments with free-floating cars or scooters instead of (or in addition to) free-floating bicycles.

For the simulation research presented in Chapter 5, there are a range of research issues that we suggest can be addressed in future work.

For one, the manual redistribution, which becomes the main concern in daily operation, can be evaluated with the proposed discrete event simulation framework. New events reflecting the process of vehicles becoming unavailable, carried to certain location and re-available can be added. The redistribution strategy is then split into several events and a cost–benefit analysis can be made with respect to different redistribution strategies.

Another interesting extension is to expand the work to multi-zone simulations and validate adjustments for analytically obtained access costs. Furthermore, we intend to obtain some of the input for this simulation from survey calibrations. We suggest that a better understanding of the ‘level of activeness’ and the ‘willingness to make detour’ to find available free-floating vehicles deserves further research. Beyond such direct model extensions, we believe further research is needed as to how negative experiences such as failure to obtain a bicycle will influence the system demand in the longer term. With appropriate parameters the framework presented here could also be extended in such a direction with varying day-to-day demand.

As for the survey research presented in Chapter 6, some notable limitations and future directions should be addressed.

The simple MNL analysis suggests the angle between origin-bicycle and origin-destination does not work as we expected. Before we reject such hypothesis we should further exclude the possibility that the direction towards destination has not been properly presented and does not raise enough attention.

Another interesting future direction is to replace the separated latent class analysis and choice modelling with the integrated latent class choice modelling approach. Considering the separated research already show very good correspondence, a more explanatory result can be respected.

REFERENCE

BABAZADEH, A., JAVANI, B., GENTILE, G., & FLORIAN, M. 2013. Reduced gradient algorithm for user equilibrium traffic assignment problem. *Transportmetrica A: Transport Science*, 16:3, 1111-1135, DOI: 10.1080/23249935.2020.1722279

BALAC, M., BECKER, H., CIARI, F. & AXHAUSEN, K. W. 2019. Modeling competing free-floating carsharing operators – A case study for Zurich, Switzerland. *Transportation Research Part C: Emerging Technologies*, 98**,** 101-117.

BÖRSCH-SUPAN, A. (1990). On the compatibility of nested logit models with utility maximization. *Journal of Econometrics*, 43(3), 373-388.

BICYCLE TRANSIT SYSTEMS. (2017). Field Review of Dockless Bike Share - Streetsblog USA. Retrieved from http://usa.streetsblog.org/wp-content/uploads/sites/5/2018/02/Bike-Transit-Dockless-bike-share-research-memo-120417.pdf

BYCYKLEN KØBENHAVN (2010), *Bycyklens historie-Den officielle hjemmeside for Bycyklen-København på to hjul* (in Danish) Available at https://web.archive.org/web/20100427032123/http://www.bycyklen.dk/dansk/nyhederhistorie/bycyklenshistorie.aspx [Accessed 7 May 2022]

BISCHOFF, J., MACIEJEWSKI, M. & NAGEL, K. 2017. City-wide Shared Taxis: A Simulation Study in Berlin. *2017 Ieee 20th International Conference on Intelligent Transportation Systems (Itsc)*.

BUCK, D., BUEHLER, R., HAPP, P., RAWLS, B., CHUNG, P. & BORECKI, N. 2013. Are Bikeshare Users Different from Regular Cyclists? *Transportation Research Record: Journal of the Transportation Research Board*, 2387**,** 112-119. DOI: 10.3141/2387-13

CHEN, Z., VAN LIEROP, D. & ETTEMA, D. 2020. Dockless bike-sharing systems: what are the implications? *Transport Reviews*, 40, 333-353. DOI: 10.1080/01441647.2019.1710306

CHOI, Y. & CHOI, E. J. 2020. Sustainable Governance of the Sharing Economy: The Chinese Bike-Sharing Industry. *Sustainability*, 12, 1195. DOI: 10.3390/su12031195

CIARI, F., BALAC, M. & AXHAUSEN, K. W. 2016. Modeling Carsharing with the Agent-Based Simulation MATSim: State of the Art, Applications, and Future Developments. *Transportation Research Record: Journal of the Transportation Research Board*, 2564, 14-20. DOI: 10.3141/2564-02

CIARI, F., BOCK, B. & BALMER, M. 2014. Modeling Station-Based and Free-Floating Carsharing DemandL test case study for Berlin. *Transportation Research Record: Journal of the Transportation Research Board*, 2416, 37-47. DOI: 10.3141/2416-05

DAVID, H. A. & NAGARAJA, H. N. 2004. Order Statistics (3rd edition). Encyclopedia of Statistical Sciences. DOI: 10.1002/0471722162

DE LUCA, S. & DI PACE, R. 2015. Modelling users' behaviour in inter-urban carsharing program: A stated preference approach. *Transportation Research Part A: Policy and Practice*, 71**,** 59-76.

DEMAIO, P. (2009). Bike-sharing: History, impacts, models of provision, and future. *Journal Of Public Transportation*, *12*(4), 3.

DEUTSCHE BAHN AG, M. (2019). Call a Bike. Retrieved from https://www.bahn.de/p/view/service/fahrrad/call_a_bike.shtml

DIAL, R. B. 1971. A probabilistic multipath traffic assignment model which obviates path enumeration. *Transportation Research*, 5, 83-111.

DICKINSON, J. E., GHALI, K., CHERRETT, T., SPEED, C., DAVIES, N. & NORGATE, S. 2014. Tourism and the smartphone app: Capabilities, emerging practice and scope in the travel domain. *Current issues in tourism,* 17**,** 84-101.

DU, M. & CHENG, L. 2018. Better understanding the characteristics and influential factors of different travel patterns in free-floating bike sharing: Evidence from Nanjing, China. *Sustainability*, 10, 1244. DOI: 10.3390/su10041244

EFTHYMIOU, D., ANTONIOU, C., & WADDELL, P. (2013). Factors affecting the adoption of vehicle sharing systems by young drivers. *Transport Policy, 29*, 64-73. doi:10.1016/j.tranpol.2013.04.009

FAN, Y., CHEN, Q., LIAO, C.-F. & DOUMA, F. 2012. Smartphone-based travel experience sampling and behavior intervention among young adults.

FISHMAN, E. (2015). Bikeshare: A Review of Recent Literature. *Transport Reviews, 36*(1), 92-113. doi:10.1080/01441647.2015.1033036

FISHMAN, E., WASHINGTON, S., & HAWORTH, N. (2013). Bike Share: A Synthesis of the Literature. *Transport Reviews, 33*(2), 148-165. doi:10.1080/01441647.2013.775612

FISHMAN, E., WASHINGTON, S., & HAWORTH, N. (2014). Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia. *Transportation Research Part D: Transport and Environment, 31*, 13-20. doi:10.1016/j.trd.2014.05.013

FISHMAN, E., WASHINGTON, S., & HAWORTH, N. (2015). Bikeshare's impact on active travel: Evidence from the United States, Great Britain, and Australia. *Journal of Transport & Health, 2*(2), 135-142. doi:10.1016/j.jth.2015.03.004

FISHMAN, E., WASHINGTON, S., HAWORTH, N., & MAZZEI, A. (2014). Barriers to bikesharing: an analysis from Melbourne and Brisbane. *Journal of Transport Geography, 41*, 325-337. doi:10.1016/j.jtrangeo.2014.08.005

FRIEDRICH, M. & NOEKEL, K. 2017. Modeling intermodal networks with public transport and vehicle sharing systems. *EURO Journal on Transportation and Logistics*, 6, 271-288. DOI: 10.1007/s13676-015-0091-7

HEILIG, M., MALLIG, N., SCHRODER, O., KAGERBAUER, M. & VORTISCH, P. 2018. Implementation of free-floating and station-based carsharing in an agent-based travel demand model. *Travel Behaviour and Society*, 12, 151-158. DOI: 10.1016/j.tbs.2017.02.002

HESS, S. & PALMA, D. (2019), Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application, *Journal of Choice Modelling*, 32, 100170

HORNI, A., NAGEL, K. & AXHAUSEN, K. W. 2016. *The multi-agent transport simulation MATSim*, Ubiquity Press London. DOI: 10.5334/baw

Gonul, F., & Srinivasan, K. (1993). Modelling unobserved heterogeneity in multinomial logit models: Methodological and managerial implications. *Marketing Science*, 12, 213–229.

GU, T., KIM, I. & CURRIE, G. 2019. To be or not to be dockless: Empirical analysis of dockless bikeshare development in China. *Transportation Research Part A: Policy and Practice*, 119**,** 122-147.

HARA, Y. & HATO, E. 2017. Analysis of dynamic decision-making in a bicycle-sharing auction using a dynamic discrete choice model. *Transportation,* 46**,** 147-173.

HEILIG, M., MALLIG, N., SCHR*Travel Behaviour and Society,* 12**,** 151-158.

HESS, S. & PALMA, D. (2019), Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application, *Journal of Choice Modelling*, Volume 32, September 2019, 100170

HERRIGES, J. AND C. KLING (1996), 'Testing the consistency of nested logit models with utility maximization', *Economic Letters* 50, 33–39.

JAMAL, S. & HABIB, M. A. 2020. Smartphone and daily travel: How the use of smartphone applications affect travel decisions. *Sustainable Cities and Society*, 53**,** 101939.

JIANRONG, GUO. (2019). 60 万辆！今年上半年上海共享单车市场就要饱和--上观. Retrieved from https://www.jfdaily.com/news/detail?id=46001

KASPI, M., RAVIV, T. & TZUR, M. 2014. Parking reservation policies in one-way vehicle sharing systems. *Transportation Research Part B: Methodological*, 62**,** 35-50.

KASPI, M., RAVIV, T., TZUR, M. & GALILI, H. 2016. Regulating vehicle sharing systems through parking reservation policies: Analysis and performance bounds. *European Journal of Operational Research*, 251**,** 969-987.

KHAN, N. A., HABIB, M. A. & JAMAL, S. 2020. Effects of smartphone application usage on mobility choices. *Transportation Research Part A: Policy and Practice*, 132**,** 932-94.

KLING, C. AND J. HERRIGES (1995), 'An empirical investigation of the consistency of nested logit models with utility maximization', *American Journal of Agricultural Economics* 77, 875–884.

KOPPELMAN, F.S., WEN, C.H., 1998. Alternative nested logit models: structure, properties and estimation. *Transportation Research Part B* 32, 289–298.

KUNMING URBAN TRANSPORT INSTITUTE. (2019). 一、共享单车 — 昆明城市交通发展年度报告 2017 1.0 文档. Retrieved from http://www.kmuti.com/jtnb/2017/chapter08/shared_bike.html

KWON, CHOI, S., KIM, E., KIM, H., KIM, M., & SHIN, G. (2020). Smartphone usage pattern while walking: A survey on 441 young users in Korea. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 64(1), 1728–1731

LEE, B. (1999), Calling patterns and usage of residential toll service under self-selecting tariffs, *Journal of Regulatory Economics* 16, 45–82.

LI, Q., LIAO, F. X., TIMMERMANS, H. J. P., HUANG, H. J. & ZHOU, J. 2018. Incorporating free-floating car-sharing into an activity-based dynamic user equilibrium model: A demand-side model. *Transportation Research Part B Methodological*, 107, 102-123. DOI: 10.1016/j.trb.2017.11.011

LIU, W., YANG, H. & YIN, Y. 2015. Efficiency of a highway use reservation system for morning commute. *Transportation Research Part C: Emerging Technologies*, 56**,** 293-308.

LIU, X., WANG, D. & GRETZEL, U. 2022. On-site decision-making in smartphone-mediated contexts. *Tourism Management*, 88**,** 104424.

MARTIN, E. W., & SHAHEEN, S. A. (2014). Evaluating public transit modal shift dynamics in response to bikesharing: a tale of two U.S. cities. *Journal of Transport Geography, 41*, 315-324. doi:10.1016/j.jtrangeo.2014.06.026

MENARD, SCOTT.(2011) Standards for standardized logistic regression coefficients. *Social Forces*, 89.4: 1409-1428.

MOBIKE GLOBAL. (2019A). About - Mobike. Retrieved from https://mobike.com/global/about

MOBIKE GLOBAL. (2019B). Tech in Asia - Connecting Asia's startup ecosystem. Retrieved from https://www.techinasia.com/mobike-score-punishes-bad-riders

MOLNAR, G. & CORREIA, G. H. D. A. 2019. Long-term vehicle reservations in one-way free-floating carsharing systems: A variable quality of service model. *Transportation Research Part C: Emerging Technologies*, 98**,** 298-322.

NAIR, R. & MILLER-HOOKS, E. 2014. Equilibrium network design of shared-vehicle systems. *European Journal of Operational Research*, 235, 47-61. DOI: 10.1016/j.ejor.2013.09.019

NATIONAL ASSOCIATION OF CITY TRANSPORTATION OFFICIALS. (2017). Bike Share in the U.S.: 2017 - National Association of City Transportation Officials. Retrieved from https://nacto.org/bike-share-statistics-2017/

PARKES, S. D., MARSDEN, G., SHAHEEN, S. A. & COHEN, A. P. 2013. Understanding the diffusion of public bikesharing systems: evidence from Europe and North America. *Journal of Transport Geography*, 31, 94-103. DOI: 10.1016/j.jtrangeo.2013.06.003

PHILIP, J. 2007. The probability distribution of the distance between two random points in a box, KTH mathematics, Royal Institute of Technology.

RAVEAU, S., GHORPADE, A., ZHAO, F., ABOU-ZEID, M., ZEGRAS, C. & BEN-AKIVA, M. 2016. Smartphone-based survey for real-time and retrospective happiness related to travel and activities. *Transportation Research Record*, 2566**,** 102-110.

RECK, D. J., HAITAO, H., GUIDON, S. & AXHAUSEN, K. W. 2021. Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland. *Transportation Research Part C: Emerging Technologies*, 124**,** 102947.

SAS INSTITUTE. 1995. Logistic Regression Examples Using the SAS System. Cary, NC: SAS Institute, Inc.

SCHONER, J., LINDSEY, G., & LEVINSON, D. (2018). Is Bikesharing Contagious?: Modeling Its Effects on System Membership and General Population Cycling. *Transportation Research Record: Journal of the Transportation Research Board*, *2587*(1), 125-132. doi:10.3141/2587-15

SHAHEEN, S. A., COHEN, A. P. & MARTIN, E. W. 2013. Public Bikesharing in North America: early operator and user understanding. *Transportation Research Record: Journal of the Transportation Research Board*, 2387, 83-92. DOI: 10.3141/2387-10

SHAHEEN, S. A., COHEN, A. P., ZOHDY, I. H. & KOCK, B. 2016. Smartphone applications to influence travel choices: practices and policies. United States. Federal Highway Administration.

SHAHEEN, S. A., GUZMAN, S. & ZHANG, H. 2010. Bikesharing in Europe, the Americas, and Asia: past, present, and future. *Transportation Research Record: Journal of the Transportation Research Board*, 2143, 159-167. DOI: 10.3141/2143-20

SHAHEEN, S. A., MARTIN, E. W., COHEN, A. P., CHAN, N. D., & POGODZINSKI, M. (2014). Public Bikesharing in North America During a Period of Rapid Expansion: Understanding Business Models, *Industry Trends & User Impacts*, MTI Report 12-29.

SHAHEEN, S. A., ZHANG, H., MARTIN, E. & GUZMAN, S. 2011. China's Hangzhou Public Bicycle Understanding Early Adoption and Behavioral Response to Bikesharing. *Transportation Research Record*, 2247, 33-41. DOI: 10.3141/2247-05

SHEFFI, Y. 1985. Urban transportation networks, Prentice-Hall, Englewood Cliffs, NJ. DOI:

SHEN, Y., ZHANG, X. & ZHAO, J. 2018. Understanding the usage of dockless bike sharing in Singapore. *International Journal of Sustainable Transportation*, 12, 686-700. DOI: 10.1080/15568318.2018.1429696

SMITH, M. J. 1979. The existence, uniqueness and stability of traffic equilibria. *Transportation Research Part B: Methodological*, 13, 295-304. DOI: 10.1016/0191-2615(79)90022-5

TAN, W. K. & LU, K.-J. 2020. Smartphone use and travel companions' relationship. *Asia Pacific Journal of Marketing and Logistics*.

TRAIN, K., 2009. Discrete Choice Methods with Simulation. second edition ed., Cambridge University Press, Cambridge, MA.

TRAIN, K., D. MCFADDEN, AND M. BEN-AKIVA (1987), 'The demand for local telephone service: A fully discrete model of residential calling patterns and service choice', *Rand Journal of Economics* 18, 109–123.

VAN LIEROP, D., GRIMSRUD, M., & EL-GENEIDY, A. 2015. Breaking into bicycle theft: Insights from Montreal, Canada. *International Journal of Sustainable Transportation*, 9(7), 490-501. DOI: 10.1080/15568318.2013.811332

WIKIPEDIA CONTRIBUTORS, (2019a). Wikipedia. Bicycle-sharing system. Retrieved from https://en.wikipedia.org/wiki/Bicycle-sharing_system

WIKIPEDIA CONTRIBUTORS, (2019b). Wikipedia. List of Bicycle-Sharing Systems. Retrieved from https://en.wikipedia.org/wiki/List_of_bicycle-sharing_systems#Bicycle_sharing_systems

WU, C., LE VINE, S., SIVAKUMAR, A. & POLAK, J. 2019. Traveller preferences for free-floating carsharing vehicle allocation mechanisms. *Transportation Research Part C: Emerging Technologies*, 102**,** 1-19.

WU, C., LE VINE, S., SIVAKUMAR, A. & POLAK, J. 2021. Dynamic pricing of free-floating carsharing networks with sensitivity to travellers' attitudes towards risk. *Transportation*.

WU, L., GU, W., & FAN, W. (2018). *A Continuum Model for Optimal Joint Designs of Bike-sharing and Transit Networks*. (No. 18-06731).

XIE, J., Y. NIE, & X. LIU. 2018. Greedy Path-Based Algorithm for Traffic Assignment. Proccedings of the 97th Transportation Research Board Annual Meeting, Washington DC, USA, January 7–11.

YANG, X.-H., CHENG, Z., CHEN, G., WANG, L., RUAN, Z.-Y. & ZHENG, Y.-J. 2018. The impact of a public bicycle-sharing system on urban public transport networks. *Transportation Research Part A: Policy and Practice*, 107**,** 246-256.

YAO, Z. & SCHMÖCKER, J.-D. (2021). Variance in access distance to free-floating services considering uncertain availability. 8th International Conference on Transport Network Reliability (Stockholm, 24-26 June, held online).

ZHANG, H., SHAHEEN, S. A., & CHEN, X. P. (2014). Bicycle Evolution in China: From the 1900s to the Present. *International Journal of Sustainable Transportation, 8*(5), 317-335. doi:10.1080/15568318.2012.699999