ENVIRONMENTAL IMPACT ASSESSMENT AND IMPROVED DESIGN OF BIKE SHARING SYSTEMS FROM THE LIFE CYCLE PERSPECTIVE

by

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A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Science

Division of Environmental and Ecological Engineering

West Lafayette, Indiana

May 2019

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

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Bike sharing system (BSS) is growing worldwide. Although bike sharing is viewed as a sustainable transportation mode, it still has environmental footprints from its operation (e.g., bike rebalancing using automobiles) and upstream impacts (e.g., bike and docking station manufacturing). Thus, evaluating the environmental impacts of a BSS from the life cycle perspective is vital to inform decision making for the system design and operation. In this study, we conducted a comparative life cycle assessment (LCA) of station-based and dock-less BSS in the U.S. The results show that dock-less BSS has a greenhouse gas (GHG) emissions factor of 118 g CO_2-eq/bike-km in the base scenario, which is 82% higher than the station-based system. Bike rebalancing is the main source of GHG emissions, accounting for 36% and 73% of the station-based and dock-less systems, respectively. However, station-based BSS has 54% higher total normalized environmental impacts (TNEI), compared to dock-less BSS. The dock manufacturing dominants the TNEI (61%) of station-based BSS and the bike manufacturing contributes 52% of TNEI in dock-less BSS. BSS can also bring environmental benefits through substituting different transportation modes. Car trip replacement rate is the most important factor. The results suggest four key approaches to improve BSS environmental performance: 1) optimizing the bike distribution and rebalancing route or repositioning bikes using more sustainable approaches, 2) incentivizing more private car users to switch to using BSSs, 3) prolonging lifespans of docking infrastructure to significantly reduce the TNEI of station-based systems, and 4) increasing the bike utilization efficiency to improve the environmental performance of dock-less systems.

To improve the design of current BSS from the life cycle perspective, we first proposed a simulation framework to find the minimal fleet size and their layout of the system. Then we did a tradeoff analysis between bike fleet size and the rebalancing frequency to investigate the GHG emission if we rebalance once, twice and three times a day. The optimal BSS design and

operation strategies that can minimize system GHG emission are identified for a dock-less system in Xiamen, China. The results show that at most 15% and 13% of the existing fleet size is required to serve all the trip demand on weekday and weekend, if we have a well-designed bike layout. The tradeoff analysis shows that the GHG emission may increase if we continue to reduce the fleet size through more frequent rebalancing work. Rebalancing once a day during the night is the optimal strategy in the base scenario. We also tested the impacts of other key factors (e.g., rebalancing vehicle fleet size, vehicle capacity and multiple depots) on results. The analysis results showed that using fewer vehicles with larger capacity could help to further reduce the GHG emission of rebalancing work. Besides, setting 3 depots in the system can help to reduce 30% of the GHG emission compared with 1-depot case, which benefits from the decrease of the commuting trip distance between depot and the serve region.

CHAPTER 1. INTRODUCTION

With the rapid growth of urban population, cities around the globe are facing severe mobility problems (Banister, 2005). In the last century, automobiles have entered billions of households due to the economic development and technical progress, making private vehicles the dominated mode of human mobility (Hu and Reuscher, 2004). The fast-increasing car traffic generated serious urban transportation issues, such as traffic congestion, air pollution, and worsening of city accessibility (Dell et al., 2014).

Many systems and technologies are changing the contemporary urban transportation systems to be more efficient and sustainable. Ride sharing allows people to share their drive with others, which is helpful to relieve the traffic pressure (Katzev, 2003). Car sharing helps to reduce car ownership through providing users accessibility to cars in the needed situations without having to own one (Nijland and van Meerkerk, 2017). Vehicle electrification has also shown great potential to reduce greenhouse gas (GHG) emissions for the transportation sector (Wu et al., 2012). Improvements of public transit infrastructure aim to support substituting private car trips with public transportation, which has higher energy and economic efficiency (Redman et al., 2013). The bike sharing system (BSS), as one type of shared urban mobility modes, has grown rapidly and attracted more and more users in recent years, because of its convenience, low-cost, and easy accessibility (Bachand-Marleau et al., 2012; Davis, 2014; Fishman, 2016; Shaheen et al., 2013). In 2004, only 13 cities globally had introduced the bike sharing systems (Fishman, 2016). As of 2018, over 1,500 bike sharing programs are in operation and the number keeps increasing rapidly (Meddin and DeMaio, 2018).

Bike sharing is not a new idea. The BSS has gone through the evolution of four generations since 1960s (Fishman, 2016). The first BSS was launched in Amsterdam in1964, named “White Bicycles” because the bikes were all painted in white. The White

Bicycles was free of charge and without any security measure. This program was shut down in quickly because the bikes were thrown into canals or embezzled for private use (DeMaio, 2009). The second generation required a coin deposit system, but the anonymity of users still exposed the system to theft (DeMaio, 2009).

The current BSSs are in the 3rd and 4th generations. The third generation of bike sharing system is station-based, which includes bikes and the sharing infrastructures (i.e. stations and docks) for picking up and returning bikes (Shaheen et al., 2013). A station normally consists of a map stand, a kiosk, a solar panel system (including batteries for energy storage), and a docking system which includes a steel base and several docking racks to hold the bikes. The users of the station-based BSS are required to pick up/return bikes from/to the stations and the automated credit payment allowed bike tracking and management. As a result, the use of the station-based BSS is mostly limited to the regions where the station infrastructure is available.

In recent years, enabled by the wide adoption of smart phones, the fourth generation of BSS, known as the dock-less bikes, station-less bikes, or floating shared bikes, has been launched in several cities. The dock-less bikes are connected to the internet with mobile communication devices to help users locate the dock-less bikes for pickup (Shaheen et al., 2010). Without being constrained by the station infrastructure, the dock-less BSS allows the users to park the bikes almost anywhere within the service region. Removing the high initial capital investment required for the docking stations, the dock-less BSS can potentially help expand the bike sharing service with lower cost.

After several years of operation, the current BSSs, both station-based and dock-less, have shown their tremendous potentials of improving urban transportation sustainability. The environmental benefit of BSS is obtained by replacing more energy intensive transportation modes, especially private car use. Shaheen et al. (2011) surveyed the bike sharing programs in Hangzhou, China and found that bike sharing was more attractive to car owners and the system had high potential to convert car trips to bike trips or "bike + public transit" multimodal trips. Fishman et al. (2014b) evaluated the car trips replacement by BSSs using survey and trip data of bike sharing programs in different cities, considering the additional truck use for bike rebalance and maintenance. The results showed a significant reduction in annual vehicle usage: 243,291 km in Washington, D.C and around 90,000 km in Melbourne and Minneapolis/St. Paul. Qiu and He (2018) investigated the environmental benefits of the BSSs by calculating the emissions from the substituted personal vehicle trips and estimated a reduction of 616,036 tons of CO_2 emissions in Beijing in 2020, compared to the 2015 value. The BSS in Shanghai, China was estimated to save 8,358 tones gasoline and reduce 25,240 tons of CO_2 emissions in 2016, assuming that all the bike trips longer than 1 km were able to replace car usage (Zhang and Mi, 2018). An investigation of 12 BSSs in Europe estimated the potential of death avoidance because of more physical activities, less road traffic fatalities and reduced air pollution benefiting from the car trip substitution (Otero et al., 2018).

Although BSS is viewed as a green travel mode, it also exists negative externalities, especially in the operation and manufacturing phase. First, BSS operation requires bike rebalancing, which is often done by automobiles. The uneven temporal and spatial distribution of customer demands could leave certain stations/regions with no bike available for pick up, especially in the peak hours (Fishman, 2016). To meet these demands, a regular bike rebalancing is required to redistribute the bikes using trucks/vans from other surplus stations/regions to meet service demands in different areas (Cruz et al., 2017). In the actual operation, the intensive bike rebalancing work requires high labor and energy costs, and also generates a significant amount of GHG emissions (Pal and Zhang, 2017). Furthermore, if a BSS could not substitute enough automobile vehicle usage to compensate for the extra vehicle trips for rebalancing, it will cause additional environmental impacts and traffic. London experienced additional 766,341 km of motor vehicle use annually after launching the bike sharing system, because the heavy rebalancing work outweighed the benefit from car trip substitution (Fishman et al., 2014). Second, BSS may also indirectly induce car use. Wang and Zhou (2017) investigated 96 urban areas in the U.S. and concluded that the introduction of BSS could worsen the congestion in cities with higher income level because the bike sharing program may induce extra trips (e.g., leisure and sightseeing trips) which would not be made without the BSS. People in these cities tend to use cars as connectors to these extra trips, leading to more traffic. Last, the embodied energy and emissions in the manufacturing phase cannot be neglected. Due to the difficulties to monitor the system, the shared bikes are at high risk of being stolen, vandalized, abused, and parked haphazardly, especially for the dock-less system (Yao et al., 2018). To maintain the system, the bike sharing operators had to launch a large number of bikes and also keep adding new bikes (Moss, 2017). The superfluous bike supply infringed public space and also increased the operation cost. Moreover, manufacturing the excessive bikes, electronic components, and sharing infrastructure wasted energy and resources and generated enormous emissions (Berkhout and Hertin, 2001; Chester and Horvath, 2009; Coelho and Almeida, 2015). In Shanghai, more than 1.5 million dock-less bikes were in the street and the retired or abandoned bikes clogged the sidewalks and created huge piles of bike wastes (Benjamin, 2017).

Therefore, to ensure that BSS can contribute to the transportation sustainability, we need to consider both the environmental benefits and negative impacts of BSSs in the design and operation of the system. The existing literature has not evaluated the BSS design and operation from the life cycle perspective. Specifically, the following research questions are yet to be answered:

(1) From the life cycle perspective, which BSSs, station-based or dock-less, is more sustainable?

(2) What are the major factors of BSS's environmental impacts?

(3) Can we improve the system performance through analyzing the tradeoff between system design (e.g. bike fleet size) and operation (e.g. rebalancing strategy)?

To address these knowledge gaps, we first conduct a comparative life cycle assessment of station-based and dock-less BSSs (Chapter 2), and then developed simulation and optimization models to evaluate the tradeoffs between bike fleet size and rebalancing frequencies to propose an optimal BSS design from the life cycle perspective (Chapter 3). Chapter 4 summarizes the conclusions and discusses future research directions.

CHAPTER 2. COMPARATIVE LIFE CYCLE ASSESSMENT OF STATION-BASED AND DOCK-LESS BIKE SHARING SYSTEMS

2.1 Introduction

To fully understand the sustainability of BSS, we need to quantify its net environmental impacts. The net impact is the difference between the environmental footprints in the life cycle of bikes and the sharing infrastructure, including manufacturing, system operation, and the end-of-life management, and the environmental benefits gained by substituting more emission and energy intensive modes. To the best of our knowledge, the only life cycle assessment (LCA) study of BSSs is conducted by Amaya et al. (2014), analyzing the BSS in the city of Lyon, France as a case study to improve the design for product-service systems (PSS). However, this study only focuses on the life cycle of the bikes, neglecting the impacts of the docking stations. Bike sharing stations and docks are a critical component of station-based BSS and should be included in the analysis.

Additionally, no study has yet compared the station-based and dock-less BSSs from the life cycle perspective. The stations required in the station-based BSS can be material and energy intensive. While the dock-less BSS removes the need of stations, electronic components are required to be installed in each bike to allow bike tracking and locking/unlocking. Given the large number of bikes required for the dock-less BSS, it is unclear which BSS can have better environmental performances. Moreover, the efficiency difference of the two systems also obscures the comparison result. Compared to station-based systems, dock-less systems tend to have lower system efficiency, resulting from bike vandalism, lack of visibility of the program, or reluctance to use smartphone apps for transactions (Nieuwesteeg, 2018). While 44% of the shared bikes in the U.S. are dock-less bikes, they only contribute to 4% of the total bike sharing trips

(NACTO, 2017). While more and more cities are planning to launch, expand, or modify their BSSs to improve urban sustainability, a comparative LCA of both BSSs is needed to better understand their environmental impacts and inform decision making for BSS development.

This chapter presents a comparative LCA of station-based and dock-less BSS, covering all life cycle stages and infrastructure support required for each system. Compared to the existing studies, this work has two major unique contributions: first, analyzing the net environmental impacts of BSSs holistically (in terms of greenhouse gas emissions and the total normalized environmental impacts), considering both life cycle environmental impacts from system development and operations and environmental benefits from substituting motorized vehicle trips; and second, comparing the station-based and the dock-less BSSs. The results of this study are expected to: 1) provide the emission factors for both station-based and dock-less BSSs, which are needed information to support system analysis of urban transportation sustainability, 2) inform decision-makers on BSS design and development for more sustainable systems, and 3) identify potential strategies for bike sharing operators and city planners to improve the environmental contributions of the BSSs. This chapter has been modified into a journal paper titled “Comparative Life Cycle Assessment of Station-based and Dock-less Bike Sharing Systems”, which has been accepted for publication by *Resources, Conservation & Recycling* (Luo et al., 2019).

2.2 Method and data

LCA is a standardized method to analyze the environmental impacts of a product through its entire life cycle, including resource extraction, raw materials processing, product assembly, transport, packaging, use, maintenance, waste treatment, and disposal (Finnveden et al., 2009; Rebitzer et al., 2004). This ‘cradle-to-grave’ method has been broadly applied by researchers and companies since the 1990s and has been standardized by ISO-14040 and ISO-14044 (ISO, 2006a, 2006b). This study is conducted following the standard LCA procedure. In the following subsections, we will discuss the four steps of our LCA study, including goal and scope definition (Section 2.2.1), life cycle inventory analysis (Section 2.2.2), life cycle impact assessment (Section 2.2.3), and result interpretation (Section 2.2.4). Because the transportation modes replaced by bike sharing trips could be different from city to city, we evaluated several substitution scenarios to analyze the range of the net impacts (Section 2.2.5).

2.2.1 Goal and scope definition

The goal of this study is to compare the environmental impacts of generic station-based and dock-less bike sharing systems in the U.S. from the life cycle perspective, and to understand the key factors affecting the environmental performance of each BSS. The functional unit chosen for this study is traveling one kilometer by one bike (i.e. bike-km). The system boundary of the bike sharing systems includes: 1) raw material extraction, processing, and product assembly (referred to as the manufacturing phase), 2) use phase, and 3) end-of-life treatment (referred to as the end of life) (Figure 2-1). The manufacturing phase includes the transportation from raw material processing factories to the bike manufacturers, but ignores the packages used in this phase due to the lack of data. The major differences between the station-based and dock-less systems are that 1) the station-based system requires the manufacturing of the sharing infrastructure (i.e. stations and docks); and 2) the dock-less bikes require photovoltaic panel as the power supplier, and electronic equipment, such as Global Positioning System (GPS), batteries and electronic locks to enable bike locating, locking, and unlocking. In the use phase, all the bikes are distributed and rebalanced by vans among warehouses and stations/locations. The maintenance work includes components manufacturing, electricity and water consumption, and waste disposal. At the end of life, the metal parts in the system can be recycled before landfill. The environmental benefits from aluminum and steel recycling are credited for avoiding the use of virgin materials. The plastic and rubber wastes are assumed to be delivered to landfills.

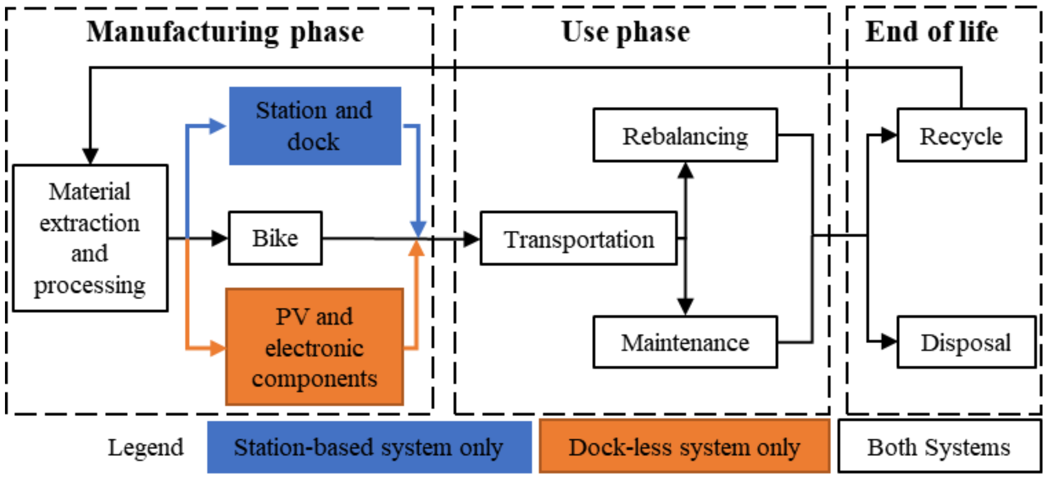


Figure 2-1 System boundary of the station-based and dock-less bike sharing systems

2.2.2 Life cycle inventory (LCI) analysis

Life cycle inventory analysis builds an inventory of the natural resources use, energy inputs, and wastes and emission outputs involved in the system. All the process data of material inputs, energy consumption, and emission outputs are collected from the Ecoinvent 3 database (Wernet et al., 2016). The input data of the station-based system, including the docks and stations manufacturing, rebalancing, maintenance, recycling, and disposal, are collected from a bike sharing program in a large metropolitan area operated in the U.S. (Interview, 2018). Each bike weights about 20 kg. The inventory data of bike productions are scaled with bike mass, based on an LCA report of manufacturing a 17 kg urban-used bicycle (Leuenberger and Frischknecht, 2010). The lifespan of the bike and the sharing infrastructure are ten years. For the dock-less system, constrained by the available data, we assume that the components for the dock-less bikes are the same as the station-based bikes, except that dock-less bikes additionally require a photovoltaic panel, 0.15 kg rechargeable battery, and 0.35 kg electronic components, the data of which are collected from a bike supplier. Although dock-less bikes could potentially be more vulnerable to vandalism due to the inherent difficulties in managing the scattered bikes, the challenging bike management also motivates the dock-less system operators adopting more durable bikes which are designed to have a longer lifetime. Therefore, whether the dock-less bikes will have shorter or longer lifespan compared to the station-based docks are not apparent. In this study, we assume that the dock-less bikes have the same lifespan of 10 years as the station-based bikes, except for the batteries which have a 5-year lifetime (Texas Instruments, 2018). The material flows of stations and docks are also included and we assume that all these materials can sustain for 10 years except that the batteries need to be renewed every 5 year (Bernstein and Woods, 2013). Table 2-1 lists the detailed material consumption and the matched unit processes in the manufacturing phase.

The material consumption for bike maintenance is based on (Leuenberger and Frischknecht, 2010). On average, serving 1 km of bike trip needs 0.0275 km's van (<3.5t) usage for bike rebalancing in the station-based system. We used the '*Transport, van <3.5t/US- US-EI U*' process to account for the life cycle impacts of the rebalancing fleet, including vehicle operation (i.e. fuel consumption), vehicle manufacturing, road construction, and waste disposal. We assume that the rebalancing demand for each bike stays constant for different systems. Although all the retired metal parts can be recycled, a recycling rate factor (95%) is applied to account for bike lost and material loss during the collection process. The 5% lost rate is based on our communication with a station-based system operator and this number is in line with other reported values for station-based systems in the U.S. (Lazo, 2019). Due to the lack of data, we assumed that the dock-less systems have the same bike lost rate in this study. Considering the possibility that dock-less systems may have higher bike lost rates, we have tested the sensitivity of results with 20% bike lost rates. As expected, higher bike lost rates increase the environmental impacts, but the conclusions are not affected (Appendix A). A recycling efficiency of 90% was applied during the recycling process, which means that 90% of the recycled metals can be reused as primary metals (Haupt et al., 2018). The recycling efficiency is highly dependent on the treatment processes. We also investigated the impact of a lower efficiency (70%). While the lower recycling efficiency increase the environmental impacts of the BSS, it does not change the main conclusions (Appendix B).

The BSS system size (the total number of stations, docks, and bikes) and ridership (the total number of trips and trip distances) can also impact the LCA results significantly. The BSS system size in the U.S. varies from city to city, ranging from 500 bikes with 60 stations to more than 10,000 bikes with 687 stations (NACTO, 2017). So does the ridership. As a result, the environmental performance of a BSS at the program level is highly case specific. Therefore, to allow comparison among different systems, we calculated the system setup based on the functional unit, to find out the number of stations, docks, and bikes the system uses to serve 1 bike-km, represented as #station/bike-km, #dock/bike-km, and #bike/bike-km, respectively. We evaluated the operation information for eight station-based BSSs in the U.S. (**Error! Reference source not found.**) (Kou and Cai, 2018) and developed a base station-based scenario using the average values as a reference system. The BSSs in New York City (NYC) and Seattle were the two systems we chose, to create the best and worst scenarios for accessing the ranges of different BSSs' environmental impacts, because these two have the highest and lowest efficiency. For the dock-less system, we used the same scenario building strategy to acquire the base, best, and worst cases.

Table 2-1 Material inventory and manufacturing process for making one bike, station, and dock

Component	**Value**	**Unit**	**Material** [c]	**Ecoinvent unit process**
Station-based bike	1.18[a]	p	-	Bicycle, at regional storage/US-/I US-EI U
Dock-less bike	1.18[a]	p	-	Bicycle, at regional storage/US-/I US-EI U
	0.35	kg	Electronic equipment	Electronics for control units/US- US-EI U
	0.15	kg	Battery (5yrs.lifetime)	Battery, Li-ion, rechargeable, prismatic, at plant/GLO US-EI U
	0.02	m^2	Photovoltaic Panel	Photovoltaic panel, single-Si wafer {GLO}| market for | APOS, U
Station[b]	1.5	m^2	Photovoltaic Panel	Photovoltaic panel, single-Si wafer {GLO}| market for | APOS, U
	45.36	kg	Steel	Chromium steel 18/8, at plant/US- US-EI U
	38.5	kg	Aluminum	Aluminum alloy, AlMg3, at plant/US- US-EI U
				Sheet rolling, aluminum/US- US-EI U
	6.8	kg	Glass	Flat glass, uncoated, at plant/US- US-EI U
	81.5	kg	Battery (5yrs.lifetime)	Battery, Li-ion, rechargeable, prismatic, at plant/GLO US-EI U

Table 2-2 Operation parameter of 10 BSS programs

	Station-based systems[a]								Dock-less systems[b]	
City	**Seattle[c]**	**L.A.**	**Bay Area**	**Philadelphia**	**Boston**	**D.C.**	**Chicago**	**NYC**	**Seattle**	**D.C.**
Total number of bikes	463	766	422	1,023	1,802	4,308	5,748	10,495	10,000	2,000
Total number of stations	55	63	37	103	172	400	568	572	-	-
Total number of docks	787	1,302	717	1,739	3,063	7,324	9,772	17,842	-	-
Annual trip counts	1.03E+05	1.84E+05	1.94E+05	4.99E+05	1.24E+06	2.56E+06	3.60E+06	1.03E+07	9.36E+05	4.92E+05
Average trip distance (km)	2.03	1.97	2.50	2.72	2.75	1.63	2.74	2.69	2.03	1.63
Total trip distance (km)	2.08E+06	3.63E+06	4.83E+06	1.36E+07	3.40E+07	4.18E+07	9.84E+07	2.76E+08	1.90E+07	8.03E+06
#bikes/bike-km	2.22E-04	2.11E-04	8.74E-05	7.53E-05	5.30E-05	1.03E-04	5.84E-05	3.80E-05	5.26E-04	2.49E-04
#stations/bike-km	2.64E-05	1.74E-05	7.66E-06	7.58E-06	5.06E-06	9.56E-06	5.77E-06	2.07E-06	-	-
#docks/bike-km	3.78E-04	3.59E-04	1.49E-04	1.28E-04	9.00E-05	1.75E-04	9.93E-05	6.47E-05	-	-

Notes:

a. Station-based systems data are based on (Kou and Cai, 2018).

b. Dock-less system data on Seattle and Washington, D.C. are based on (Lloyd, 2018; Lucas, 2018).

c. The program in Seattle has been closed, the operation information was collected from year 2014 to 2016

Table 2-3 Base, worst, and best scenarios

	Base scenario		**Worst scenario**		**Best scenario**	
Parameter	**Station-based**	**Dock-less**	**Station-based**	**Dock-less**	**Station-based**	**Dock-less**
#bike/bike-km[a]	1.06E-04	3.87E-04	2.22E-04	5.26E-04	3.80E-05	2.49E-04
#station/bike-km[b]	1.02E-05	-	2.64E-05	-	2.07E-06	-
#dock/bike-km[c]	1.80E-04	-	3.78E-04	-	6.47E-05	-
rebalance distance (km/bike-km) [d]	2.75E-02	1.00E-01	5.76E-02	1.36E-01	9.87E-03	6.46E-02

Notes:
a. '#bike/bike-km' refers to the average number of bikes serving 1 km's trip, which is calculated as the total bike count divided by the total trip distance in a program.
b. '#station/bike-km' refers to the average number of stations serving 1 km's demand, which is calculated as the total station count divided by the total trip distance.
c. '#dock/bike-km' refers to the average number of docks serving 1 km's demand, which is calculated as the total dock count divided by the total trip distance.
d. For the station-based system, the 'rebalance distance (km/bike-km)' refers to the motor vehicle usage per km of bike trip, which is estimated as the total annual van mileages divided by total annual trip distance. The rebalancing demand /bike-km for the station-based system of the base scenario was collected from the interview we conducted with the BSS operator. Due to the lack of data, we assume that the rebalancing demand for each bike is the same as that in the station-based base scenario for all other scenarios in Table 2-3. The rebalancing demand for each bike is $\frac{Rebalance\ distance}{number\ of\ bike} = \frac{2.75E{-}02\frac{km}{bike\ km}}{1.06E{-}04\ \#\frac{bike}{bike\ km}} = 260\ km/bike.$

2.2.3 Life cycle impact assessment (LCIA)

The LCIA quantifies the environmental impacts based on the developed inventory (Pennington et al., 2004). Because the systems are based in the U.S., we used the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI 2.1) developed by the U.S. EPA in this study to conduct the LCIA (EPA, 2012). TRACI covers eight impact categories: Ozone depletion, Climate change, Acidification, Eutrophication, Smog formation, Human health impacts (Cancer, Non-cancer and Respiratory effects), Ecotoxicity, and Resource use. Each characterized impact category can be normalized to calculate the total normalized environmental impacts (TNEI) (Ryberg et al., 2014). The normalized result of each category was calculated as emission impact of each category divided by the total impact result in the U.S. in 2008 (Table 2-4). The normalized value of each category was the emission value times the normalization factor.

Table 2-4 Normalization factors for TNEI

Impact category	Total impact per year
Ecotoxicity-non-metals (CTUe)	2.3×10^{10}
Ecotoxicity-metals (CTUe)	3.3×10^{12}
Carcinogens-non-metals (CTUcanc.)	1.7×10^{3}
Carcinogens-metals (CTUcanc.)	1.4×10^{4}
Non-carcinogens-non-metals (CTUnon-canc.)	1.1×10^{4}
Non-carcinogens-metals (CTUcanc.)	3.1×10^{5}
Global warming (kg CO_2 eq)	7.4×10^{12}
Ozone depletion (kg CFC-11 eq)	4.9×10^{7}
Acidification (kg SO_2eq)	2.8×10^{10}
Eutrophication (kg N eq)	6.6×10^{9}
Photochemical ozone formation (kg O_3 eq)	4.2×10^{11}
Respiratory effects (kg $PM_{2.5}$ eq)	7.4×10^{9}
Fossil fuel depletion (MJ surplus)	5.3×10^{12}

Note: The table 2-4 was based on (Ryberg et al., 2014).

2.2.4 **Result interpretation**

To evaluate the environmental impacts, we first analyzed the GHG emissions of the two systems. Additionally, we investigated the TNEI to attain the overall impact, considering all the impact categories. Due to the uncertainties in the input data, especially for the dock-less BSS, we applied sensitivity analysis to evaluate how different system setup and operation would impact the GHG emissions and TNEI values. Additionally, in order to better evaluate these two systems to inform BSS development, we analyzed the break-even points to identify key parameter values that will make the two systems have the same environmental impacts.

2.2.5 **Transportation mode substitution**

The BSSs can provide environmental benefits if they can replace more energy and resource intensive transportation modes. However, different cities may have very different mode substitution scenarios. Martin and Shaheen (2014) compared the public transit mode (bus and rail) change before and after employing the BSSs in two U.S. cities and found totally different modal shifts in these cities. Therefore, to capture the ranges of potential environmental benefits from BSSs, we conducted scenario analysis to evaluate how different transportation modal shift patterns due to BSSs can impact the overall system GHG emissions and TNEI values. The transportation modes that can be replaced by bike sharing include car, bus, personal bike, and walking. We used Ecoinvent to obtain the emission results for these transportation modes. The dataset we choose are: 'Transport, passenger car/US- US-EI U', 'Transport, regular bus/US* US-EI U', 'Transport, electric bicycle/US* US-EI U', and 'Transport, bicycle/US* US-EI U'. The SimaPro 8.4 software was used to perform the inventory analysis. The mode substitution rates are based on BSS user survey in Melbourne, Brisbane, Washington, D.C., Minneapolis/St. Paul, and London, which are listed as Scenarios 1 to 5, respectively, in Table 2-5 (Fishman, 2016). The survey asked the participants to "Thinking about your last bike share trip, which transportation mode you would take if BSS not existed". Scenario 6 was built as a representative case, where all parameters except for walking are the median values from Scenarios 1 to 5. In addition, Scenarios 7 to 10 use Scenario 6 as the basis and adjust the car trip and walking substitution rates to find the minimum level of car substitution to achieve neutral impacts from each of the GHG emission and TNEI value perspective for each of the station-based and dock-less system.

Table 2-5 Transportation mode substitution scenarios

		Mode substitute rate			
	New trip	**Car**	**Bus**	**Bike**	**Walk**
Scenario 1	1%	20%	40%	9%	30%
Scenario 2	2%	24%	44%	8%	22%
Scenario 3	4%	14%	45%	6%	31%
Scenario 4	13%	22%	20%	8%	37%
Scenario 5	3%	6%	57%	8%	25%
Scenario 6[a]	3%	20%	44%	8%	25%
Scenario 7-10[b]	3%	TBD	44%	8%	TBD

Notes:
a: Median value selected from Scenarios 1 to 5 for car, bus, and bike substitution and new trips. The rest of the share is allocated to walking substitution.
b: Based on scenario 6, these scenarios modify the car and walk substitution rates to identify the breakeven car trip substitution rate to achieve neutral GHG emission or zero TNEI for each of the station-based and dock-less system.

2.3 Results and discussions

This section first presents the LCIA results of the station-based and dock-less bike sharing systems, without considering the transportation mode substitution by bike sharing trips (Section 2.3.1). Due to the limited space, we will focus our discussion on the environmental impacts of each system from two aspects: global warming potentials and TNEI. Additionally, to analyze how system setup and operation changes impact the results, we also discuss the breakeven points of the two BSSs and the sensitivity of key parameters. Then, in Section 2.3.2, we add the potential environmental benefits from transportation mode substitution into our analysis, evaluating how different substitution scenarios change the overall system GHG emission and TNEI results. The detailed emission results for each category were listed in Appendix C.

2.3.1 BSS environmental footprints

2.3.1.1 Global warming potentials

GHG emission impacts are obtained thorough the LCIA procedure. The station-based system has a carbon emission factor of 65 g CO_2-eq per bike-km in the base scenario (Figure 2-2). The range of this emission rate is between 26 and 147 g CO_2-eq per bike-km from the best-and-worst case scenarios, respectively. For the dock-less system, the base emission rate is 118 g CO_2-eq per bike-km, with a range of 78 to 160 g CO_2-eq per bike-km. The overlap between the two systems implies that, if not designed and operated efficiently, the station-based system may not be more environmentally friendly than the dock-less system. The bike rebalancing using automobiles is the main source of GHG emissions for both systems, contributing 36% and 73% of the total global warming potential impacts, respectively (Figure 2-2). Because we assumed that the rebalancing need for each bike would remain the same, the larger number of bikes required for the dock-less system also leads to high rebalancing demand compared to the station-based system.

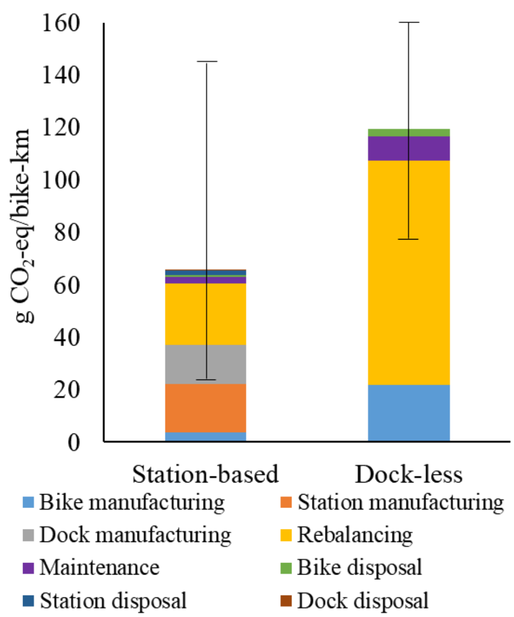


Figure 2-2 Life cycle GHG emissions of the station-based and dock-less BSSs, with breakdown by life cycle stages

To account for the uncertainties in the input data and identify key factors that impact the GHG emissions, we conducted a sensitivity analysis of having different number of stations, docks, bikes, and rebalancing needs to serve the same demands. Figure 2-3 shows the sensitivity analysis results and GHG emission breakeven points of the two systems. The slops of the lines show how sensitive the result is to the change of the parameter, with a steeper slop indicating higher sensitivity. As shown in Figure 2-3a, the rebalancing needs (rebalance distance/bike-km) is the factor that the station-based system is most sensitive to. The GHG emission factors of the two systems could be the same when the rebalancing need becomes 325% of the base scenario. These results show that, when station-based BSSs require much more rebalancing to meet the same demands, they may lose their GHG emission reduction advantages over the dock-less systems. The station-based systems may also have a higher carbon footprint than the dock-less systems, if the system requires 2.5 times stations or 3.5 times number of docks more than the base scenario. Frequent replacement of the sharing infrastructure (e.g., due to change of contractors, improper maintenance of the stations, or redundant station siting) may lead to these scenarios (Chrisafis, 2018). For the dock-less system (Figure 2-3b), the GHG emissions rate can be improved to the same level as in the station-based system, when the 'rebalance distance/bike-km' is decreased to 35% of the base scenario value. Optimizing the distribution of the dock-less bikes is an effective approach to reduce the rebalancing impacts.

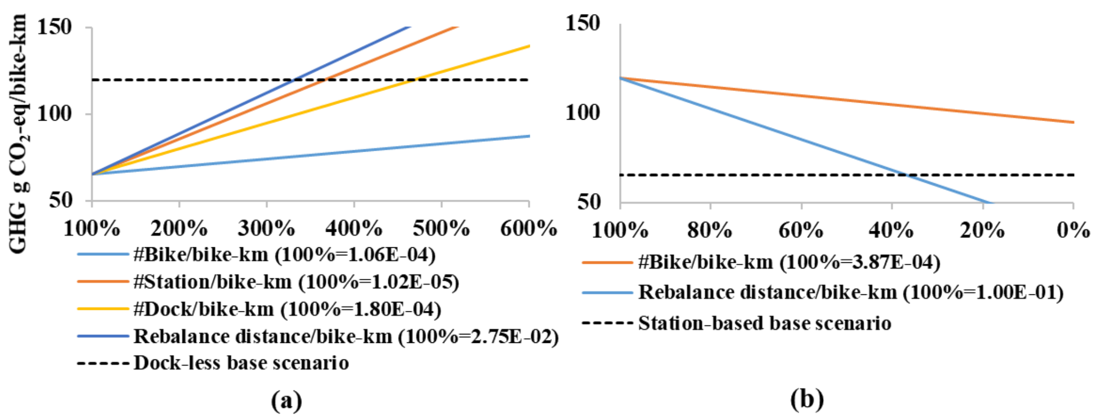


Figure 2-3 GHG emission break-even points and parameter sensitivities. (a) changing parameters in station-based BSS; (b) changing parameters in dock-less BSS

2.3.1.2 Total normalized environmental impact (TNEI)

To allow comparisons across different systems with different types of environmental impacts, the impacts in different categories are normalized and summed into a single score to calculate the TNEI. Figure 2-4 shows that the TNEI of the station-based system (2.30E-04 unit/bike-km) is 54% higher than that of the dock-less system (1.49E-04 unit/bike-km), in the base scenario. The potential human health impacts from carcinogenic compounds dominates the TNEI of the station-based system. The main source of carcinogenicity is from Chromium (Cr) VI, a strong carcinogenic, emitted during the aluminum and steel smelting processes. Compared to the dock-less bike sharing system, the station-based system consumes significantly more aluminum and steel materials for the stations (38.5 kg aluminum and 45.4 kg steel per station) and docks (13.6 kg aluminum and 67.8 kg steel per dock) manufacturing. The contributions of each life cycle stage to the TNEI are summarized in Figure 2-4b. For the station-based system, the sharing facility (docks and stations) manufacturing accounts for 61% and 23% of the overall environmental impact due to the carcinogenic materials discharged. Bike manufacturing is the major TNEI contributor (52%) for the dock-less system because of the high volume of bikes used to meet the trip service. The additional PV panel and electronic components installed on each dock-less bike also increase the TNEI impacts for dock-less bikes. The rebalancing stage accounts for 39% of the TNEI for the dock-less system due to the smog, ozone depletion, SO_2, and other impact categories.

The value of TNEI ranges from 7.75E-05 to 5.09E-04 for the station-based system and from 1.10E-04 to 2.02E-04 for the dock-less system when considering the best and worst scenarios. The overlap implies that the station-based system may potentially have lower TNEI if the service can be provided with less number of stations and docks. Hence, the different BSS setup and operation practices in different cities may result different conclusions on whether the station-based or dock-less system has lower TNEI.

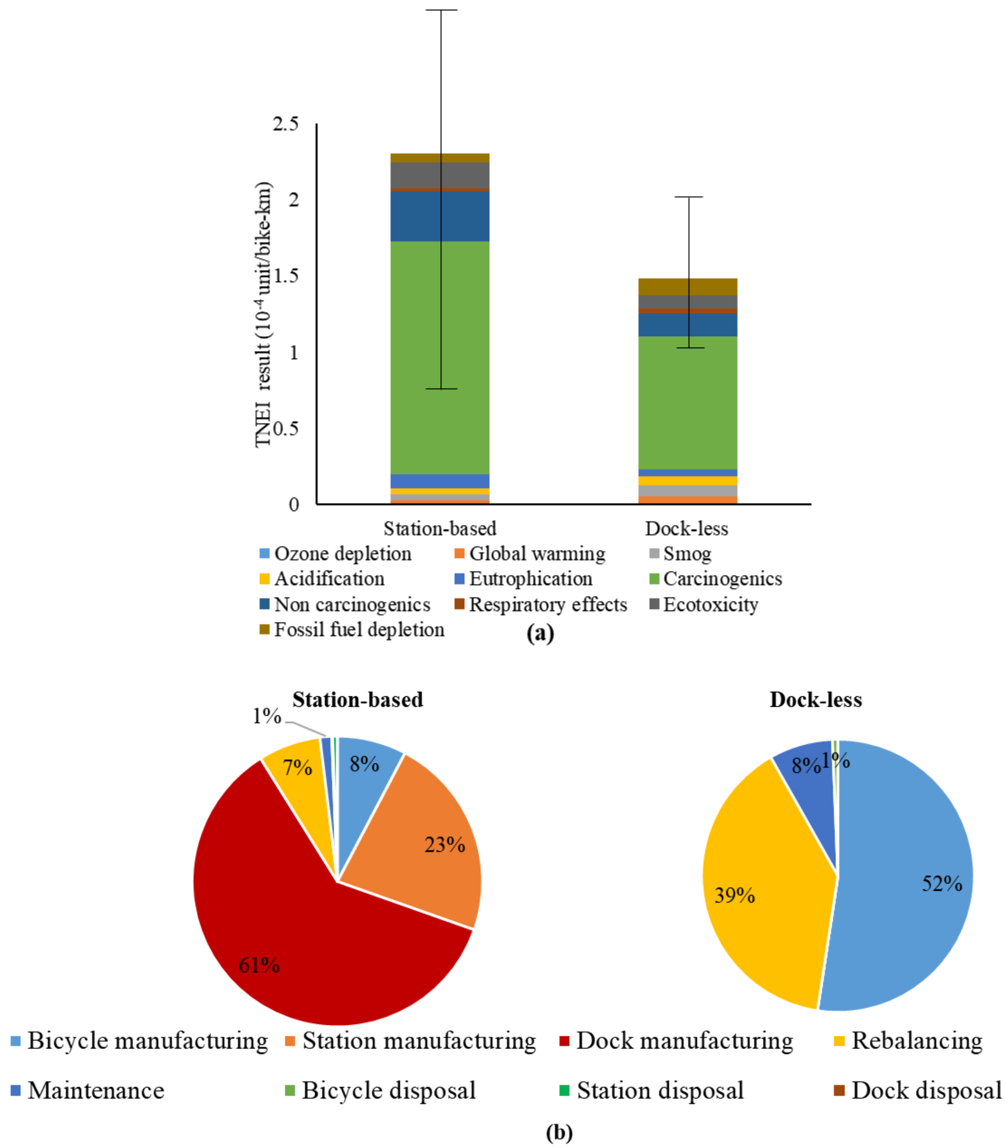


Figure 2-4 TNEI results of station-based and dock-less BSSs. (a) aggregated impacts from different impact categories; (b) contributions to TNEI from different life cycle stages

Similar to the GHG emission analysis, we analyzed the sensitivity of key parameters and the break-even points where the two systems are able to obtain the same TNEI values. For the station-based system (Fig. 5a), TNEI is the most sensitive to the number of docks in the system (#dock/bike-km). If the number of docks can be reduced by 40% without sacrificing the service, the station-based system would have less TNEI than the dock-less system. This improvement is attainable through several methods. First, design the system with the consideration to minimize underutilized docks. Second, prolong the service time of the docking infrastructure (#dock/bike-km value can be reduced by increasing the total trip distances served by these docks). Most of the station-based systems are still relatively new, and none of the existing programs have gone through replacing the stations and docks. Proper maintenance may be able to extend the use life of the sharing infrastructure beyond the estimated 10-years life time to 15-years. In terms of the dock-less system (Figure 2-5b), its TNEI can be higher than the station-based system, when it needs twice the bikes as in the base scenario. Because the dock-less bikes may be more vulnerable to vandalism than the station-based bikes (O'Kane, 2018), it is possible that the dock-less bikes have a shorter lifetime and need more frequent bike replacement. In this case, the operator will need to continuously add more bikes into the system to maintain its service, requiring a larger #bike/bike-km value.

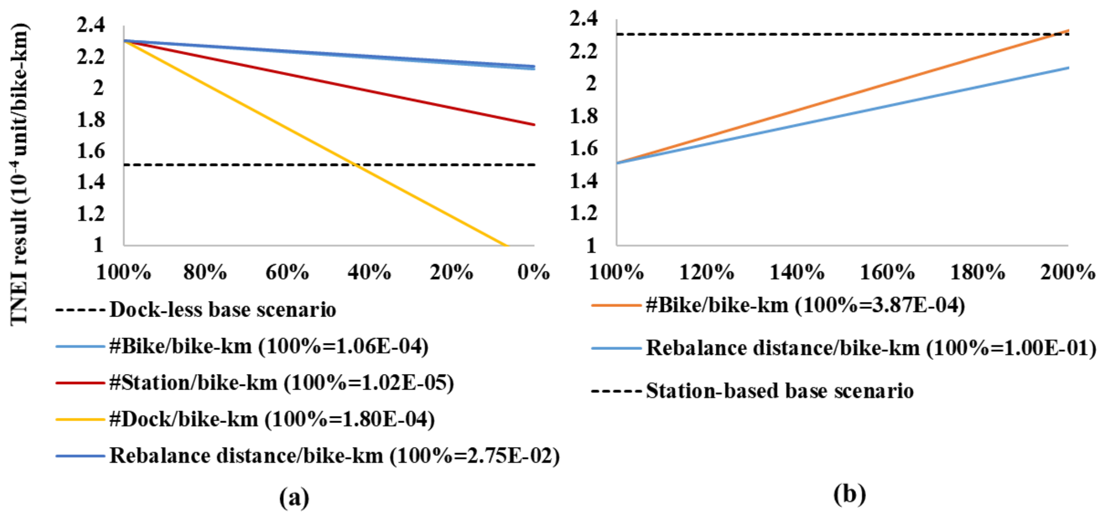


Figure 2-5 TNEI break-even points and parameter sensitivities: (a) changing parameters in the station-based BSS to achieve same TNEI as the base dock-less BSS; (b) changing parameters in the dock-less BSS to achieve same TNEI as the base station-based BSS

2.3.2 Net environmental impacts with the consideration of mode substitution

The results discussed above only include the negative environmental impacts caused by establishing and operating the BSS. However, BSS may also make positive environmental benefits by substituting more emission intensive transportation modes. In this section, we analyze the net impacts of BSS under different transportation mode substitution scenarios in terms of GHG emissions and TNEI value.

Figure 2-6 summaries the GHG emission and TNEI results of different transportation modes. Traveling by passenger car has the highest impacts for both GHG emissions rate and TNEI value. According to the base scenario results of BSSs, BSSs are not necessarily the more sustainable transportation modes compared to bus, electric bikes, and personal bikes. Hence, to counteract the environmental footprints from the BSSs, car trip substitution rate is the primary concern. Table 2-6 lists the GHG emission and TNEI values for 10 mode substitution scenarios. The method of setting the scenarios has been discussed in Section 2.2.5 and the emission rates presented in the Figure 2-6 are used as inputs to calculate the results.

The results in Table 2-6 BSS environmental impacts with different mode substitution scenarios suggest that the station-based system has a greater potential in contributing to GHG emission reduction in the real-world scenarios. In the scenarios with real-world transportation mode substitution data (Scenarios 1 to 5), the station-based system shows the ability of reducing GHG emissions (-3 to -34 g CO_{2}-eq/km). Only 7% of the bike sharing trips are required to substitute car trips to reach neutral GHG emission (Scenario 7), on the basis of the median scenario (Scenario 6). On the other hand, however, under the current operation efficiency, dock-less system may not be able to serve as a GHG abatement mode. At least 34% of the bike sharing trips need to substitute car usage for dock-less BSS to achieve GHG emission reduction, which is much higher than the currently reported level. Hence, if the bike share trips cannot replace a higher ratio of car trips, the current dock-less system may increase the GHG emission burden to a city. An effective way to lower the breakeven car trip substitution rate is to lighten the GHG emission rate of the dock-less system. Based on the sensitivity analysis in section 3.1.1, increasing the dock-less BSS efficiency through more strategic rebalancing and higher bike utilization can reduce the emission factor for the dock-less BSS.

In terms of TNEI, none of the five real-world substitution scenarios have positive TNEI values, regardless of being station-based or dock-less BSS. At least 45% and 26% of the bike sharing trips need to replace car trips in order to obtain TNEI benefits for the station-based and the dock-less system, respectively. This result shows that it may not be feasible for BSS to have positive TNEI benefits only through increasing the car trip substitution rate, because the thresholds are much higher than the survey results in Scenarios 1 to 5. Thus, it is necessary to combine car trip replacement with other improvements we discussed in section 3.1.2 to reduce the unit TNEI impact per bike-km of BSS.

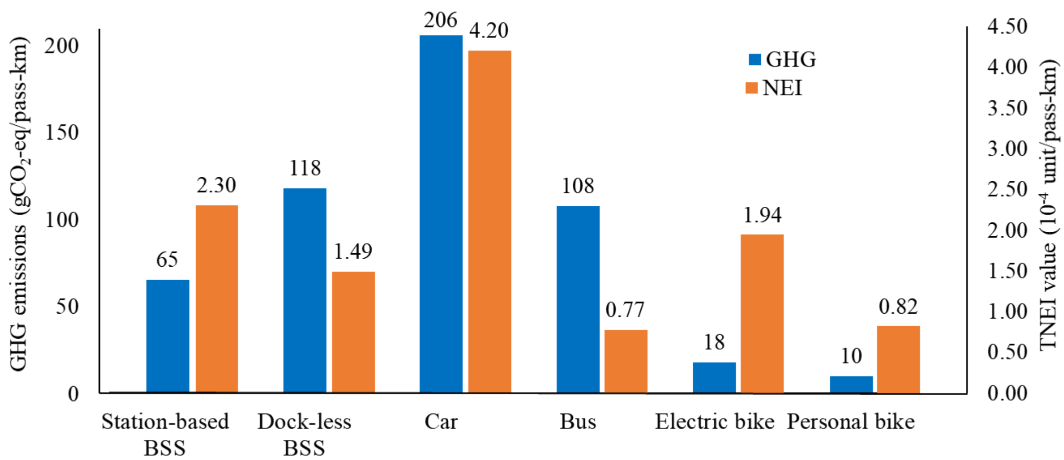


Figure 2-6 GHG emission rates and TNEI values per passenger-km of different transportation modes

Notes: The data of station-based and dock-less BSSs are from the base scenario of this study. The data of car, bus, electric bike, and personal bike are from Ecoinvent (Wernet et al., 2016).

Table 2-6 BSS environmental impacts with different mode substitution scenarios

	New trip	Car	Bus	Bike	Walk	GHG Emission ($g\ CO_2$ eq/km) Station-based	GHG Emission ($g\ CO_2$ eq/km) Dock-less	TNEI (10^{-4} unit/km) Station-based	TNEI (10^{-4} unit/km) Dock-less
Scenario 1	1%	20%	40%	9%	30%	-21	34	1.08	0.28
Scenario 2	2%	24%	44%	8%	22%	-34	21	0.89	0.09
Scenario 3	4%	14%	45%	6%	31%	-14	41	1.32	0.52
Scenario 4	13%	22%	20%	8%	37%	-3	52	1.16	0.36
Scenario 5	3%	6%	57%	8%	25%	-11	44	1.54	0.74
Scenario 6	3%	20%	44%	8%	25%	-25	30	1.06	0.26
Scenario 7	3%	**7%**	44%	8%	**38%**	**0**	55	1.58	0.78
Scenario 8	3%	**34%**	44%	8%	**11%**	-55	**0**	0.45	-0.35
Scenario 9	3%	**45%**	44%	8%	**0%**	-77	-22	**0.00**	-0.80
Scenario 10	3%	**26%**	44%	8%	**19%**	-38	17	0.80	**0.00**

2.4 Conclusions

This study compared the life cycle environmental impacts of the station-based bike sharing system and the dock-less system. The base scenario results show that the dock-less bike sharing system has a higher GHG emission factor than the station-based system, mainly due to the more intensive rebalancing demands. The analyses of break-even points and parameter sensitivity further support this point. Rebalancing need is the most sensitive parameters for the GHG emission performance in both BSSs.

The TNEI analysis of the two systems shows that, taking all the impact categories into account, the station-based system has a higher TNEI value than the dock-less system in the base scenarios. The additional environmental impact is mainly due to the upstream impacts of aluminum and steel components used for docking infrastructure manufacturing, especially the carcinogenic emissions in metal processing. For the dock-less system, bike manufacturing and rebalancing work are the two major contributors of the environmental impacts. The results of breakeven points and parameter sensitivity test suggest that the number of docks and bikes needed to serve the same demand are the key determinants of the TNEI performance for the station-based and dock-less system.

We also considered the environmental benefits that the BSS could bring through transportation mode substitution. To achieve environmental benefits and contribute to GHG emission reduction, the bike sharing trips need to substitute car trips. With the current system setup and operation efficiency, station-based system can better help reduce GHG emission than the dock-less system. For the dock-less system, to realize carbon reduction, at least 34% of the bike sharing trips need to replace car usage. Besides increasing the car mode substitution rate, the system efficiency of BSS also needs to be improved through prolonging service time of docks and improving bike utilization level in order to achieve positive TNEI.

The results from this study provide several insights for the city decision-makers and bike sharing operators to improve the sustainability of bike sharing systems. The most efficient way to decrease the GHG emission rates for the two systems is alleviating the rebalancing needs. This can be achieved by optimizing the bike distribution and rebalancing scheme and a lot of effort has been put into this field. Liu et al. (2016) applied a heuristic algorithm to optimize the station site allocation. The improved station sites could help reduce the unbalanced demand and improve the bike usage, compared with the existing system. Shui and Szeto (2018) minimized the unmet trip demand and CO_2 emission cost via optimizing the vehicle loading/unloading and route planning problem with a dynamic approach. Another way to reduce the environmental cost of rebalancing work is to change the rebalancing strategy. The BSS in Portland employed the financial incentives to encourage users helping to rebalance. Also, the staffs could ride electric cargo bikes instead of driving vans, to perform the rebalancing work (Maus, 2016). Through these innovative rebalancing strategies, the automobile usage and the system operation costs can be decreased significantly. However, riding the e-cargo bikes would require higher labor cost and extend the rebalancing time which may impact ridership. Additionally, incentivizing car users to switch to use bike sharing is critical. Setting stations and bikes in regions with higher demands or coordinating BSS with public transport infrastructure can help make it easier for bike sharing to substitute car use. Developing less car-centered and more bike friendly cities could also encourage the trip mode switch and increase bike share use. Furthermore, prolonging the service time of the docks and stations in station-based systems can significantly mitigate the impacts in the manufacturing phase. This can be realized via careful maintenance on these infrastructures. Developing lighter dock designs is another way to reduce the impacts. For the dock-less system, increasing the utilization rate of existing bikes (each bike serving more trips) is an effective method to reduce the environmental footprints. To achieve this, careful planning and design are crucial. Another emerging operation strategy is to only allow users to check in/out the dock-less bikes inform/to specific areas marked by signs or geo-fences. These areas can serve as 'virtual stations' to increase the system efficiency, reduce the rebalancing demand, and avoid consuming metals for building physical stations and docks.

Although this study has the merit of being the first comparative LCA of station-based and dock-less bike sharing systems, there are several limitations need to be noted. First, the input data for the station-based system was based on our communication with one bike share program in a large metropolitan area. Many factors can impact the BSS operation (such as weather, local culture, spatial layout of the city, management strategies etc.) City-to-city variations or program-to-program differences may exist. When BSS operation data from multiple programs or cities become available, comparisons across cities and different programs will help us better understand the life cycle environmental impacts of BSS. Second, because dock-less systems are still very new in most cities, very few data can be obtained, which makes the uncertainty of our dock-less system analysis high. Dock-less BSS may have different bike lifespan, the number of bikes in operation, bike lost rate, and rebalancing needs. Although we have identified the breakeven points between the two systems to capture the potential changes due to different input data, better operation data from the dock-less system can improve the accuracy of the results. Third, we still omit some stages in the life cycle, including component packages, paving bike lane and road, construction of material extraction and bike manufacture factories. Additionally, depending on the locations of the stations, the solar panels may not be able to provide sufficient energy to meet all the demands at each station. In this case, the batteries need to be recharged using grid power. Due to the limited data on this, we did not include this additional electricity consumption in the analysis. In terms of the environmental benefit, we only consider the emission reduction from mode substitution. We did not account for the reduced ownership of bikes and private cars as a result of the shared economy. Additionally, the bike sharing system could encourage users to switch from car trips to multi-modal trips with the shared bikes serving as the first and/or last mile mode and public transportation as the middle leg. This can further increase the potential emission reduction contributed by BSSs. A survey on the car, bike, and electric bike ownership change due to having access to bike sharing, and more detailed data on travel mode change can provide the relevant data to fill these gaps. Furthermore, system expansion of BSS is not considered in the analysis. Putting in more bikes in the system can change the rebalance needs, and at the same time influence the usage rate and maintenance frequency. A model captures the dynamics of system evolution can bring additional insights.

In summary, the BSSs, both station-based and dock-less systems, are promising to serve as sustainable transportation modes, if they are well designed and operated. When determining which system is greener for developing new BSS or modifying the existing system, the decision makers should consider two key factors. First, from the global warming’s perspective, an optimal distribution of stations and bikes can significantly decrease the rebalancing demand and increase the car trip replacement rate, thereby alleviate the carbon emission for both systems. Second, from the perspective of TNEI, how to prolong the service life of stations and how to increase bike utilization are the crucial determinants for the station-based and dock-less system, respectively.

CHAPTER 3. OPTIMAL DESIGN OF BIKE SHARING SYSTEM FROM THE LIFE CYCLE PERSPECTIVE

3.1 Introduction

The life cycle assessment results on station-based and dock-less BSSs (Chapter 2) show that thoughtful design and operation is required for the BSS to provide emission reduction and other environmental benefits. If not well designed and operated, such as the worst scenarios in Chapter 2, the BSS may generate more emissions than other transportation modes (e.g., the bus). An inefficient system not only causes material waste and emission generations but also increases the operation cost and creates negative user experience. However, currently, the city planners and BSS operators lack guidelines to help them improve system design and operation from the life cycle perspective. From the results in Section 2.3.1, we can see that the dock-less system is more GHG emission intensive than the station-based one, and the bike rebalancing and bike manufacturing are the two major factors contributing to GHG emissions. In addition, more and more cities are planning to launch dock-less systems (NACTO, 2017). Therefore, this chapter will focus on the dock-less system to provide improvement suggestions for the decision-makers and operators from the life cycle perspective, considering both bike fleet size and the rebalancing frequencies.

Bike rebalancing is one of the most important factors for both operation cost and environmental impacts (Shui and Szeto, 2018). A lot of researches have focused on optimizing the bike rebalancing strategies in recent years. The bike-sharing rebalancing problem (BRP) is well-known as solving optimal rebalancing routes and loading/unloading quantities to improve the system performance and customer satisfaction (Liu et al., 2018). Szeto & Shui (2018) investigated the solution of the static bike rebalancing problem with multiple rebalancing vehicles, aiming to minimize the demand dissatisfaction and total service time. Although they reduced the demand dissatisfaction through changing the target inventory level of each station, the total number of bikes was fixed in their study. However, the bike fleet size is an important system design factor shat should be optimized as well. Shui and Szeto (2018) proposed a dynamic solution of BRP, using a hybrid rolling horizon artificial bee colony algorithm to minimize the total unmet trip demand and also the GHG emission from vehicle travelling. They found that shorten the loading/unloading time per bike can help to reduce the unmet trips and fuel consumption. However, they only considered the GHG emission of rebalancing vehicle operation, ignoring the upstream impact of manufacturing different number of shared bikes and rebalancing vehicles, which will also impact the system's life cycle emissions.

The existing studies only focus on improving the operation of a given BSS, having the number of bikes, stations, and rebalancing vehicles as fixed constants (e.g., optimum operation for an existing system). However, the existing system may not have the optimum design. For example, there are many signs that the dock-less systems are over supplied with bikes. In Beijing, there were more than 16 million shared bikes in this traffic-clogged city, but many of them were abandoned and piled on the street (Hernandez, 2017). Additionally, potential tradeoffs exist between the number of bikes required in a system and the rebalancing frequency, from the life cycle perspective. Studies on the car sharing system found that having more cars can reduce the empty vehicle miles due to car rebalancing, and understanding this tradeoff could help operators make decisions on the fleet-size and rebalancing strategy for a specific city (Spieser et al., 2016). Similar to the car sharing system, the tradeoff between fleet size and rebalancing demand could also affect the life cycle environmental impacts of a BSS.

To identify the optimal BSS design and rebalancing strategies, we proposed a two-phase framework to minimize the system carbon footprint from the life cycle perspective, using a real-world dock-less BSS in Xiamen, China as a case study. First, we developed a simulation model to identify the minimum bike count and bike locations required to satisfy all customer demands within a given period. The length of the period is linked to the bike rebalancing frequencies. Then, we followed the cluster-first and route-second procedure to solve the BRP for each bike rebalancing event, minimizing the total rebalancing vehicle distances. Using the minimum required bike fleet size and corresponding rebalancing vehicle distances, we can use the LCA model we developed in Chapter 2 to analyze the tradeoffs between bike fleet size and rebalancing frequency in terms of the system's life cycle GHG emissions. Based on the results, we can identify the optimal system design that generates the lowest system carbon emissions. This study can provide decision makers tools and guidelines to improve dock-less system design and operation strategies to maximize the system's environmental performance.

3.2 Data and method

3.2.1 Data

The dataset we used in this study is from a dock-less BSS in Xiamen, China, containing 408,119 bike trip records from 7AM to 12AM over six days (09/11, 09/13, 09/15, 10/01, 10/04 and 10/07) in 2017, retrieved using global positioning system (GPS) devices installed on the bikes. Each data point includes a unique bike ID, start and end time (to the seconds) of the trip, the location (longitude and latitude) of trip origins and destinations (OD), the trip distance (to the meters), and the bike trajectories. To clean the raw data, we applied the following procedures: 1) convert all the locations from the GCJ-02 coordinate system to the WGS-84 system, including the trajectories; 2) eliminate trips with OD locations outside of the city boundaries, which is a polygon that sketches the city outline; 3) for trips missing either origin or destination locations, we assigned the first or the last trajectory point as their O/D location, respectively; 4) eliminate trips whose durations are less than 10 seconds; and 5) eliminate trips whose distances are less than 10 meters. We chose 10 seconds and 10 meters as the cutoff values because that most of the data error reported as 0 second and 0 meter and only very few trips (<0.01%) reported duration or distance between 0 to 10 second/meters. 10 is safe enough to exclude all error data but will not have impacts on the further study. After data cleaning, 92.8% of the trips were retained.

In this study, we chose 09/13/2017 (Wednesday) and 10/07/2017 (Saturday) as a typical weekday and weekend, respectively, to build the base scenario and represent the city's bike use demand. After the data cleaning process, we found that 50,564 unique bikes served 79,854 bike trips on the weekday, while 35,681 unique bikes served 54,661 bike trips on the weekend. To acquire a representative result, we also analyzed the other days and compared with the typical days we chose in section 3.3.4

3.2.2 Identifying the minimum number of bikes required to serve the demand

As shown in the above described data, currently, one bike only serves an average of 1.6 trips on a weekday and 1.5 trips on a weekend. The low bike utilization rate indicates system inefficiency and an oversupply of bikes. As discussed in Section 2.3.1, low bike utilization rate leads to a large bike fleet, causing unnecessary material waste and emission generation. In this section, we built a simulation model to identify the minimum bike fleet size that can meet all the existing trip demands. Because the current system is over-supplied with bikes, we can reasonably assume that the recorded demands reflect the bike sharing use demands in the city.

As a simplification, we assume that the daily demand is representative and will be repeated in the following day. Within the day, the system operator may rebalance the bikes one or more times. Before each rebalancing, we can use the simulation model presented in Figure 3-1 to identify the minimum number of bikes required and the bike locations at the beginning of the period to satisfy all the trip demands within this period of time. In the simulation model, an ***event$_i$*** is a BSS user activity, either picking up or dropping off a bike, containing ***tripID***, ***bikeID***, ***time***, demand ***location*** and ***demand type*** (pick up or dropoff). The variables ***bikescheme*** and ***endstatus*** are created to store the bike information, both containing ***bikeID***, ***location*** and ***availability***. For every pickup demand, we identify the nearest available bike ***j*** to this user's trip origin. If the distance between the nearest available bike and the user is less than a predefined threshold, we assume that the user will pick up this nearest available bike to serve the trip and we assign the bike to this trip. We used 500m in this study to represent a preferable walking distance. Other relevant studies used walking distances ranging from 300m to 700m, so we chose a middle value for our study (Mete et al., 2018; Zhang et al., 2017). If the identified nearest available bike is too far away (exceeding this predefined threshold), we will generate a new bike ***k*** at the demand location and also add it to the required initial bike distribution ***bikescheme***. For every drop-off demand, the specific bike used for this trip is then located at the drop-off location and becomes available for pick up. We sort the events by time and run the simulation model to go through all the events to account for the bike availability change over time, recording the bike ***endstatus*** and the addition of new bikes. At the end of the simulation, we will obtain the updated required initial ***bikescheme*** at the beginning of the period and the bike locations at the end of the period. We then rerun the simulation with the updated initial bike distribution (the obtained output from the model) as model inputs. With new bikes added into the system as part of the initial distribution, the nearest available bike to a customer could change, which modifies the bike flow and causes the nearest available bike to another customer exceeding the predefined threshold. In this case, another bike will need to be added. We repeat this process until the required initial bike fleet size is stabilized. Then the initial bike distribution ***bikescheme*** and the final ***bikestatus*** locations of the bikes are recorded to identify the bike rebalance demands.

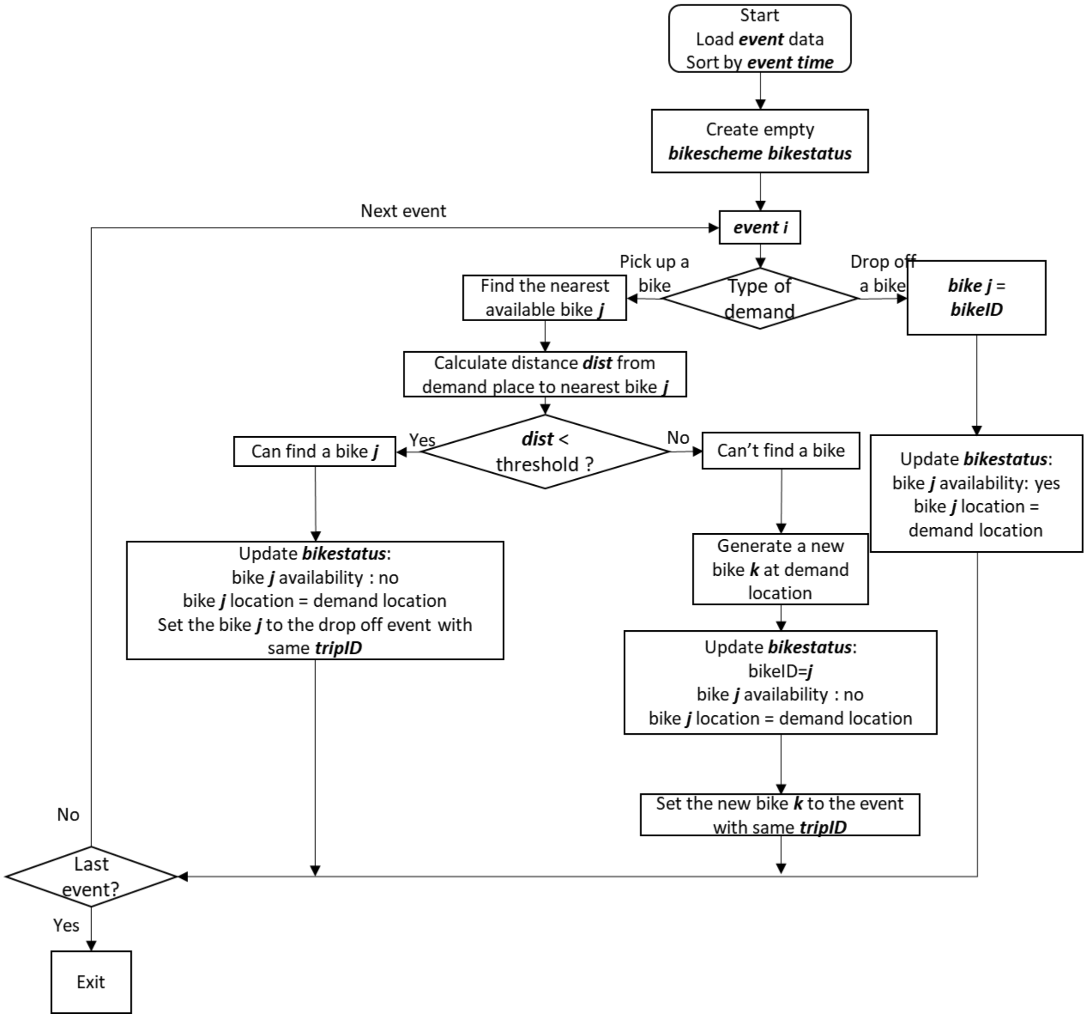


Figure 3-1 Model framework to identify the minimum bike fleet size to satisfy the demands within a given period of time

3.2.3 Bike rebalancing

Using the initial and end bike locations for a given period identified in Section 3.2.2., this section identifies the rebalancing demand and optimizes the rebalancing vehicle routing. Before the operator assigns rebalancing vehicles to move the bikes, a pre-planned route needs to be determined for each vehicle. This pre-planned route should minimize the total distances traveled by the rebalancing vehicle to minimize operation costs, energy consumption, and the GHG emission from the bike rebalancing.

3.2.3.1 Rebalancing demand

Ideally, the operator of a dock-less system should distribute individual bikes at scattered locations (e.g., one at each block), matching the ideal initial bike distribution scheme to minimize walking for potential customers. However, this will be very time consuming and inefficient. In the actual operation, the operator will collect the scattered bikes from over-supplied zones and drop them as a group to some specific nodes (e.g. metro station, bus station, shopping mall, residential areas), which can be treated as pseudo-stations (compared to the physical stations in a station-based system). To simplify our model, we divide the Xiamen City into grids with a resolution of $500m \times 500m$, and the center of each grid is the potential node for bike rebalancing. The number of bikes in each grid before and after the rebalancing is known from the end locations and the bike distribution scheme locations, respectively. The bike rebalancing demand is defined as the difference of total bike count in each grid at the end of the period and the bike distribution scheme at the beginning of the next period. We assume no bike demand change during the rebalancing time. The BRP in this study is to find the shortest vehicle routes that can move bikes from the grid cells with excessive bikes to those with insufficient bikes.

3.2.3.2 Problem description and key assumptions

The basic setting of the optimization problem is described as follows. Given a complete directed graph $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{A})$, where $\boldsymbol{V}$ is the set of nodes and $\boldsymbol{A}$ is the set of all possible edges between two nodes. Vertex 0 is the depot which is located at the center of the city, which is used by other similar studies (Andriankaja et al., 2015). We will discuss the effect of having multiple depots and the depot locations later in Section 3.3.4. The depot is the bike warehouse and rebalancing vehicle parking lot of the BSS and serves as the start and end point for each vehicle route. We assume that the depot can store sufficient bikes for the rebalancing vehicles to load/unload. A travelling distance $\boldsymbol{dist_{i,j}}$ is associated with each possible arc $\boldsymbol{(i,j)} \in \boldsymbol{A}$ and is calculated as the great circle distance from node $\boldsymbol{i}$ to $\boldsymbol{j}$. Each node $\boldsymbol{i}$ has a demand $\boldsymbol{d_i}$, which is decided beforehand (Section 3.2.3.1). If $\boldsymbol{d_i} > 0$, the rebalancing vehicle needs to collect bikes from this node; and if $\boldsymbol{d_i} < 0$ then the vehicle will deposit $\boldsymbol{d_i}$ bikes to the node, for $\boldsymbol{i} \in \boldsymbol{V} \backslash \{\boldsymbol{0}\}$. The node with $\boldsymbol{d_i}=0$ will not be visited and we can ignore these nodes in our model. A rebalancing fleet of a total $\boldsymbol{m}$ homogeneous vehicles with the same capacity $\boldsymbol{C}$ is available at the depot. The number of bikes stored in each vehicle at any given time can never be negative or exceed the capacity limit $\boldsymbol{C}$. Each vehicle route starts from the depot, travels to a sequence of target nodes, and returns to the depot after finishing the rebalancing work, without visiting the depot during the rebalancing. Each vehicle can load some bikes to start and carry some bikes back to the depot at the end of the route. Each node is only visited once by one vehicle. In the case that a grid has a rebalancing demand of more than $\boldsymbol{C}$ bikes, we created "ghost nodes" to account for the additional trips required to revisit this node (more details in Section 3.2.3.4). In this problem, we ignore the routes during bike collection inside of the grid and we only optimizes the routes among the nodes that have unbalanced demand. The BRP determines the optimal routes of $\boldsymbol{m}$ vehicles through the graph, with the goal of minimizing the total travelling distance of all the operating vehicles.

3.2.3.3 Node clustering

The BRP described in Section 3.2.3.2 is a sub-problem of the multiple travelling salesman problem (**m-TSP**) with pickup and drop-off demands. The m-TSP is defined as the shortest route allowing more than one salesman to collectively visit all destinations. The m-TSP has a much higher level of complexity and computational intensity compared to TSP (Bektas, 2006). As a simplification, we convert the m-TSP into TSP through node clustering. By identifying a cluster of nodes that will be visited by one rebalancing vehicle, the optimum routing of this vehicle is a TSP.

A common clustering method is k-means clustering, which assigns the closest points into a cluster. However, if we only consider the distance among nodes, the total bike rebalancing demand in a cluster may not be satisfied by one vehicle due to the capacity limitation. For example, the sum of $\boldsymbol{d_i}$ in a set of nodes could be 70 (this collection of grids have an overall excessive bike supply of 70) while the vehicle capacity could be only 60 (the rebalancing vehicle can only carry a maximum of 60 bikes back to the depot). This problem is known as a capacitated clustering problem (CCP) (Shieh and May, 2001). To cluster the nodes under the limit of vehicle capacity, we proposed a modified k-means clustering algorithm (Figure 3-2**)**. We used a Mixed Integer Linear Programming (MILP) problem to solve the cluster assignment, instead of setting the node to their closest centroid. The MILP minimizes the total distance of each node to their assigned cluster centroid, with the constraints of vehicle capacity. Given a set of nodes $\boldsymbol{i} \in \boldsymbol{V}\backslash\{\boldsymbol{0}\}$ and a set of centroids $\boldsymbol{k} \in \boldsymbol{K}$**,** where the number of elements in $\boldsymbol{K}$ equals to

$\boldsymbol{m}$, we first calculated the distance $\boldsymbol{dist_{ik}}$ where each element is equal to the distance from node $\boldsymbol{i}$ to centroid $\boldsymbol{k}$. We introduced a binary variable $\boldsymbol{y_{ik}}$, which equals to 1 when node $\boldsymbol{i}$ is assigned to the centroid $\boldsymbol{k}$ and 0 otherwise. The formulation of the modified k-means clustering problems is presented in equations (1) to (3).

$$\boldsymbol{min\ obj} = \sum_{\boldsymbol{i} \in \boldsymbol{V}} \sum_{\boldsymbol{k} \in \boldsymbol{K}} \boldsymbol{dist_{ik}}\, \boldsymbol{y_{ik}}, \quad \boldsymbol{y_{ik}} \in \{\boldsymbol{0}, \boldsymbol{1}\}, \boldsymbol{i} \in \boldsymbol{V} \backslash \{\boldsymbol{0}\}, \boldsymbol{k} \in \boldsymbol{K} \tag{1}$$

$$\boldsymbol{s.t.} \sum_{\boldsymbol{k} \in \boldsymbol{K}} \boldsymbol{y_{ik}} = 1,\ i \in \boldsymbol{V} \backslash \{\boldsymbol{0}\} \tag{2}$$

$$-\boldsymbol{C} \leq \sum_{\boldsymbol{i} \in \boldsymbol{V} \backslash \{\boldsymbol{0}\}} \boldsymbol{d_i} \boldsymbol{y_{ik}}, \leq \boldsymbol{C},\ \boldsymbol{k} \in \boldsymbol{K} \tag{3}$$

The objective function (Equation 1) minimizes the sum of the distances from each node to their assigned cluster centroid. Equation 2 ensures that each node will only be assigned to one cluster. Equation (3) imposes that the net rebalancing demand imbalance in each cluster should satisfy the vehicle capacity limitation. The output of the model is the optimal cluster assignment which minimizes the sum of distance from node $\boldsymbol{i}$ to their assigned cluster centroid $\boldsymbol{k}$. After the first run, we will move the centroids to the center of each cluster we obtained in the last step, and then repeat the clustering assignment until the termination criteria is met. The gap of the objective value is calculated as the absolute value of the percent change rate on ***obj*** of this run compared to the last run.

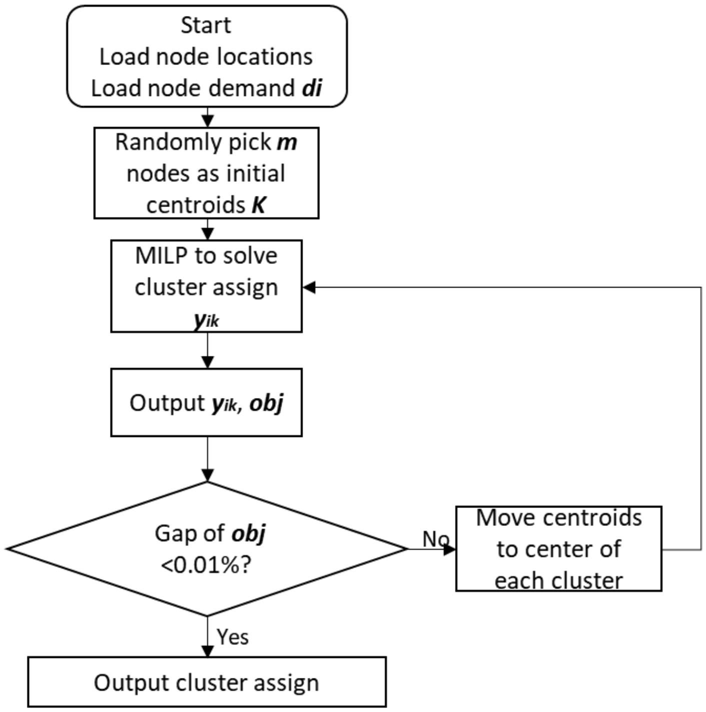


Figure 3-2 Modified k-means clustering algorithm

3.2.3.4 Vehicle routing problem formulation

After identifying the rebalancing clusters, this section solves the optimal vehicle routing and bike loading/unloading within each cluster (i.e. the sequence to visit the nodes). $\boldsymbol{Vp}$ is the set of nodes in cluster $\boldsymbol{P}$, including the depot ($\boldsymbol{V_P\{0\}}$). For a given cluster $\boldsymbol{P}$, we formulate the vehicle routing problem as a Mixed Integer Linear Programming (MILP) problem, adopting the approach presented in (Dell'Amico et al., 2014). We first introduced a binary variable $\boldsymbol{x_{ij}}$, which equals to 1 when a vehicle travels from node $\boldsymbol{i}$ to node $\boldsymbol{j}$, and 0 otherwise. The $\boldsymbol{dist_{ij}}$ is defined as the great circle distance from $\boldsymbol{i}$ to $\boldsymbol{j}$, which is pre-calculated for each cluster. Then, an integer variable $\boldsymbol{q_j}$ is defined as the quantity of bikes in the rebalancing vehicle after loading/unloading bikes at node $\boldsymbol{j}$. The BRP can be formulated as:

$$\boldsymbol{min \sum_{i \in V_P} \sum_{j \in V_P} dist_{ij}\, x_{ij}} \tag{4}$$

$$\textbf{s.t.} \quad \boldsymbol{\sum_{i \in V_P} x_{ij} = 1,\ j \in V_P} \tag{5}$$

$$\boldsymbol{\sum_{j \in V_P} x_{ij} = 1,\ i \in V_P} \tag{6}$$

$$\sum_{i\in S}\sum_{j\in S} x_{ij} \leq |S| - 1,\ S \subseteq V_P\backslash\{0\}, S \neq \emptyset \tag{7}$$

$$q_i \geq (q_j - d_j)x_{ij},\ i \in V_P, j \in V_P\backslash\{0\} \tag{8}$$

$$q_j \geq (q_i + d_j)x_{ij},\ i \in V_P, j \in V_P\backslash\{0\} \tag{9}$$

$$max\{0, d_j\} \leq q_j \leq min\{C, C + d_j\},\ j \in V_P \tag{10}$$

$$q_0 = \begin{cases} \sum_{i\in V_P} d_i, & if \sum_{i\in V_P} d_i > 0 \\ 0, & if \sum_{i\in V_P} d_i < 0 \end{cases} \tag{11}$$

$$x_{ij} \in \{0, 1\},\ i, j \in V_P \tag{12}$$

The objective function (Equation 4) minimizes the total travel distance of the vehicle. Equations (5) and (6) ensure that each node, including the depot, can only be visited exactly once. Equation (7) is the subtour elimination constraint (Gutin and Punnen, 2007), which assures that each vehicle route is a Hamiltonian cycle. Equations (8) and (9) are the vehicle capacity constraints. When a vehicle travels from node $\boldsymbol{i}$ to node $\boldsymbol{j}$ (i.e. $\boldsymbol{x_{ij}} = 1$), $\boldsymbol{q_j} = \boldsymbol{q_i} + \boldsymbol{d_j}$., and if otherwise ($\boldsymbol{x_{ij}} = 0$), these equations give the lower bound of bike stocks in the vehicle (i.e. nonnegative). Equations (8) and (9) are nonlinear constraints. A standard ‘big M’ method can be applied to transform them into linear constraints as shown in Equations (13) and (14) (Dell’Amico et al., 2014).

$$q_i \geq (q_j - d_j) - M(1 - x_{ij}),\ i \in V_P, j \in V_P\backslash\{0\} \tag{13}$$

$$q_j \geq (q_i + d_j) - M(1 - x_{ij}),\ i \in V_P, j \in V_P\backslash\{0\} \tag{14}$$

where M is an extremely large number.

Equations (10) and (11) ensure the upper and lower bounds of bike quantities in the vehicle after visiting node $\boldsymbol{j}$. Although we limit each node can only be visited once, there are nodes which have too many bikes need to be loaded/unloaded, exceeding the vehicle capacity. For example, node $\boldsymbol{i}$ may have a total of 100 bikes to be moved, but the vehicle capacity is only 30. To allow multiple trips to be made to serve this rebalancing demand, we can create three “ghost nodes” $\boldsymbol{g_1}$, $\boldsymbol{g_2}$, $\boldsymbol{g_3}$ and add them to the original node set $\boldsymbol{Vp}$. The “ghost nodes” have the same locations as the original node $\boldsymbol{i}$. The original node i and the first 2 ghost nodes $\boldsymbol{g_1}$, $\boldsymbol{g_2}$, have

$\boldsymbol{d_i} = \boldsymbol{d_{g1}}=\boldsymbol{d_{g2}}=30$ and the last node has $\boldsymbol{d_{g3}} = 10$. This can simplify the multi-visit problem without modifying our model.

3.2.4 Evaluating the tradeoffs between bike fleet size and rebalancing frequency

In the Sections 3.2.2 and 3.2.3, we proposed the modeling framework to obtain the minimum bike fleet size and the corresponding shortest vehicle routes to serve all the rebalancing demand during a given time period. The different rebalancing frequencies will cut the day into different periods and will have different initial and ending bike distributions and rebalancing needs. This section evaluates different rebalancing frequencies and the corresponding life cycle carbon emissions to identify the optimal system design and rebalance strategies.

In this study, we ranged the rebalancing frequency from one to three times a day. If the system only rebalances the bikes once a day, it normally happens during the night (12AM, a.k.a. night rebalancing). The system will reposition the bikes at the end of the day to their initial locations at the beginning of the day. When the system has additional rebalancing during the day, it should happen in the periods with low bike use demand. Based on the demand distribution presented in Figure 3-4 Pickup demand pattern, we chose 10AM and 1PM as potential mid-day rebalancing options. Therefore, when the rebalancing frequency is one, two, and three times a day, the rebalancing points will be 12AM, 12AM + 1PM, and 12AM + 10AM + 1PM, respectively.

Different bike rebalancing frequencies will lead to different bike distribution schemes and rebalancing demands. As shown in Figure 3-3, if the system only rebalances once at night (the Rebalance 1 case), we first run all the trip demand in the day with the simulation framework and we can obtain the bike initial locations ***Scheme 1*** and end locations ***End 1***. The rebalancing work will redistribute the bikes at the end of the day to their initial locations and the rebalancing demand will be the differences between ***End 1*** and ***Scheme 1*** in each grid cell. If the system rebalances twice each day (the ***Rebalance 2*** case), we separated the demand into 2 segments (***Demand 1*** and ***Demand 2***) and conducted the simulation for each demand period separately to obtain the minimum fleet size for each segment and the corresponding bike distribution ***Scheme1, End1, Scheme 2,*** and ***End2***. The minimum fleet size of the entire day is the largest value of the fleet size of each segment. For the smaller part, I added the ***scheme*** of extra bikes in the bigger part to the end of ***scheme*** and ***end*** in the smaller segment. By doing this, the fleet sizes of each segment are the same and these extra bikes will stay their initial locations in the smaller segment. The first rebalance work will redistribute the bikes from ***End 1*** to ***Scheme 2*** and the second one is from ***End 2*** to ***Scheme 1***. Similar process applies when the system is rebalanced for three times in a day (the ***Rebalance 3*** case), having the demand separated into 3 segments.

The minimum fleet sizes and the corresponding rebalancing distances of the three rebalancing strategies are inputted into the LCA model we built in Chapter 2 to analyze the system GHG emissions. We assume that all other parameters are the same as the base scenario for the dock-less system, except for #bike/bike-km and rebalancing distance km/bike-km, which are based on the results we obtained in this section. Also, the fuel economy will be calculated based on the loading status of every part of the trip. By changing these two parameters, we can compare the system GHG emissions and identify the optimal system design and rebalancing strategies from the life cycle perspective. To compare the proposed system design and operation strategies to the current system in Xiamen, the vehicle use of the current system rebalancing is needed. However, our data set doesn’t contain this information. Therefore, we use the same factor ‘rebalance distance km/bike-km’ as in Chapter 2 to estimate the current rebalance demand.

The simulation and optimization models were executed on the Purdue Research Computing Cluster with 2 Haswell CPUs and 64 GB RAM. The routing optimization was solved by a commercial solver Gurobi 8.0 invoked by a Python 3.6 program.

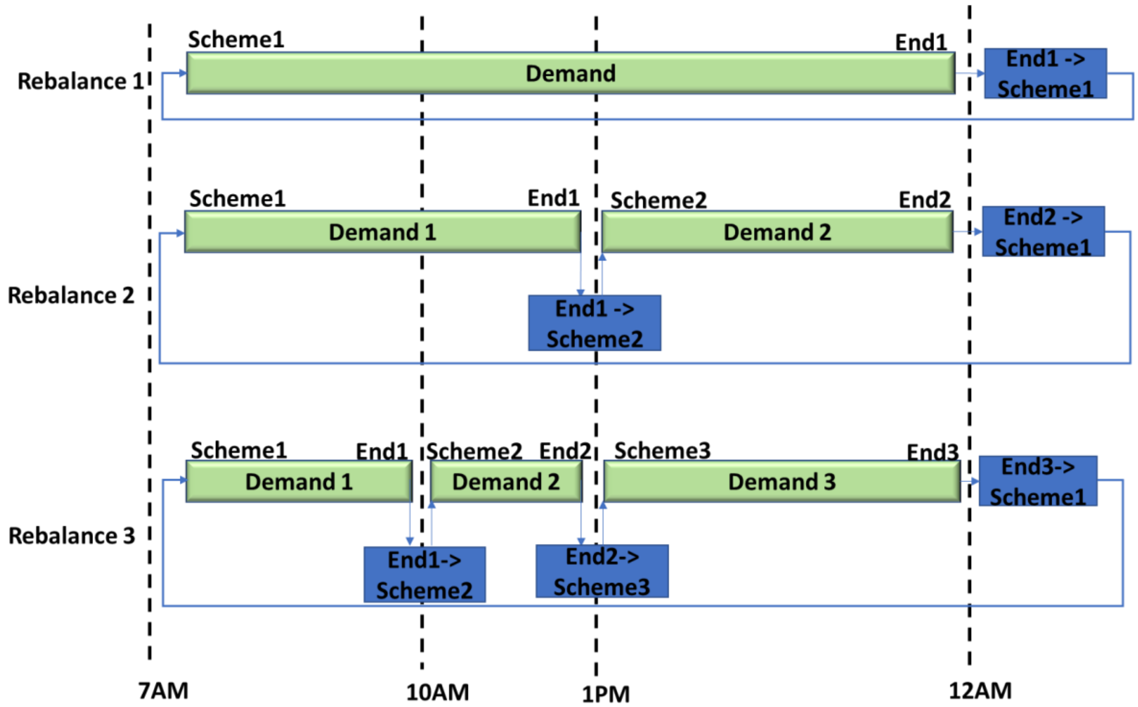


Figure 3-3 Different bike rebalancing frequencies will lead to different bike distribution schemes and rebalancing demands

3.2.5 Sensitivity analysis

To test the impacts of key assumptions on our results, we first set a base scenario to obtain benchmark results and then conduct a sensitivity analysis changing the key parameters. In the base scenario, the system has one depot located in the center of the city, and the rebalancing fleet contains 40 vehicles with a capacity of holding 30 bikes each, based on the current station-based BSS operated in a large metropolitan city. Each vehicle serves 43 stations in that system, averagely. Based on our simulation results, the number of imbalanced nodes ranges from 1500 to 2000, so we chose 40 vehicles (38~ 50 nodes/vehicle) which is about the same level with the real-world operation. Also, the van can load at most 30 bikes in the station-based system we got data from, so we use this value in the base scenario.

We first tested the impacts of different rebalancing fleet sizes (ranging from 30 to 50) and different vehicle capacities (ranging from 20 to 50). The fuel economy factor we used in the LCA model is based on the Ecoinvent data '*Transport, van <3.5t/US- US-EI U*'. However, to load 40 or 50 bikes at a time, a heavy-duty truck is needed, and the fuel economy may be different. Here we add a correction factor, 300%, when calculating the GHG emission of vehicle travelling for the vehicles with 40 or 50 capacity, based on the fuel consumption of heavy truck and van (Department of Transport (DOT), 2015; USEPA, 2014).

Secondly, to investigate the effect of having multiple depots, we set another two scenarios with two depots and three depots in the system. In the base scenario, the depot locates at the center of the city. For the multiple depots scenarios, we first separated the city into two or three regions based on its geographical boundaries, such as strait and river, and then we set the depots to the center of nodes located in each region (Figure 3-9) after determining the imbalanced nodes. The number of rebalancing vehicles (same as the number of clusters) of each region is allocated based on the proportion of nodes in each region. In the multi-depot scenarios, the vehicle will only start from the depot in its region and serve one cluster in its region. After that, we applied the vehicle routing optimization for each region and analyzed the system GHG emissions using the LCA model.

3.3 Results and discussions

In this section, we first investigated the trip pattern to find the appropriate time for bike rebalancing. Then, we analyzed the tradeoffs between bike fleet size and rebalancing frequencies from the life cycle GHG emission's perspective for the base scenario on weekday and weekend. Finally, we examined the effects of rebalancing fleet size, vehicle capacity and multiple depots on the system GHG emissions.

3.3.1 Trip pattern

Figure 3-4 shows the daily trip demand pattern for a typical weekday and weekend. In the weekday, two peak hours (from 7 to 9 AM and from 4 to 9 PM) are clearly visible and a small lunch peak at 12 PM exists. Besides, 10 AM and 1 PM are the two troughs. The weekend shares the similar pattern with the weekday, except for the lower peak values, especially in the morning. The trip demand pattern serves as important basis for the decision for bike rebalancing time. An appropriate rebalancing should happen during the low demand hours to minimize the impact of operation and should be completed before the peak hour to better satisfy customer demands.

Therefore, we set 12 AM for the night rebalancing, and 10 AM and 1 PM for the daytime rebalancing.

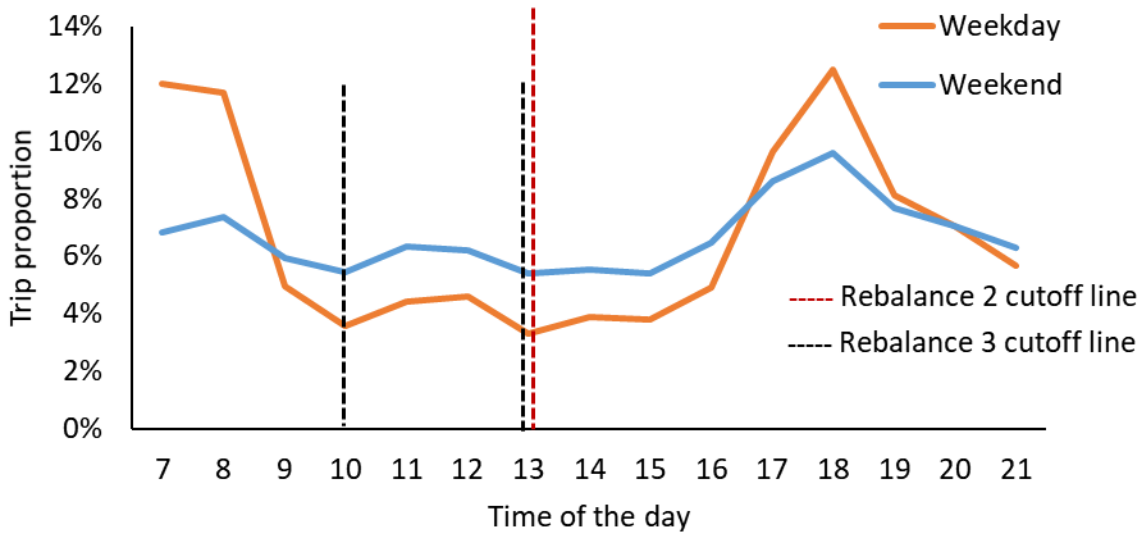


Figure 3-4 Pickup demand pattern

3.3.2 **Weekday base scenario analysis**

3.3.2.1 Simulation results of weekday

Table 3-1 Fleet size of the base scenarioshows the minimum bike fleet size from the simulation for the weekday and the rebalancing demand of each grid is also shown in Appendix D. Compared to the current system, our results show that only a small fraction (15.8 %) of the bikes are actually needed to meet the same demand, for all three rebalancing strategies on weekday . The results suggest that the current system launched superfluous bikes and the system design can be improved from both fleet size and their initial distribution locations. Compared with the 3 rebalancing strategies, the bike fleet size could be further reduced by rebalancing more frequently.

The fleet size change is due to the improvement of bike usage level. As shown in Figure 3-5(a), the majority of the bikes in the existing system are only used once or twice in a day. In our rebalancing once case, 75% of the bikes can be used at least 7 times a day. The bike utilization rate can be further increased with more frequent rebalance and the median level is increased from 9 times/day to 13 times/day. Through our simulation model, we understood the optimal initial bike distribution of each time period, which supports the rebalancing strategy and significantly improved the system efficiency.

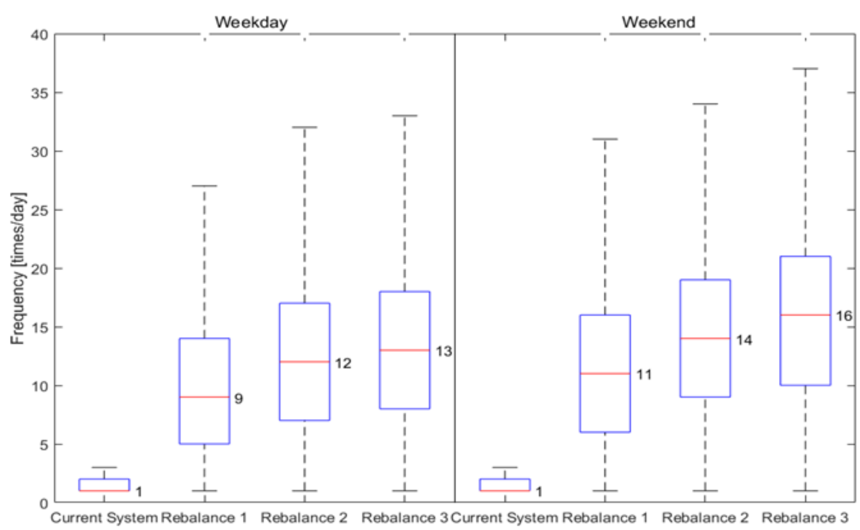
Table 3-1 Fleet size of the base scenario on weekday(a) and weekend(b)

(a)

	Weekday
Current system	50,564
Rebalance 1	7,998
Rebalance 2	6,639
Rebalance 3	5,870

(b)

	Weekend
Current system	35,681
Rebalance 1	4,673
Rebalance 2	3,711
Rebalance 3	3,404



(a) (b)

Figure 3-5 Bike use frequency in the base scenario on weekday(a) and weekend(b)

3.3.2.2 Vehicle routing optimization of weekday

As we mentioned in section 3.2.3.3, the first step of solving this multivehicle routing problem is to cluster the nodes under the vehicle capacity limitation. Figure 3-6 shows the clustered nodes in the weekday for our base scenario. Two of the vehicle routes are shown in Figure 3-7 and the bike load after visiting each node is also presented as insert in each figure. In cluster 1, most of the nodes have low rebalancing demands and the route is not influenced by the capacity constrain. Therefore, the route of cluster 1 is straightforward and has no turn-back route. In cluster 2, two of the nodes have extremely large bike unloading demands that exceed the vehicle capacity and have to be visited twice. For example, the total demand of this cluster is -30 (i.e. vehicle should load 30 bikes at the beginning from the depot) and the vehicle needs to unload all the 30 bikes at the first node. After that, the vehicle keeps loading bike from node 2 to node 10. The node 24 also requires unloading more than 30 bikes, so we can see several turn-back journeys before and after visiting node 24 due to the capacity limitation. Evaluating the bike stock in these two clusters, we found that cluster 1 may not need to use the large vehicle to perform the rebalancing work because its maximum stock level is only 16. Using smaller vehicles could reduce fuel consumption. Hence, using a mixed fleet of rebalancing vehicles based on the actual need can further reduce the system GHG emissions.

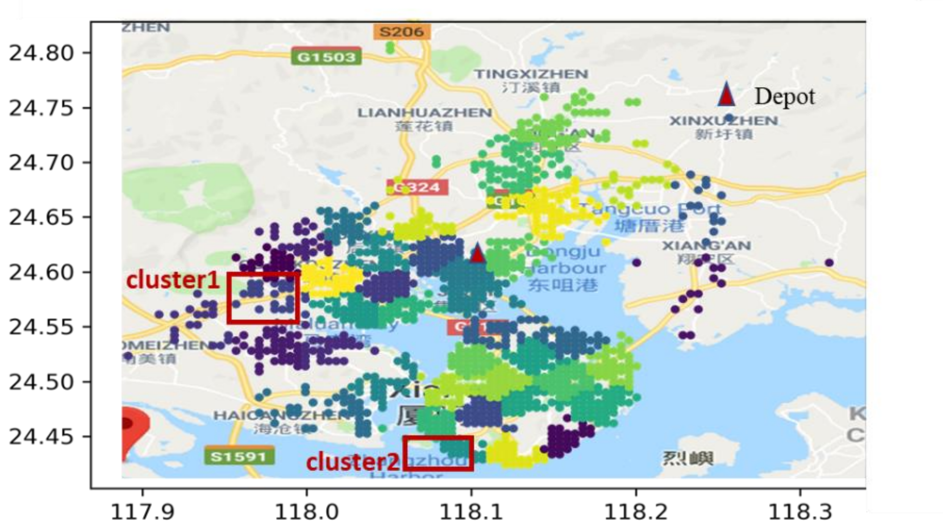
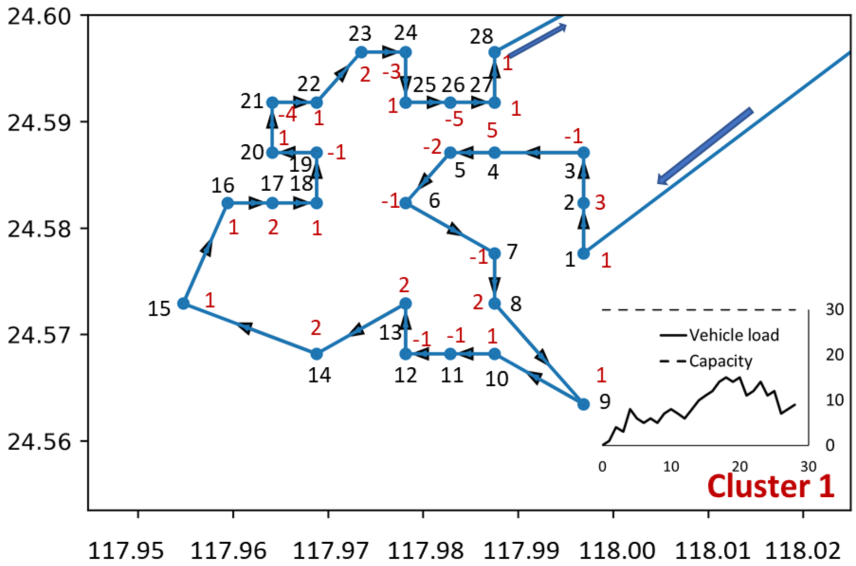
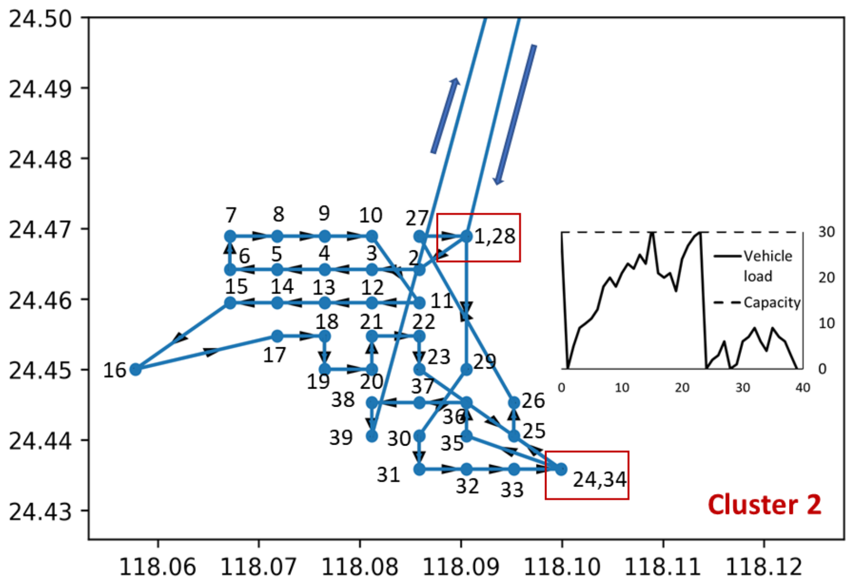


Figure 3-6 Clusters of the nodes with rebalancing demands for the weekday base scenario



(a)



(b)

Figure 3-7 Vehicle routes of two example clusters. The insert figure shows the bike stock in the truck after visiting each node.

3.3.2.3 The tradeoff between bike fleet size and rebalancing frequency on weekday

The results of the base scenario on weekday are listed in Table 3-2(a) Comparing the fleet size and rebalancing distance of the three system designs, we can see a tradeoff between these two factors. With more frequent rebalancing, the system needs less bikes, but more vehicle travels due to rebalancing. The GHG emission results show that ***Rebalance 1*** has the least carbon emission factors, 43 g CO_2-eq/bike-km for weekday. However, with the more frequent rebalancing, the emission rates increase rapidly, even to a level that is higher than the current system. The total rebalance distance constitutes two parts: the “commuting trip”, which is the journey that each vehicle travel between the depot and the service region (clusters), and the “effective rebalancing trip” which is the routing for completing the rebalancing work. As shown in the Figure 3-6, the depot is far away from many clusters and the “commuting trip” could take up a high proportion of the total rebalancing distance for the clusters that are located on the edge of the city. The “commuting trip” ranges from 40% to 60% in all cases of the base scenario, which may not be beneficial to the system efficiency. Therefore, scattering several depots around the city could reduce the “commuting trip” and then decrease the GHG emission rate. We will further discuss the effect of having multiple depots in Section 3.3.4.

Table 3-2 Numerical results of base scenario and emission rate on weekday(a) and weekend(b)

(a)

Weekday			
	Fleet size	**Total rebalance distance km/day**	**CO_2-eq g/bike-km**
Current system	50,564	7,556	101
Rebalance 1	7,998	3,295	43
Rebalance 2	6,639	6,715	84
Rebalance 3	5,870	8,475	105

(b)

Weekend			
	Fleet size	**Total rebalance distance km/day**	**CO_2-eq g/bike-km**
Current system	35,681	5,237	101
Rebalance 1	4,673	2,859	51
Rebalance 2	3,711	5,678	99
Rebalance 3	3,404	8,248	144

3.3.3 Weekend base scenario analysis

3.3.3.1 Simulation results of weekend

Table 3-1 (b) shows the simulation results of the minimum bike fleet size on weekend. Similar to the weekday, the fleet size can also be reduced to a low level on weekend (only 13% of the current system) through the optimal bike layout based on our simulation model. Additionally, the fleet can be further decreased by more frequent rebalancing work, from 13% of the current system to 9.5% when rebalancing 3 times a day. The bike use frequency is also increased to more than 11 times per day (Figure 3-5(b)).

Compared with the simulation results with weekday and weekend, the fleet size demand on weekend is less than the weekday, due to the fewer trip demand (54,661 trips on the typical weekend and 79,854 on weekday). Moreover, the average bike use rate during the weekend is higher than weekday in the same rebalancing strategy. This is due to the steeper peak demand which requires additional bikes during the rush hours in the weekday, while these extra bikes may not be needed to serve the demand in other time periods.

3.3.3.2 The tradeoff between bike fleet size and rebalancing frequency of weekend

The results of the base scenario of weekend are listed in Table 3-2 (b) The tradeoff shares the similar pattern with the weekday. The **rebalance 1** case reports the lowest GHG emission rate, only 50% of the current system, and it also requires the least rebalancing demand. Comparing the three rebalancing strategies, when the fleet size was reduced to a certain level, it may not be helpful to reduce the GHG emission by further decrease the fleet size but cost higher rebalancing demand. As is shown in the Table 3-2 (b), the GHG emission rate of rebalancing 3 case is 44% higher than the current system and the rebalancing intensity is 57% higher. As we mentioned in section 3.3.2.3, the 'commuting trip' during the rebalancing work is the main cause of the GHG emission and setting multiple depots would reduce the commuting distance and improve the GHG emission.

Compared with the GHG emission on weekday and weekend, we found that the weekend will generate a higher emission rate in each rebalancing strategy. As is shown in Table 3-2, although the weekday needs both more bikes and more rebalancing demand, the total served trips and distance on weekday is much higher than the weekend. On the weekday, the bike sharing system served 75,564 km of bike trip per day, and only 53,272 bike-km on weekend. Therefore, the system on weekday generates a lower life cycle impact to serve 1 km bike trip than weekend when allocating environmental impact to per bike-km level. Hence, the bike sharing system on weekday shows a better efficiency than the weekday.

3.3.4 The results of other days

In the section 3.3.2 and 3.3.3, we discussed the results of base scenarios on two typical days 09/13/2017 and 10/07/2017. In this section, we also investigated the life cycle GHG emission of other days that we have data on, to compare with the two typical days we chose. Table 3-3 Tradeoff analysis results of all six daysshows the GHG emission of all 6 days of three different rebalancing strategies. Among these days. 09/11, 09/13, 09/15 are weekdays, 10/04, 10/07 are the weekends and 10/01 is a national holiday. When we compared the three rebalancing strategy cases of each day, they shared the similar pattern with the two typical days. The **Rebalance 1** case has the lowest GHG emission rate among all 6 days and applying more frequent rebalancing work to further reduce the fleet size will cause additional GHG emission. Besides, similar to the conclusion in 3.3.3.2, the weekends (10/04, 10/07) showed more intensive GHG emission than the weekdays (09/11, 09/13, 09/15) due to the lower daily trip demand.

Table 3-3 Tradeoff analysis results of all six days

Rebalance 1				
		Fleet size	Rebalance distance km	CO_2 eq g/bike-km
Weekday	2017/9/11	7568	3376	42.8
	2017/9/13	7998	3487	43.5
	2017/9/15	7855	3295	41.8
Holiday	2017/10/1	5052	2080	42.2
Weekend	2017/10/4	4398	2908	58.5
	2017/10/7	4673	2859	51.3
Rebalance 2				
		Fleet size	Rebalance distance km	CO_2 eq g/bike-km
Weekday	2017/9/11	6171	6695	82
	2017/9/13	6639	6715	84.4
	2017/9/15	6541	6509	75.3
Holiday	2017/10/1	3830	4133	80.7
Weekend	2017/10/4	3488	5846	115
	2017/10/7	3711	5678	99.4
Rebalance 3				
		Fleet size	Rebalance distance km	CO_2 eq g/bike-km
Weekday	2017/9/11	5439	8433	103
	2017/9/13	5870	8475	105.4
	2017/9/15	5666	7842	90.1
Holiday	2017/10/1	3479	5712	111
Weekend	2017/10/4	3208	8171	160
	2017/10/7	3404	8248	143.5

3.3.5 The impact of rebalancing vehicle fleet size and capacity

Having more rebalancing vehicles (more clusters) or larger vehicles (more capacity) can potentially impact the results. Figure 3-8 shows that the ***Rebalance 1*** case always has a better performance under the same operation conditions (i.e. having the same number of rebalancing vehicles and capacity), which is consistent with the base scenario. With a fixed vehicle capacity, having more rebalancing vehicles always lead to higher emission rates due to the "commuting trips". When more vehicles are used, each vehicle will serve less nodes and the proportion of the effective rebalancing trip among the imbalanced nodes decreases. On the other hand, with a fixed number of rebalancing vehicles, we can achieve a small GHG emission reduction with higher vehicle capacity because the vehicles can be less constrained by the capacity and reduce turn back trips between nodes as presented the cluster 2 example in Figure 3-7. Hence, in general, fewer vehicles with greater capacity of each can further reduce the GHG emission rate, and the optimal case can be found (30 vehicles, 50 capacity) for three rebalancing strategies in both weekday and weekend. However, in some cases (e.g. weekend, rebalance 1, vehicle 40, capacity from 30 to 50), we find the opposing situation. This can be explained that the vehicle load in these cases are high throughout the journey and the benefit of shorter route is overweighed by the worse fuel consumption.

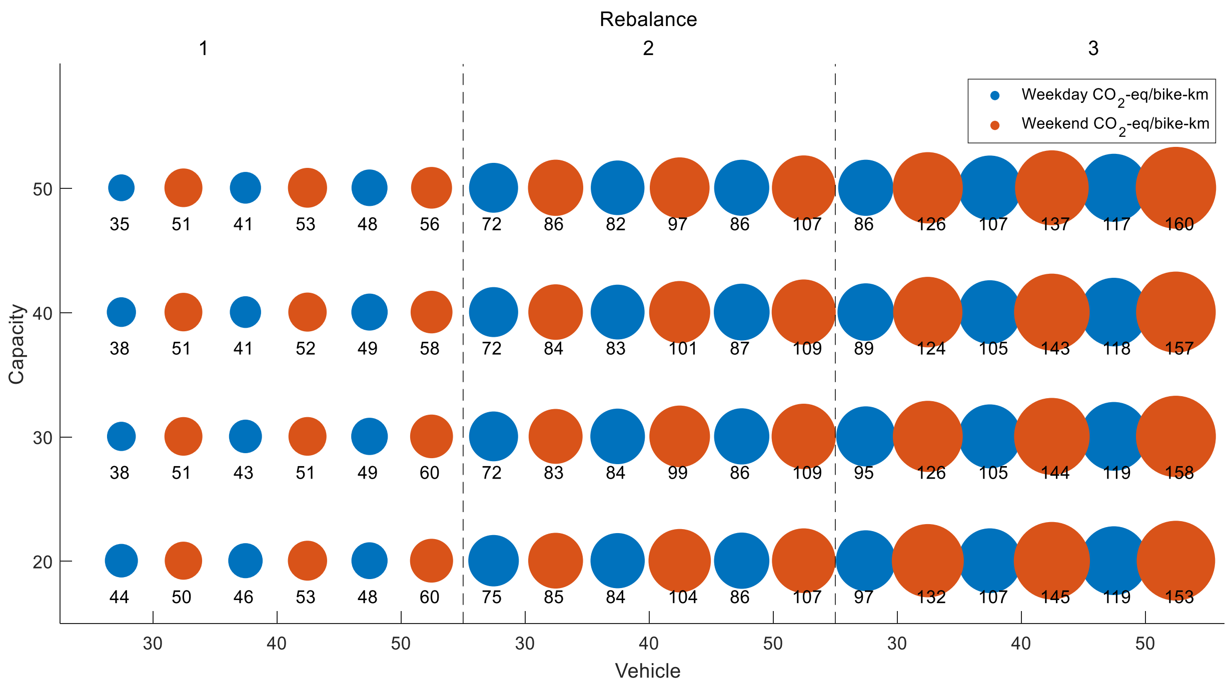
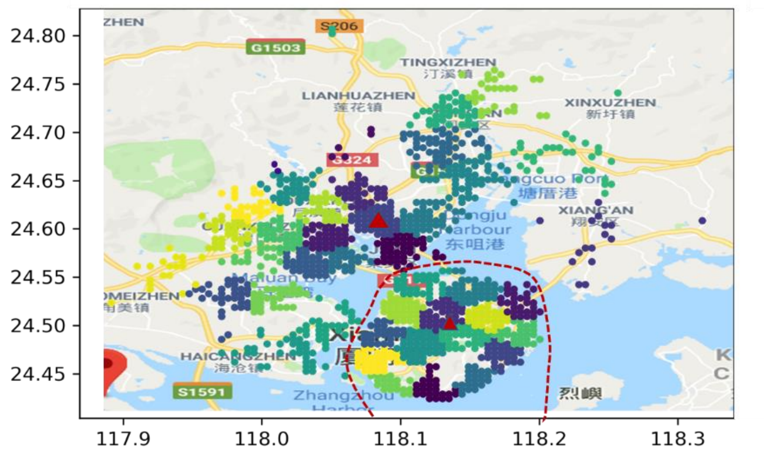


Figure 3-8 The impact of rebalancing vehicle fleet size and capacity on system greenhouse gas emissions

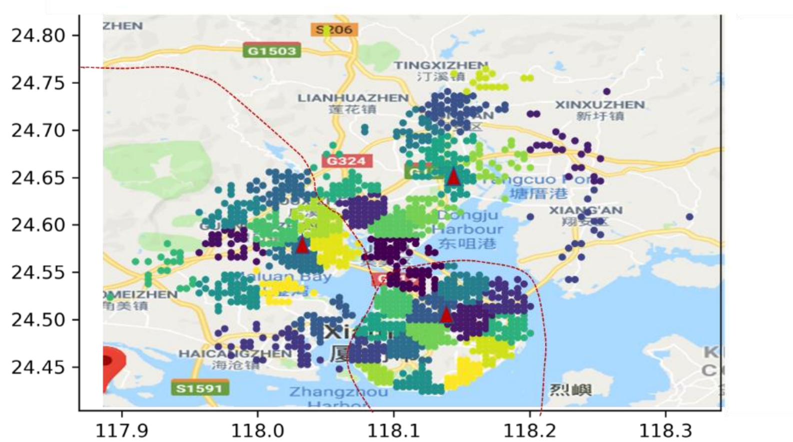
3.3.6 The impact of having multiple depots

In the base scenario analysis, we observed that the long-distance journey between the depot and the service cluster makes up a significant portion of the total vehicle distance, especially when rebalancing multiple times in a day. This section analyzing the impacts of having a total of two of three depots, dividing the city into multiple service regions according to its geographic features. Figure 3-9 shows that having multiple depots only has marginal impacts on the clustering, which means that the vehicle routes and travelling distance for the “effective rebalancing trips” will stay at the same level while reducing the “commuting trips” (Figure

3-10). Therefore, setting multiple depots reduce the system's carbon emission intensity by about 30% for the three-depot scenario in all the three rebalancing strategies. However, the marginal benefit from having two depots to three depots is reduced.



(a)



(b)

Figure 3-9 Nodes and depot locations of multi-depot scenario

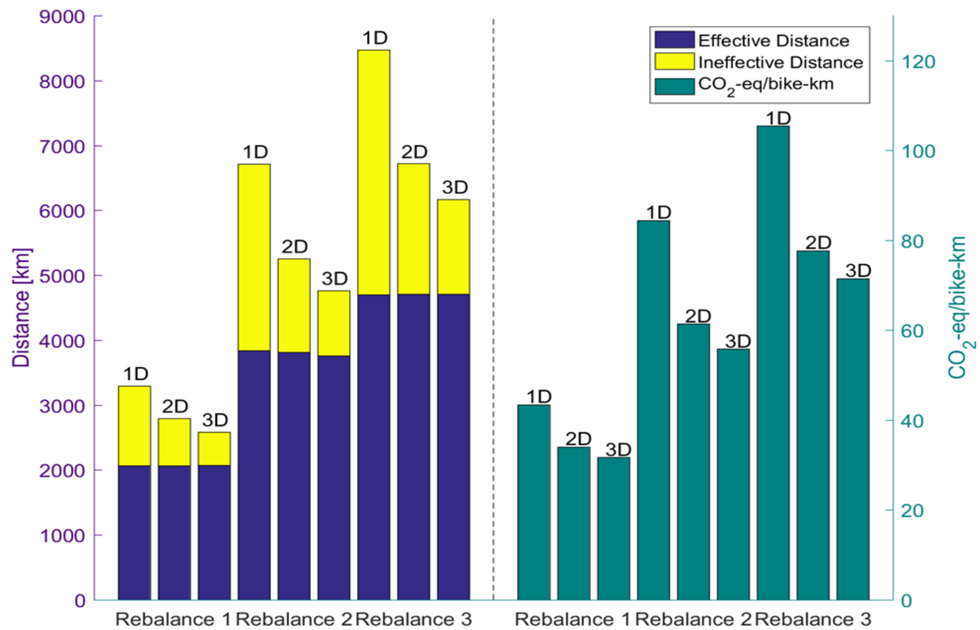


Figure 3-10 Effect of different multiple depots

Note: The ineffective distance is the journey between depot and the first/last node. The effective rebalancing distance is the vehicle travelling distance exclude the journey between the depot and the first/last node.

3.4 Conclusions and limitations

This study proposed a simulation-optimization framework to explore the optimal design for the dock-less system, in terms of life cycle GHG emission. We also conducted a tradeoff analysis between fleet size and rebalancing frequency from the life cycle perspective. The results from this study provide several insights for the city decision-makers and bike sharing operators to improve the sustainability of bike sharing systems. First, the base scenario results show a significant reduction on the bike fleet size to serve the same demand as the existing system. Hence, the excessive bike supply in the current system could be improved and our simulation model provides a useful tool to determine appropriate bike fleet sizes for a city. Second, the tradeoff analysis shows that rebalancing once a day during the night has the lowest emission rate for both weekday and weekend. From the life cycle GHG emission's perspective, using more frequent rebalancing to operate a smaller bike fleet is not a good idea. Using fewer vehicles with greater capacity has the potential to further decrease the GHG emission. Finally, we found that setting multiple depots can further reduce rebalancing intensity and emission rate which benefits from the shorter journey between the depot and the service cluster.

While this work has the merit being the first study to propose optimal BSS design from the life cycle perspective, the following limitations need to be addressed in future work. First, due to the data limitation, we had to choose two specific days as the typical weekday and weekend to run the simulation, but the trip demand pattern may change by many factors such as weather, holidays, major events. More detailed data would be helpful to further understand the system demand pattern in order to obtain a representative design. Second, we didn't consider the impact of rebalancing time window to the system. In the actual operation, the rebalancing work could result in lots of bikes being unavailable to users. An improved simulation framework which takes the bike availability change during the rebalancing into consideration can be helpful to investigate the potential impacts of this. Third, we forced the system to satisfy all demands. How the system environmental impact would be changed if we can tolerate some unmet trips which could reduce the rebalancing intensity or the total number of bikes? Evaluating the marginal impacts of the trips in different regions can bring helpful insights.

In summary, the current BSS operated in Xiamen has over-supplied bikes that could be dramatically decreased to improve system efficiency and environmental performance. When the fleet size was decreased to a certain level, it won't be helpful to continue reducing the fleet size by higher intensive rebalancing work. The optimal rebalancing strategy is that to assign fewer vehicles with more capacity to do the rebalancing once a day during the night and setting multiple depots in the system.

CHAPTER 4. CONCLUSION

In this thesis, we discussed two studies investigating the sustainability of bike sharing systems from the life cycle perspective. We first conducted a comparative life cycle assessment of station-based and dock-less system, considering each phase throughout the entire BSS life cycle (Chapter 2). And this part of study can help answer the first two research questions we proposed in Chapter 1: 1) From the life cycle perspective, which BSSs, station-based or dock-less, is more sustainable? 2) What are the major factors of a BSS's environmental impacts?

Contrary to the popular belief, the BSS may not guarantee to improve the urban sustainability, because the manufacturing and operation phases of BSS's life cycle have environmental externalities. From the aspect of GHG emissions, the station-based system may have a less GHG emission rate than the dock-less system and the highly energy intensive rebalancing work is the dominant contributor, for both station-based and dock-less system. From the aspect of TNEI, the dock-less system shows the advantage. The manufacturing of massive sharing facilities is the main cause for the station-based system while the manufacturing of a large number of dock-less bikes is the core of the issue for the dock-less system. Although the BSS can provide environmental benefits through replacing high pollution-intensive transportation modes, the effectiveness of emission reduction would be severely degraded, if the system is not designed as an attractive mode for users to replace car trips. Based on our study results, we proposed several suggestions for decision-makers to improve the environmental performance of BSSs. For a station-based system, prolonging the service time of sharing facilities and reducing the meal use in stations and docks can effectively relieve the environmental burden generated from the system. Besides, a well-designed plan of station and dock distribution can increase the potential environmental benefit of the BSS by encouraging more users to replace car trips with bike trips.

For the dock-less system, the bike manufacturing and bike rebalancing are the essential determinants of its environmental impacts. In the second study, we focused on these two points and proposed the improved system design from the life cycle perspective. The second part of the thesis could answer the third research question: Can we improve the system through understanding the tradeoff between system design (e.g. bike fleet size) and operation (e.g. rebalancing strategy)?

Through the system simulation, we found that the current dock-less system in our case study city, Xiamen, China, did launched superfluous bikes exceeding the actual demand. At most 15% bikes are needed to satisfy all the current demand and the avoiding manufacturing excessive bikes could significantly reduce the GHG emission. However, trading a smaller bike fleet size with more frequent bike rebalancing is not emission effective. To further relieve the impact of rebalancing work, an efficient strategy is to use fewer vehicles with greater loading capacity each and setting multiple depots.

Several research limitations exist in our study which require future work to further understand the sustainability of bike sharing system. First, the operation data on the dock-less system was not available and we made a lot of assumptions in the LCA study. Although we did the sensitivity analysis on several parameters to evaluate the effect of data limitation, valid data of several dock-less systems is necessary to evaluate its environmental performance comprehensively and acquire a more representative result. When more real world data become available, the framework developed in this study needs to be applied on the updated data to validate the assumptions we used in this study and the conclusions from the life cycle assessment. Second, the bike sharing system could encourage users to switch from car trips to multi-modal trips with the shared bikes serving as the first and/or last mile mode and public transportation as the middle leg. This can further increase the potential emission reduction contributed by BSSs. A survey on the car, bike, and electric bike ownership change due to having access to bike sharing, and more detailed data on travel mode change can provide the relevant data to fill these gaps. Third, in our simulation-optimization study, we ignored the effect of operation time for rebalancing work on the bike sharing system but the long rebalancing time would cause many bikes being unavailable to the customers and lost bike trips. A further improved system simulation framework that includes the time window based on the rebalancing demand results we obtained in this study could help to evaluate the impact of rebalancing operation time and give a more reliable guidance for other BSS operators.

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APPENDIX A. THE IMPACT OF HIGHER BIKE LOSS RATE

In order to evaluate the environmental impact of potential higher bike lost risk, we set an extra scenario where 20% of the bikes are lost in 10 years. In this case, all the lost bikes cannot be collected for recycling and the system needs to supply additional 20% bikes to satisfy the same demand. In other words, the recycling rate is 80% and the factor '# bike/bike-km' will increase by 20% in this case. The results of this extra scenario are presented in the Table A-1. As expected, higher bike lost rates increased the environmental impacts. However, the increase doesn't change the main conclusions even if we compare the station-based system with the 5% bike lost rate with the dock-less system with the 20% bike lost rate.

Table A-1. Comparison of different bike lost rate cases

	Bike lost rate			
	5% (base)		20%	
	Station-based	Dock-less	Station-based	Dock-less
GHG (g CO_2-eq/bike-km)	65	118	68	131
TNEI (10^{-4} unit/bike-km)	2.30	1.49	2.8	1.78

APPENDIX B. THE IMPACT OF LOWER RECYCLING EFFICIENCY

To investigate the effect of lower recycling rate, we built a scenario where the recycling efficiency is reduced to 70%. In this scenario, 70% of the metals that were collected to the recycling plants can be reused as secondary materials. As shown in Table A-3, the lower recycling efficiency increases the environmental impacts. But it doesn't change the main conclusions even if we reduce the recycling efficiency from 90% to 70%.

Table B-1. Comparison of different recycling efficiency cases

	Recycling efficiency			
	90% (base)		70%	
	Station-based	Dock-less	Station-based	Dock-less
GHG (g CO_2-eq/bike-km)	65	118	69	136
TNEI (10^{-4} unit/bike-km)	2.30	1.49	3.0	1.89

APPENDIX C. LCIA RESULTS BY DIFFERENT CATEGORIES AND LIFE CYCLE STAGES

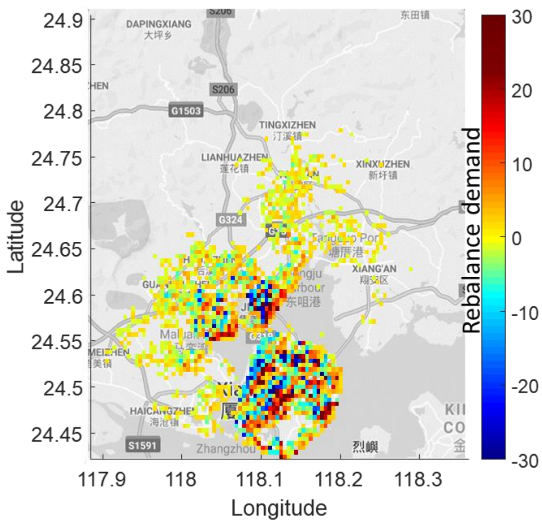
Table C-1. LCIA results of station-based and dockless bike sharing systems in the base, worst, and best scenarios

	Base scenario										
Station-based System	Impact category	Unit	Total	Bike mfg.	Station mfg.	Dock mfg.	Rebalancing	Maintenance	Bike disposal	Station disposal	Dock disposal
	Ozone depletion	kg CFC-11 eq	6.92E-09	3.35E-10	1.51E-09	7.82E-10	3.89E-09	3.05E-10	1.06E-11	8.59E-11	1.56E-12
	Global warming	kg CO2 eq	6.54E-02	3.63E-03	1.87E-02	1.47E-02	2.35E-02	2.40E-03	7.41E-04	1.78E-03	2.64E-05
	Smog	kg O3 eq	4.86E-03	3.28E-04	1.22E-03	8.37E-04	2.29E-03	9.73E-05	1.31E-05	7.55E-05	1.54E-06
	Acidification	kg SO2 eq	3.66E-04	2.48E-05	1.42E-04	7.30E-05	1.03E-04	7.78E-06	4.67E-07	1.55E-05	1.29E-07
	Eutrophication	kg N eq	2.07E-04	1.79E-06	9.05E-05	9.83E-05	1.47E-05	8.80E-07	5.02E-08	8.15E-07	1.56E-08
	Carcinogenics	CTUh	8.06E-09	7.44E-10	1.46E-09	5.38E-09	3.37E-10	1.05E-10	4.54E-12	2.04E-11	3.20E-13
	Non carcinogenics	CTUh	3.44E-08	1.57E-09	1.03E-08	2.03E-08	1.65E-09	2.47E-10	1.81E-11	2.50E-10	1.42E-11
	Respiratory effects	kg PM2.5 eq	4.78E-05	3.65E-06	2.32E-05	6.54E-06	1.22E-05	1.04E-06	2.93E-08	1.09E-06	8.50E-09
	Ecotoxicity	CTUe	1.92E-01	9.76E-03	5.58E-02	1.14E-01	8.43E-03	2.00E-03	7.89E-04	1.10E-03	2.88E-05
	Fossil fuel depletion	MJ surplus	1.02E-01	7.24E-03	2.25E-02	2.20E-02	4.41E-02	4.74E-03	1.13E-04	1.44E-03	3.00E-05
Dock-less System	Impact category	Unit	Total	Bike mfg.	Rebalancing	Maintenance	Bike disposal				
	Ozone depletion	kg CFC-11 eq	1.73E-08	1.91E-09	1.42E-08	1.14E-09	4.62E-11				
	Global warming	kg CO2 eq	1.18E-01	2.05E-02	8.58E-02	8.99E-03	2.91E-03				
	Smog	kg O3 eq	1.04E-02	1.64E-03	8.36E-03	3.64E-04	5.47E-05				
	Acidification	kg SO2 eq	5.44E-04	1.35E-04	3.76E-04	2.91E-05	2.86E-06				
	Eutrophication	kg N eq	9.75E-05	4.04E-05	5.36E-05	3.29E-06	2.49E-07				
	Carcinogenics	CTUh	4.62E-09	2.97E-09	1.23E-09	3.94E-10	1.85E-11				
	Non carcinogenics	CTUh	1.59E-08	8.81E-09	6.05E-09	9.26E-10	8.89E-11				
	Respiratory effects	kg PM2.5 eq	6.82E-05	1.96E-05	4.45E-05	3.89E-06	1.88E-07				
	Ecotoxicity	CTUe	9.79E-02	5.66E-02	3.08E-02	7.50E-03	3.04E-03				
	Fossil fuel depletion	MJ surplus	2.15E-01	3.49E-02	1.61E-01	1.78E-02	5.31E-04				

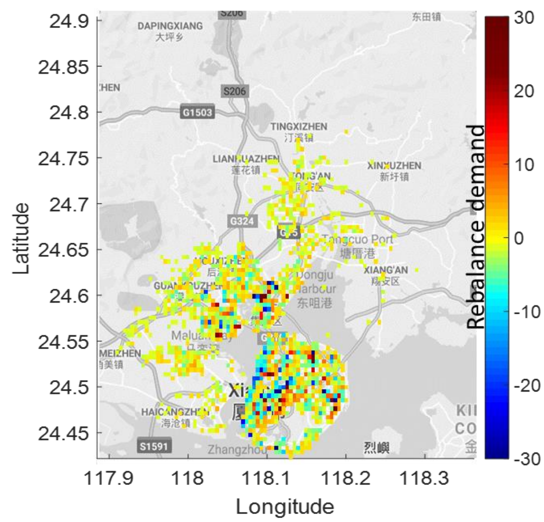
	Worst scenario										
Station-based System	Impact category	Unit	Total	Bike mfg.	Station mfg.	Dock mfg.	Rebalancing	Maintenance	Bicycle disposal	Station disposal	Dock disposal
	Ozone depletion	kg CFC-11 eq	1.53E-08	7.01E-10	3.92E-09	1.64E-09	8.15E-09	6.38E-10	2.23E-11	2.23E-10	3.26E-12
	Global warming	kg CO2 eq	1.47E-01	7.61E-03	4.83E-02	3.08E-02	4.92E-02	5.03E-03	1.55E-03	4.60E-03	5.53E-05
	Smog	kg O3 eq	1.08E-02	6.87E-04	3.17E-03	1.75E-03	4.79E-03	2.04E-04	2.74E-05	1.96E-04	3.23E-06
	Acidification	kg SO2 eq	8.45E-04	5.18E-05	3.67E-04	1.53E-04	2.16E-04	1.63E-05	9.78E-07	4.00E-05	2.69E-07
	Eutrophication	kg N eq	4.79E-04	3.75E-06	2.34E-04	2.06E-04	3.07E-05	1.84E-06	1.05E-07	2.11E-06	3.27E-08
	Carcinogenics	CTUh	1.76E-08	1.56E-09	3.79E-09	1.13E-08	7.06E-10	2.20E-10	9.51E-12	5.29E-11	6.70E-13
	Non carcinogenics	CTUh	7.73E-08	3.28E-09	2.68E-08	4.25E-08	3.47E-09	5.18E-10	3.79E-11	6.47E-10	2.97E-11
	Respiratory effects	kg PM2.5 eq	1.12E-04	7.65E-06	6.02E-05	1.37E-05	2.55E-05	2.18E-06	6.13E-08	2.81E-06	1.78E-08
	Ecotoxicity	CTUe	4.29E-01	2.04E-02	1.44E-01	2.38E-01	1.77E-02	4.19E-03	1.65E-03	2.85E-03	6.03E-05
	Fossil fuel depletion	MJ surplus	2.26E-01	1.52E-02	5.83E-02	4.60E-02	9.24E-02	9.93E-03	2.36E-04	3.74E-03	6.28E-05
Dock-less System	Impact category	Unit	Total	Bike mfg.	Station mfg.	Dock mfg.	Bicycle disposal				
	Ozone depletion	kg CFC-11 eq	2.35E-08	2.59E-09	1.93E-08	1.55E-09	6.27E-11				
	Global warming	kg CO2 eq	1.60E-01	2.79E-02	1.16E-01	1.22E-02	3.95E-03				
	Smog	kg O3 eq	1.41E-02	2.23E-03	1.13E-02	4.94E-04	7.42E-05				
	Acidification	kg SO2 eq	7.38E-04	1.84E-04	5.11E-04	3.95E-05	3.89E-06				
	Eutrophication	kg N eq	1.32E-04	5.48E-05	7.28E-05	4.47E-06	3.38E-07				
	Carcinogenics	CTUh	6.26E-09	4.03E-09	1.67E-09	5.34E-10	2.51E-11				
	Non carcinogenics	CTUh	2.15E-08	1.19E-08	8.20E-09	1.26E-09	1.21E-10				
	Respiratory effects	kg PM2.5 eq	9.26E-05	2.66E-05	6.04E-05	5.28E-06	2.55E-07				
	Ecotoxicity	CTUe	1.33E-01	7.68E-02	4.18E-02	1.02E-02	4.12E-03				
	Fossil fuel depletion	MJ surplus	2.91E-01	4.74E-02	2.19E-01	2.41E-02	7.20E-04				

Best scenario											
Station-based System	Impact category	Unit	Total	Bike mfg.	Station mfg.	Dock mfg.	Rebalancing	Maintenance	Bicycle disposal	Station disposal	Dock disposal
	Ozone depletion	kg CFC-11 eq	2.46E-09	1.20E-10	3.08E-10	2.81E-10	1.40E-09	1.09E-10	2.23E-11	2.23E-10	5.58E-13
	Global warming	kg CO2 eq	2.58E-02	1.30E-03	3.80E-03	5.28E-03	8.42E-03	8.61E-04	1.55E-03	4.60E-03	9.47E-06
	Smog	kg O3 eq	1.75E-03	1.18E-04	2.49E-04	3.00E-04	8.20E-04	3.49E-05	2.74E-05	1.96E-04	5.54E-07
	Acidification	kg SO2 eq	1.45E-04	8.88E-06	2.88E-05	2.62E-05	3.69E-05	2.79E-06	9.78E-07	4.00E-05	4.61E-08
	Eutrophication	kg N eq	6.21E-05	6.42E-07	1.84E-05	3.53E-05	5.27E-06	3.16E-07	1.05E-07	2.11E-06	5.60E-09
	Carcinogenics	CTUh	2.72E-09	2.67E-10	2.98E-10	1.93E-09	1.21E-10	3.77E-11	9.51E-12	5.29E-11	1.15E-13
	Non carcinogenics	CTUh	1.13E-08	5.63E-10	2.10E-09	7.29E-09	5.94E-10	8.87E-11	3.79E-11	6.47E-10	5.09E-12
	Respiratory effects	kg PM2.5 eq	1.60E-05	1.31E-06	4.73E-06	2.35E-06	4.37E-06	3.73E-07	6.13E-08	2.81E-06	3.05E-09
	Ecotoxicity	CTUe	6.39E-02	3.50E-03	1.14E-02	4.08E-02	3.02E-03	7.18E-04	1.65E-03	2.85E-03	1.03E-05
	Fossil fuel depletion	MJ surplus	3.66E-02	2.60E-03	4.59E-03	7.88E-03	1.58E-02	1.70E-03	2.36E-04	3.74E-03	1.08E-05
Dock-less System	Impact category	Unit	Total	Bike mfg.	Station mfg.	Dock mfg.	Bicycle disposal				
	Ozone depletion	kg CFC-11 eq	1.12E-08	1.23E-09	9.14E-09	7.34E-10	6.27E-11				
	Global warming	kg CO2 eq	7.81E-02	1.32E-02	5.52E-02	5.78E-03	3.95E-03				
	Smog	kg O3 eq	6.74E-03	1.06E-03	5.37E-03	2.34E-04	7.42E-05				
	Acidification	kg SO2 eq	3.52E-04	8.70E-05	2.42E-04	1.87E-05	3.89E-06				
	Eutrophication	kg N eq	6.29E-05	2.60E-05	3.45E-05	2.12E-06	3.38E-07				
	Carcinogenics	CTUh	2.98E-09	1.91E-09	7.92E-10	2.53E-10	2.51E-11				
	Non carcinogenics	CTUh	1.03E-08	5.66E-09	3.89E-09	5.96E-10	1.21E-10				
	Respiratory effects	kg PM2.5 eq	4.40E-05	1.26E-05	2.87E-05	2.50E-06	2.55E-07				
	Ecotoxicity	CTUe	6.74E-02	3.85E-02	1.98E-02	4.82E-03	4.28E-03				
	Fossil fuel depletion	MJ surplus	1.40E-01	2.34E-02	1.04E-01	1.14E-02	9.25E-04				

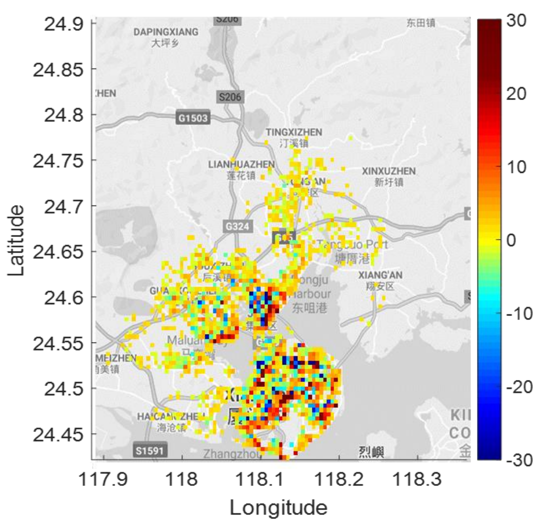
APPENDIX D. REBALANCE DEMAND OF BASE SCENARIOS



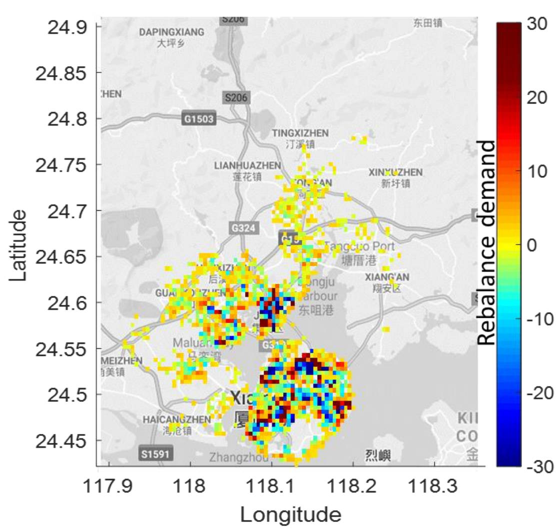
(a)



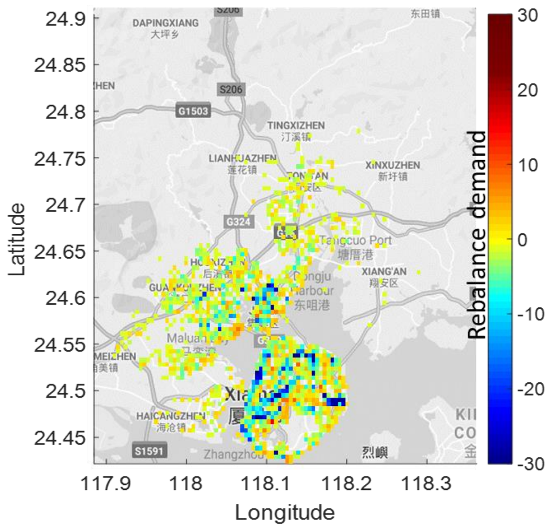
(b)



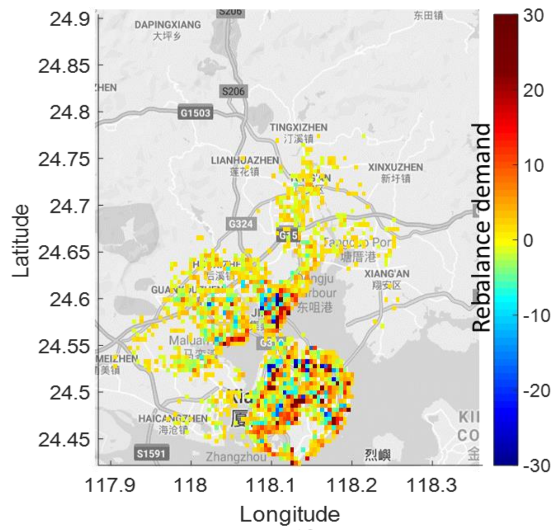
(c)



(d)



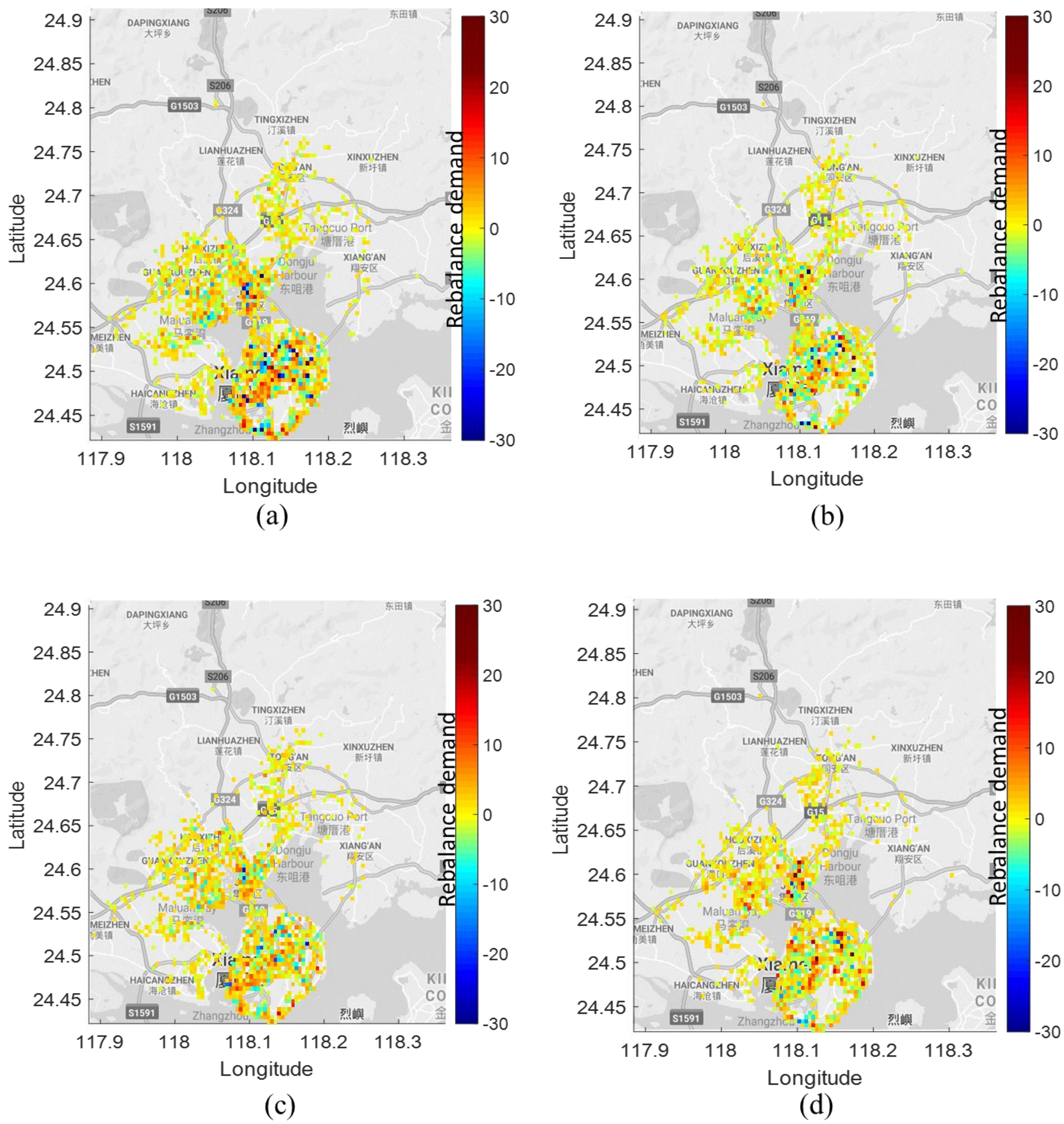
(e)



(f)

Figure D-1. Spatial distribution change in terms of rebalancing demand on weekday. (a) Rebalance 1 case on weekday at 12 am. (b) Rebalance 2 case on weekday at 1 pm. (c) Rebalance 2 case on weekday at 12 am. (d) Rebalance 3 case on weekday at 10 am. (e) Rebalance 3 case on weekday at 1pm. (f) Rebalance 3 case on weekday at 12 am.

Note: The grid size is $500m \times 500m$. The ‘positive value’ of the rebalancing demand refers to the node has redundant bikes need to be picked up by the rebalancing vehicle and the negative value means that the node needs additional bikes.


Latitude
Longitude
Rebalance demand
(a)
(b)
(c)
(d)

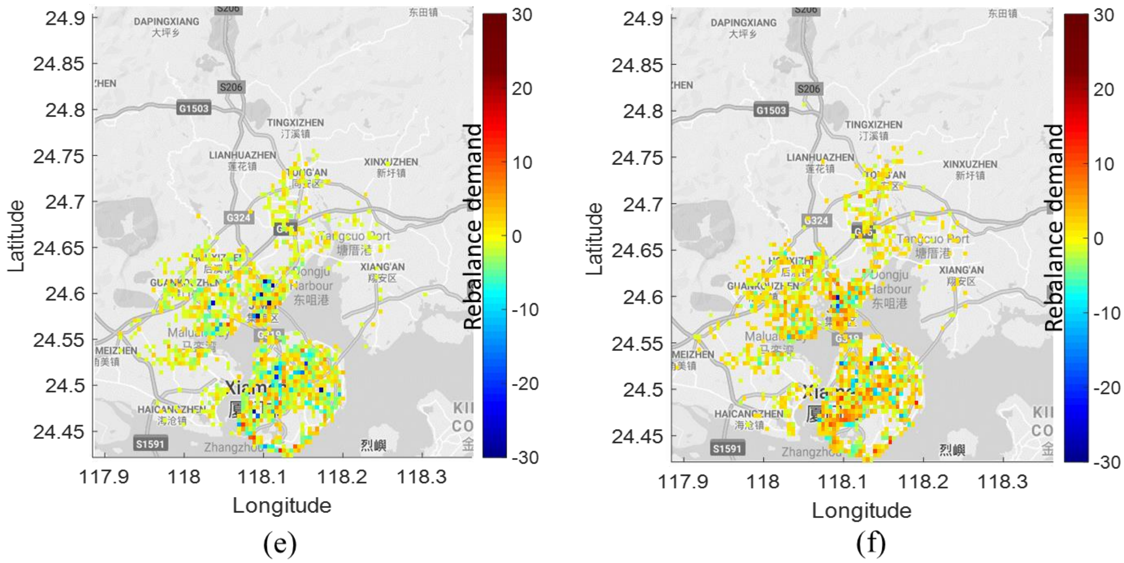


Figure D-2. Spatial distribution change in terms of rebalancing demand on weekend. (a) Rebalance 1 case on weekend at 12 am. (b) Rebalance 2 case on weekend at 1 pm. (c) Rebalance 2 case on weekend at 12 am. (d) Rebalance 3 case on weekend at 10 am. (e) Rebalance 3 case on weekend at 1pm. (f) Rebalance 3 case on weekend at 12 am.

Note: The grid size is $500m \times 500m$. The 'positive value' of the rebalancing demand refers to the node has redundant bikes need to be picked up by the rebalancing vehicle and the negative value means that the node needs additional bikes.