Analysis of The Sharing Bike Relocation Problem:

Shanghai Metro System and Mobike

by

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Abstract

As one of the largest market of the sharing economy, China has been witnessed the fast development of the bike sharing systems. The biggest issue in the operation of sharing bike systems is bike relocation, which is to make the supply amount of sharing bikes meet the spatial demand of users. The study takes data from the highly developed metro system in Shanghai, China, to help demonstrates the problem of unbalanced bicycle distribution caused by metro passenger flows. To analyze the sharing bike allocation in the vicinity of major metro stations, this research uses clustering and regression that most literature focuses on to conduct quantitative analysis. This paper aims to research the interaction of Mobike usage and Shanghai Metro system to provide strategic suggestions for bike relocation problem in order to raise the bike sharing company's operating efficiency as well as benefit the users in terms of daily transportation convenience. Results have showed that at specific metro stations, there are strong patterns of tide effect during rush hours and correlations between the amount metro users entering or exiting the station with people using Mobike, and therefore, Mobike and other bike sharing companies could focus on these areas for bike relocation. The further application of the research could extend to urban planning solutions for bike parking area and bike lanes in Shanghai.

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1. Introduction

The sharing economy is a novel solution to the demand and supply in the marketplace since it offers platforms for individuals to involve directly in economic activities. As a market where there exists huge demand in different sectors due to large population scale, China has witnessed the vigorous development of sharing economy in the past few years in various sectors including transportation, accommodation and other innovative industries. The bike sharing system, which has a high user volume and economic impact on the society, has aroused public attention in every aspect.

According to the China Sharing Bike Industry Development Report[1] by China Academy of Information and Communications Technology (CAICT) and Mobike Policy Research Institute, sharing bike system is estimated to bring total economic value of 71.4 billion RMB to the society. In 2017, the amount of registered users for bike sharing has reached 221 million and the accumulated trip length was 29.947 billion kilometers. However, along with the rapid development of this the bike sharing sector, there are problems coming out into the bike sharing industry, such as user credit system, deposit, information fraud and security. Taking bike sharing companies as an example, in early December, sharing bike companies such as Wukong, Kuqi, and Bluegogo failed their business[2]. Millions of deposits are not able to pay back to users, which arouse people's concerns about not only the financial risk and regulatory on these companies, but also the well-being of the general sharing economy industry.

Mobike, one of the major competitor in bike sharing, was launched on April 16th, 2016 in Shanghai. It is now operating 7.6 million bikes in over 180 cities in 8 countries[3].

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[1] Please refer to the official WeChat account of Mobike Research Institute for the post: https://mp.weixin.qq.com/s/A9ijdjUNmdsn6i8Ob0EpdA

[2] http://fortune.com/2017/11/18/chinas-bike-sharing-bubble-goes-bust/

3 How Mobike Data Help Improve the Operation and City Planning, Dr. Yin Dafei's speech at NYU Shanghai

Mobike is able to differentiate itself from the other competitor ofo by the using high-tech smart lock and high-quality bike when launching the business. The smart lock enables Mobike's back-end to communicate with bikes mutually, and thus help the data center conduct machine learning with the algorism to improve the operating efficiency, the major goal of which is to reduce individual bike's idle time. In addition to manual bike relocation by offline workers, in March 2017, the "Fortune Bike" campaign was launched to help to relocate bikes. Users help Mobike to move a bike which might be idle for a long time or parked in a rare area to Smart Mobike Preferred Location (SMPL). The campaign not only promotes Mobike, but also eliminate costs in daily operation, for instance, labor cost for bike maintenance. According to CATIS and Mobike's report, during the campaign, there are on average 200 users per second participating, which has led to an increase of 20% in Mobike's operation efficiency. The bike relocation solution involves turnover and demand prediction in the specific area, priority of bike relocation, user participated operation and etc.

However, the vigorous sharing bike system has caused problems, mainly for the parking area in the urban traffic system. The overload and disordered placement of bikes around metro systems blocks sidewalks and streets, which brings inconvenience to pedestrians. More importantly, it affects the regular traffic and makes traffic jam more severe. Different local governments such as Transportation Commission of Shanghai and Beijing announced sharing bike amount control plan in September 2017, given the fact the current amount of sharing bikes has significantly impacted regular transportation operations. Furthermore, there is a plan under development about assigning legal licenses to sharing bikes to control the amount of bikes in use in the market. In big cities in China, the population and bike ratio is about 1:8 (e.g. Beijing and Shanghai). Nationwide ratio is estimated to be 1:30.

Though Mobike has applied algorithm and strategies in operation, the bike sharing system still faces problem of tide effect during rush hours, that might cause hundreds of bikes piling up at a popular bike trip destination, for example, metro stations. As reported in news, the sharing bikes has strongly impacted the normal use of pedestrian ways and caused traffic problems, especially around metro stations in Shanghai.

Given the background that Shanghai has highly developed the metro system that plays a crucial role in the urban transportation, the transportation mode of "Metro + Bike" has become a major transportation option for citizens. In the speech of Mobike's data scientist Dr. Dafei Yin at NYU Shanghai, "Big Data Transforms How We Travel", he mentioned that after Mobike came into market, the way that people define "metro apartments" (those apartments that are close to metro stations, as one of the advantages to boost for higher price) has expanded since Mobike benefits people by increasing the accessibility of public transportation infrastructures. But the side effect of the phenomenon is that it will exacerbate the tide effect on current tide effect on the bike sharing system since people will park and lock bikes at the origin metro stations and use bikes at the destinations. Thus, there will be hundreds of idle bikes at popular departure stations, for example, high-density residency area in Songjiang, Jiuting in the morning. In the evening, such stations around business districts, for instance, Xiaonanmen Station, have the same problem of parking spatial limitation.

Therefore, to figure out a better solution for users' convenience, Mobike's operation efficiency and urban transportation utilization, the research focus on analyzing the relationship between the use of Shanghai Metro system and Mobike for optimizing sharing bike relocation problem.

2. Literature Review

Bike sharing in China has a great number of users. Guo, Zhou, Wu and Li (2017) conducted a survey-based research to identify factors for bike-sharing use and user satisfaction, taking Ningbo, China as an example. It shows that 79% of interviewed users in Ningbo agrees that bike sharing system helps them adopt more flexible route in daily transportation. They find out the positive correlation between sharing bike usage and users' degree of satisfaction. Therefore, bike relocation could be a solution for bike sharing companies to reduce idle time and better solve the problem of demand and supply, which makes sharing bikes more accessible and increase user satisfaction.

Scientific research also shows that usage of bike sharing system attributes to the public transportation infrastructures. Wang, Lendsey, Schoner and Harrison (2016) brings up the model that infrastructure variables such as trail could increase the usage of sharing bikes. It provides direction for looking into secondary dataset to help to analyze Mobike's case. However, given the specific information that more and more people tend to choose "Mobike + Metro" as their transportation option, this research will focus on the association between Mobike's usage and Shanghai Metro system for relocation suggestions.

Scholars have been focusing on bike relocation problems using mathematical models with case analysis on different cities' bike sharing systems. There have been different approaches towards modeling for bike relocation problems. Considering real-world application, dynamic models have stronger implication than static models. Researchers use integer linear programming with different objectives that have corresponding optimization goals, for example, minimizing the assorted repositioning cost (Kek et al. (2009)), meeting potential demand (Sayarshad et al. (2012)), and optimizing capacity and inventories (Angeloudis et al. (2014)). These research objectives have the similar implication on Mobike's case. However, the significant difference between the prerequisite of these models and Mobike's case is that these research are all based on bike sharing systems with stations; in contrast, Mobike has scattered distribution over the urban area that does not require users to have station to station bike trips. In addition, since Mobike adopted the "Fortune Bike" strategy to encourage users to participate in bike relocation with cash bonus, the calculation of optimized relocation cost or supply and demand satisfaction becomes more complicated since the "Fortune Bike" algorithm has already applied a layer of programming based on the information. In such case, building another optimization model over the algorithm is weigh more too challenging.

To solve the non-station problem of Mobike, one of the strategy that the research could adopt is to use clustering to create the stations for the models. It has the theory base on transportation analysis. The Four-Step Travel Demand Model is a fundamental model that transportation analysis researches often use in urban planning, which includes trip generation, trip distribution, mode choice and trip assignment[4]. In this research, due to the data limitation, it will focus on trip generation basing on current data and trip distribution through clustering and network construction. The clusters could represent the nodes in traffic network. The traffic flow among the nodes could help calculate traffic distribution, for example, the gravity model[5] could be a solution.

In addition, as most existing research in bike relocation and transportation analysis involves spatial population density as a variable for supply and demand analysis, this research adopted a detailed secondary dataset of Shanghai Metro system to examine the relationship between the usage of Mobike's and Shanghai Metro. Other than integer linear programming for modeling, this research will use linear regression for spatial analysis. In previous research Zhou (2015) points out the over-demand due to the asymmetric flow, which has the similar implication in Mobike's case, given the fact of strong tide effect during rush hours in Shanghai, where the inflow of population to city center is far larger than outflow. The similar

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[4] https://www.massdot.state.ma.us/Portals/17/docs/StatewideModel/StatewideModelDescription.pdf
[5] http://www.princeton.edu/~alaink/Orf467F08/The%20Gravity%20Model.pdf

effect also applies to different metro stations. For Zhou's analysis, he aggregates the data at different bike sharing stations within the time-windows of two hours to conduct clustering.

3. Methodology

The main methodology is k-means clustering and linear regression based on time series.

The k-means clustering first divides the data entries into random groups, and calculate the center of the groups and compare the data point's distance with these centers. It brings the data point to the nearest center and does the next round calculation until the result is constant. By clustering and analyzing the cluster size, the research can help observe the general spatial usage pattern and hotness of Mobike in Shanghai. The research adopted this method because Mobike and other bike sharing companies does not have bike returning stations. In contrast, other bike sharing systems, such as Citi Bike in New York City, is designed with fixed bike returning spots. Therefore, the bike flow has finite choices for model simulation. However, for Mobike's case, since there is no fixed station, the bike flow is hard to detect and simulate for further modeling.

The linear regression models aim to analyze how Metro usage is associated with Mobike usage. There are two logic flow patterns: 1. Mobike users lock the bike and enter the metro station and 2. Users exit the metro station and need to find a bike, and the bike lock event is associated with the increase of idle bike supply in the specific hour. The first logic flow shows whether Mobike is following the tide effect of Metro use and how it contributes to the tide effect. The dependent variable is the hourly inflow population data of individual metro station and the independent variable is the hourly number of events that user locks Mobike in the surrounding area of each metro station. The second logic flow focuses on the ratio of the hourly number of events that user locks Mobike in the surrounding area of each metro station and the hourly outflow population data of individual metro station to examine the supply level.

The calculation of the bike lock event amount is processed manually by selecting major street cross around the area and recording the GPS location, and filtering the spatial bike amount result out.

4. Data Description

The primary dataset is Mobike daily operation data in Shanghai. The columns include bike ID, time stamp, longitude and latitude. Each entry records the event of a Mobike user lock the bike.

The secondary dataset, Shanghai Metro hourly operation, it has columns including specific station name with sub-column in/out and hour.

<u>Challenges for data collection:</u>

The reason that regression model and clustering analysis is based on one-day data is because the other data are not in GPS coordinates format. Therefore, it requires data processing in ArcGIS with local Shanghai urban map coordinates to transform to GPS coordinates. However, the transformation failed.

Mobike data summary:

The dataset contains 46,405 individual bikes with 182,297 user lock actions from Jan. 3rd, 2018 0:00AM to 11:59PM in Shanghai. Here is the summary data for bike use:

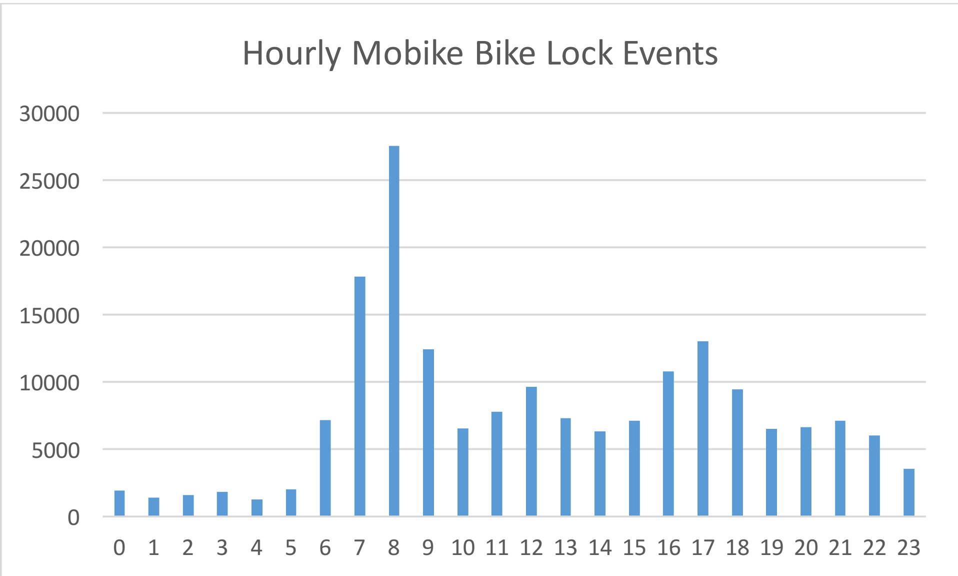
	Amount
Total Number of bikes	46,405
Max User Lock Frequency on single bike	229[6]

[6] Bikes that have 100 ~ 229 user interactions (59 bikes in total) have the same feature that the GPS location repeat to appear within a certain area, which indicates the possibility that the bike is broken. Therefore, for further calculation, these data entries are excluded.

Min User Lock Frequency on single bike	1
Average Frequency	3.918
Median	3
Standard Deviation	8.302

Table - 1 Summary of Mobike's dataset

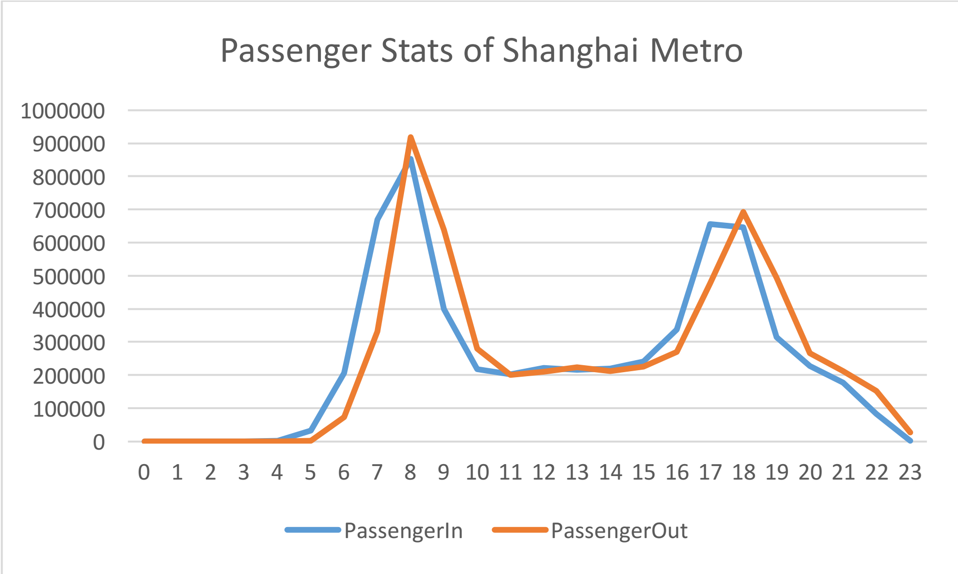
From summary for hourly bike use, Graph - 1 shows an intensive use during rush hours in the morning (7-8AM) and more averaged performance during afternoon (4-6PM):



Graph - 1 Histogram of Hourly Mobike Lock Events

Metro data summary:

The dataset contains 15 metro lines (Line 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 16 and 17) of Shanghai Metro system on Jan. 3rd, 2018. In Graph – 2, it is observed a similar pattern that the passengers have a more intensive demand on metro transportation during peak hours in the morning than in the afternoon.



Graph - 2 Hourly Passenger Stats of Shanghai Metro System

	Quantity
Total Number (In/Out)	5,921,701/5,903,981
Max Passenger	852,254/ 918,250
Min Passenger	0/0
Average Frequency	227,758/227,076
Median	211,008/210,735
Standard Deviation	242343.5/244721.6

Table - 2 Summary of Mobike's dataset

For hourly data summary for each station in the research, please refer to Appendix I.

5. Data Analysis

a. Clustering

The geographic visualization (Appendix II) are hourly clustering results which show the 25 clustering center with corresponding clusters' sizes.

Figure - 1, 2, 3 Clustering Visualization at 2am, 7am and 8am

Figure 1, 2 and 3 are the clustering results of hourly Mobike lock data at 2am, 7am and 8am on Jan. 3rd, 2018. The pictures show strong contrast of Mobike traffic pattern during regular hours and peak hours. In regular hours, for example, 2am, the clustering centers are more spread over the urban area. There are series clustering centers appearing in Pudong and Minghang area (right and down side of the map) with a small volume of Mobike usage. During peak hours, Figure 2 and Figure 3, the volume of Mobike lock events increases sharply within an hour. The allocation of the clustering centers moves towards the center of urban area, and tends to show up within the Inner Ring Highway. The largest cluster at 8am reaches the volume of 2,161 times of Mobike lock events in Baoshan (upper east in Puxi), and following by the second largest cluster with the volume of 1,482 times of Mobike lock events in Minhang (lower middle in Puxi). These large clustering centers locate in mostly high-density residential areas in Shanghai.

b. Regression and ratio

Referring to the clustering result of strong traffic patterns in Inner Ring Highway area, the research selects subway stations in the area[7] with the criteria of having metro line intersection at the metro station. The regression uses the hourly inflow population data of

[7] Metro Line 4 is built according to the Inner Ring Highway, and therefore, the research uses Line 4 to measure whether the metro stations are on/in Inner Ring Highway area.

individual metro station as a dependent variable and the hourly number of events that user locks Mobike in the surrounding area of each metro station as an independent variable.

	Passengers Entering Metro Station ~ Mobike Lock Event Count				
Station Name	Intercept	Coefficient	Intercept Pr(>|t|)	Coef Pr(>|t|)	R-Square
Caoyang	662.72	28.5	0.0474 *	0.0182 *	0.1934
Changshou	849.93	40.93	0.0738 .	0.0885 .	0.08644
Changshu	1167.13	109.45	0.0450 *	0.0547 .	0.1194
Dalian	1084.626	4.364	0.00184 **	0.89377	-0.04459
Hailun	837.21	33.64	0.0123 *	0.244	0.01847
Hanzhong	964.18	11.76	0.0514 .	0.5654	-0.02952
Hongqiao	681.669	13.699	0.0108 *	0.0801 .	0.09328
Shanghai Indoor Stadium	1490.14	39.29	0.0412 *	0.2944	0.006643
Jiangsu	540.78	26.36	0.0889 .	0.0280 *	0.1646
Jiaotong	594.42	30.53	0.0713 .	0.0399 *	0.1408
Jiashan	515.11	59.83	0.06498 .	0.00705 **	0.2539
Jingan	3150.661	-3.355	0.0139 *	0.9682	-0.04538
Jinshajiang	1045.148	10.463	0.000214 ***	0.18672	0.18672
Lancun	519.1	77.62	0.1528	0.0121 *	0.2195
Laoximen	461.52	49.03	0.1101	0.0124 *	0.2181
Longde	278.09	61.68	0.14913	0.00305 **	0.3047
Lujiabang	663.35	31.3	0.1059	0.0353 *	0.1491
Madang	489.91	21.21	0.0761 .	0.0986 .	0.07909
E. Nanjing	3474.98	-26.68	0.00221 **	0.72724	-0.03956
W. Nanjing	3632.76	-14.47	0.0064 **	0.8367	-0.04339
Pudian	1889.719	1.629	0.0604 .	0.9253	-0.04503
Qufu	443.7	36.34	0.0988 .	0.0625 .	0.1102
Shanghai Railway	1463.97	91.91	0.02457 *	0.00383 **	0.2912
S. Shaanxi	2552.03	10.83	0.00263 **	0.87849	-0.04432
Tiantong	1274.69	-18.76	0.00918 **	0.52596	-0.02609
Xintiandi	220.934	16.487	0.42678	0.00612 **	0.2627
XizangS	799.21	47.37	0.0151 *	0.0236 *	0.1761
Xujiahui	3534.1	91.94	0.0798 .	0.2054	0.02964
Zhaojiabang	711.2	307.7	0.0680 .	0.0208 *	0.02078
Zhenping	162.29	55.337	0.197	5.55e-09 ***	0.7837
Zhongshan	612.29	50.65	0.223188	0.000291 ***	0.4318

Table - 3: Linear Regression report for different metro stations in Inner Ring Highway

In Table - 3, it shows the result of linear regression model of individual stations. The key information is R-square and Coefficient of independent variable. Since it's a single variable model, it might be underfitting because there are other factors such as weather, traffic situation, and etc. could impact the result.

The stations, Zhenping Road Station and Zhongshan Park, with highest R-square value also show strong significance of the independent variable the hourly number of events that user locks Mobike in the surrounding area of each metro station. A unit change in the hourly number of events that user locks Mobike in the surrounding area of each metro station is associated with 5.55e-09 and 0.000291unit change of hourly metro user inflow. However, the low coefficient shows that the impact of Mobike use on Metro use is trivial for these two stations.

In comparison, such stations as Caoyang Road, Lancun Road and Laoximen, have relatively high R-square, relatively strong significance (not smaller than 0.005 but still small, around 0.01) of independent variable the hourly number of events that user locks Mobike in the surrounding area of each metro station and relatively high coefficients of the independent variable. A unit change in the hourly number of events that user locks Mobike in the surrounding area of each metro station is associated with 0.0182, 0.0121 and 0.0124 unit change of hourly metro user inflow.

Other stations, such as East Nanjing Road and West Nanjing Road station, the R-square is negative, which means the time series linear regression model doesn't fit well. This result reflects that it is possible that Mobike lock event is not associated with the metro user inflow around the stations. For example, both East Nanjing Road and West Nanjing Road have a walking pedestrian area where transportation tools including bikes are prohibited so that it is more likely metro users are not using Mobike as their transportation connection to metro stations.

In Appendix III, the table shows the hourly supply ratio of bikes in each station, most stations show a decrease in supply ratios during peak hours, which means bike might scarce for outflow metro users. However, Lujiabang Road shows in increase in supply ratio during peak hours, from 0.004 to 0.009 from 8AM to 9AM, which is contrary to the general pattern. The change in the supply ratio might indicate there exists more redundant bike in the surrounding area. Therefore, sharing bike system could monitor the real-time supply ratio around major metro stations, especially those with less pedestrian spaces, to react according to the passenger flow. In addition, as concluded from Appendix III, after 9PM, there are a few stations that are with high Mobike supply ratio verses passenger outflow that would need bike relocation staffs to work with.

6. Conclusion

The research aims to explore the relationship of Mobike and Shanghai Metro system usage to figure out a better solution for Mobike relocation problem by analyzing Mobike and Shanghai Metro hourly geographic and usage data on a workday.

The analysis focuses on clustering to study the traffic pattern and conducts linear regression model for the highlighted area in clustering results. First, the strong traffic flow pattern in the center of urban area is detected. Second, through the regression over the metro stations in city center, the research finds out several stations, including Caoyang Road, Lancun Road and Laoximen, has a relatively strong linear relationship between Mobike and Metro inflow usage. At these stations, Mobike could have bike relocation staff around to manage the parking of bikes since the volume of bike inflow is large. If the Mobikes are parked in good order, it will reduce the negative impact on surrounding traffic system and make it convenient for exiting metro users to pick up the bike and redirect the bikes to other destinations. For such stations as Lujiabang Road, Mobike could have bike mobility staff to remove bikes from the station to bring the bike supply down to the average level as other stations. Therefore, it could reduce the idle time that Mobike bikes have around the subway stations.

In the future, the research might collect more data with different variables and with longer time period coverage for more accurate model to run a thorough regression and prediction. In addition, there are other research objectives that have strong connection with the metro system and Mobike. As indicated in Mobike's report[8], Mobike has redefined the notion of "metro apartment" in Shanghai, which usually has a higher price than other housing. Objectives such as housing price increase pattern around metro stations could be the next research steps.

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8. Appendix (starting from next page)

Appendix I: Hourly summary data of different metro stations:

Station	X1	X2	Y1	Y2	mean In	max In	min Out	mean Out	max Out	min Out	mean Lock	max Lock	min Lock
Caoyang	31.235442	31.245349	121.41164	121.420463	1238.583	3937	0	1197.792	5931	0	20.20833	92	0
Changshou	31.237235	31.243455	121.433017	121.440635	1479.208	5308	0	1487.708	6495	0	15.375	58	0
Changshu	31.211879	31.215513	121.444725	121.454476	1974.333	7569	0	2049.583	9839	0	7.375	27	0
Dalian	31.259426	31.256142	121.50893	121.517148	1108.083	4666	0	1133.667	5875	0	5.375	32	0
Hailun	31.255431	31.260788	121.48609	121.491476	1074.083	4089	0	1101.25	5988	0	7.041667	37	0
Hanzhong	31.238884	31.245727	121.453886	121.463757	1171	5836	0	1212.708	8021	0	17.58333	63	0
Hongqiao	31.195333	31.201002	121.413192	121.424243	971.625	3354	0	1005.042	5003	0	21.16667	117	0
Indoor Stadium	31.17934	31.185857	121.432373	121.442565	2035.292	8783	0	2075.75	11327	0	13.875	46	0
Jiangsu	31.216354	31.221345	121.42472	121.43532	1074.5	3975	0	1073.125	5178	0	20.25	77	0
Jiaotong	31.199517	31.204638	121.478092	121.486697	1098.167	3921	0	1135.333	4916	0	16.5	62	0
Jiashan	31.201188	31.204345	121.45569	121.4679	1081	3790	0	1078.167	4663	0	9.458333	37	0
Jingan	31.220002	31.224902	121.442562	121.450931	3114.458	14813	0	3165.708	16929	0	10.79167	32	0
Jinshajiang	31.228776	31.233555	121.411223	121.419227	1186.833	3736	0	1167.875	3942	0	13.54167	142	0
Lancun	31.208495	31.214515	121.522824	121.531815	1207.958	5025	0	1178.25	7200	0	8.875	37	0
Laoximen	31.219332	31.221479	121.478076	121.491122	1045.75	3263	0	1049.042	3726	0	11.91667	36	0
Longde	31.229305	31.232755	121.41705	121.427457	743.25	2438	0	752.5833	2951	0	7.541667	29	0
Lujiabang	31.208908	31.212964	121.481402	121.497235	1374.167	4157	0	1370.833	4749	0	22.70833	68	0
Madang	31.20732	31.212807	121.470914	121.480419	841.6667	3025	0	856.9167	3449	0	16.58333	53	0
NanjingE	31.23556	31.239595	121.48116	121.490408	3220.375	12244	0	3270.792	16808	0	9.541667	35	0
NanjingW	31.227345	31.230666	121.454853	121.466762	3453.75	16562	0	3586.125	18471	0	12.375	47	0
Pudian	31.215701	31.223701	121.524332	121.494816	1957.875	12068	0	2026.792	19343	0	41.83333	168	0
Qufu	31.239814	31.244621	121.466648	121.476497	849.4583	2829	0	852.0833	3752	0	11.16667	27	0
Railway	31.245766	31.252792	121.454929	121.462353	2968.917	6997	0	2704.208	8969	0	16.375	46	0
ShaanxiS	31.214017	31.216935	121.452928	121.462444	2631.917	10147	0	2660.25	11158	0	7.375	33	0

Tiantong	31.24076	31.24586	121.478092	121.486697	1045.667	4936	0	1061.792	5881	0	12.20833	31	0
Xintiandi	31.213496	31.217827	121.471746	121.497235	898.2917	3513	0	954.7083	3971	0	41.08333	105	0
Xizang	31.200515	31.203745	121.481795	121.494816	1304.542	3941	0	1275.583	4173	0	10.66667	37	0
Xujiahui	31.189803	31.196063	121.431407	121.442179	5522.333	20579	0	5455.583	24546	0	21.625	65	0
Zhaojiabang	31.198716	31.203433	121.455719	121.457349	1352.292	5959	0	1386.25	7970	0	2.083333	8	0
Zhenping	31.245712	31.245349	121.42422	121.433661	888.5833	3966	0	864.5833	2906	0	13.125	75	0
Zhongshan	31.215074	31.220451	121.411031	121.422533	2250	6770	0	2347.542	7567	0	32.33333	100	1

Notes:

1. X1, X2, Y1, Y2 are collected manually to locate a certain area around the metro station to filter Mobike lock events surrounded.

2. Min/Max/Mean In refers to Min/Max/Mean hourly number of passengers entering the metro station.

3. Min/Max/Mean Out refers to Min/Max/Mean hourly number of passengers exiting the metro station.

4. Min/Max/Mean Lock refers to Min/Max/Mean hourly number of users' locking Mobike after the bike trips.

5. The hourly data comes from Jan. 3rd, 2017, 0:00AM to 23:59PM.

App

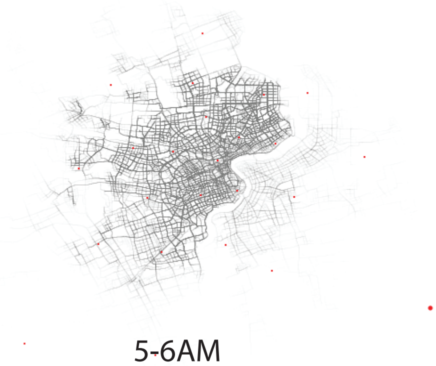
0-1AM

1-2AM

2-3AM

3-4AM

4-5AM



5-6AM

6-7AM

7-8AM


8-9AM


9-10AM


10-11AM


11AM-12PM


12-1PM


1-2PM


2-3PM


3-4PM

4-5PM

5-6PM

6-7PM

7-8PM

8-9PM

9-10PM

10-11PM

11PM-12AM

Appendix III: Supply Ratio of Mobike at different metro stations

Station Name	0AM	1	2	3	4	5	6	7	8	9	10	11
Caoyang	Inf	Inf	Inf	Inf	Inf	1.500	0.134	0.070	0.006	0.005	0.014	0.025
Changshou	Inf	NaN	Inf	Inf	Inf	1.000	0.056	0.035	0.004	0.002	0.007	0.018
Changshu	NaN	NaN	NaN	NaN	NaN	0.133	0.011	0.005	0.000	0.001	0.001	0.007
Dalian	NaN	Inf	NaN	NaN	Inf	0.636	0.083	0.015	0.001	0.001	0.006	0.008
Hailun	NaN	Inf	NaN	Inf	Inf	0.778	0.101	0.032	0.003	0.001	0.007	0.018
Hanzhong	Inf	NaN	0.022	0.043	0.069	0.196	0.082	0.051	0.004	0.003	0.003	0.031
Hongqiao	Inf	NaN	Inf	NaN	NaN	0.467	0.113	0.059	0.010	0.007	0.014	0.038
Shanghai Indoor Stadium	Inf	Inf	NaN	NaN	Inf	1.091	0.063	0.014	0.003	0.001	0.002	0.004
Jiangsu	NaN	NaN	Inf	Inf	NaN	0.476	0.060	0.051	0.009	0.006	0.011	0.041
Jiaotong	Inf	Inf	Inf	Inf	NaN	0.500	0.095	0.028	0.007	0.005	0.010	0.025
Jiashan	NaN	NaN	NaN	NaN	Inf	0.500	0.042	0.027	0.005	0.002	0.012	0.014
Jingan	NaN	Inf	NaN	NaN	Inf	0.133	0.017	0.007	0.002	0.001	0.003	0.004
Jinshajiang	NaN	NaN	NaN	NaN	NaN	1.111	0.086	0.137	0.003	0.001	0.004	0.016
Lancun	NaN	Inf	NaN	NaN	NaN	0.385	0.070	0.024	0.003	0.003	0.005	0.016
Laoximen	NaN	NaN	NaN	NaN	Inf	2.714	0.037	0.021	0.006	0.003	0.006	0.012
Longde	NaN	NaN	NaN	NaN	NaN	1.333	0.054	0.035	0.002	0.002	0.009	0.027
Lujiabang	Inf	Inf	Inf	Inf	Inf	7.333	0.080	0.020	0.004	0.009	0.019	0.017
Madang	Inf	Inf	Inf	NaN	Inf	8.333	0.148	0.057	0.009	0.008	0.026	0.039
NanjingE	Inf	Inf	Inf	Inf	Inf	0.139	0.030	0.008	0.001	0.002	0.000	0.005
NanjingW	NaN	NaN	NaN	Inf	NaN	0.310	0.025	0.010	0.002	0.001	0.002	0.005
Pudian	Inf	NaN	Inf	NaN	Inf	10.500	0.195	0.057	0.003	0.004	0.026	0.053
Qufu	NaN	Inf	NaN	Inf	Inf	1.857	0.045	0.023	0.007	0.007	0.017	0.019
Shanghai Railway	Inf	Inf	NaN	Inf	Inf	0.103	0.030	0.010	0.004	0.003	0.007	0.005
ShaanxiS	NaN	NaN	Inf	Inf	Inf	0.079	0.017	0.007	0.002	0.000	0.001	0.004
Tiantong	Inf	NaN	NaN	Inf	Inf	2.818	0.044	0.021	0.003	0.002	0.006	0.004
Xintiandi	NaN	Inf	Inf	Inf	Inf	4.500	0.344	0.093	0.013	0.010	0.023	0.044
XizangS	NaN	Inf	Inf	Inf	NaN	0.583	0.035	0.009	0.007	0.003	0.006	0.015

Xujiahui	Inf	NaN	NaN	Inf	Inf	0.174	0.030	0.009	0.002	0.001	0.003	0.005
Zhaojiabang	NaN	NaN	NaN	NaN	Inf	0.125	0.002	0.002	0.000	0.000	0.001	0.004
Zhenping	Inf	Inf	NaN	NaN	NaN	0.800	0.031	0.035	0.026	0.011	0.010	0.020
Zhongshan	Inf	Inf	Inf	Inf	Inf	0.250	0.037	0.030	0.014	0.008	0.013	0.014

Station Name	**12PM**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Caoyang	0.015	0.014	0.010	0.037	0.016	0.015	0.007	0.005	0.018	0.024	0.018	0.000
Changshou	0.016	0.014	0.009	0.013	0.014	0.008	0.004	0.006	0.021	0.013	0.009	0.000
Changshu	0.002	0.003	0.005	0.004	0.016	0.005	0.003	0.004	0.006	0.004	0.011	0.000
Dalian	0.005	0.011	0.003	0.002	0.005	0.002	0.000	0.001	0.003	0.002	0.005	0.000
Hailun	0.006	0.005	0.002	0.010	0.004	0.005	0.000	0.001	0.004	0.008	0.008	0.000
Hanzhong	0.021	0.017	0.016	0.042	0.047	0.014	0.011	0.006	0.026	0.039	0.032	0.000
Hongqiao	0.012	0.009	0.028	0.023	0.055	0.012	0.009	0.012	0.032	0.027	0.009	0.000
Shanghai Indoor Stadium	0.004	0.012	0.007	0.019	0.012	0.006	0.001	0.006	0.018	0.007	0.015	0.000
Jiangsu	0.037	0.019	0.022	0.022	0.027	0.017	0.006	0.016	0.030	0.018	0.024	0.000
Jiaotong	0.018	0.012	0.008	0.038	0.024	0.018	0.004	0.003	0.016	0.023	0.022	0.000
Jiashan	0.005	0.007	0.005	0.026	0.010	0.006	0.004	0.005	0.011	0.011	0.008	0.000
Jingan	0.004	0.004	0.005	0.005	0.006	0.004	0.001	0.002	0.004	0.006	0.004	0.000
Jinshajiang	0.007	0.000	0.005	0.004	0.008	0.005	0.005	0.006	0.010	0.018	0.015	0.000
Lancun	0.019	0.011	0.012	0.011	0.015	0.007	0.003	0.003	0.008	0.004	0.002	0.000
Laoximen	0.008	0.009	0.019	0.013	0.027	0.008	0.006	0.006	0.025	0.019	0.002	0.000
Longde	0.012	0.005	0.007	0.020	0.018	0.007	0.007	0.008	0.019	0.012	0.015	0.000
Lujiabang	0.011	0.008	0.019	0.037	0.032	0.009	0.005	0.008	0.016	0.009	0.017	0.000
Madang	0.037	0.010	0.016	0.023	0.000	0.005	0.011	0.009	0.027	0.016	0.031	0.000
NanjingE	0.004	0.004	0.002	0.002	0.003	0.001	0.000	0.002	0.003	0.006	0.003	0.000
NanjingW	0.007	0.002	0.003	0.006	0.008	0.002	0.001	0.001	0.008	0.009	0.005	0.000
Pudian	0.044	0.032	0.043	0.042	0.069	0.028	0.016	0.030	0.063	0.047	0.039	0.000
Qufu	0.004	0.011	0.020	0.024	0.023	0.006	0.006	0.008	0.005	0.032	0.016	0.000

Shanghai Railway	0.003	0.002	0.003	0.004	0.005	0.005	0.004	0.005	0.011	0.025	0.001	0.000
ShaanxiS	0.000	0.006	0.004	0.002	0.004	0.002	0.001	0.003	0.002	0.005	0.005	0.000
Tiantong	0.008	0.005	0.005	0.008	0.021	0.008	0.016	0.033	0.061	0.042	0.013	0.000
Xintiandi	0.026	0.043	0.041	0.090	0.093	0.045	0.024	0.062	0.081	0.101	0.061	0.000
XizangS	0.006	0.002	0.002	0.014	0.020	0.006	0.002	0.001	0.008	0.008	0.002	0.000
Xujiahui	0.003	0.003	0.006	0.005	0.008	0.003	0.002	0.005	0.006	0.016	0.004	0.000
Zhaojiabang	0.001	0.002	0.000	0.006	0.003	0.004	0.001	0.001	0.007	0.004	0.000	0.000
Zhenping	0.029	0.016	0.001	0.003	0.014	0.012	0.004	0.012	0.015	0.014	0.018	0.056
Zhongshan	0.023	0.013	0.022	0.014	0.024	0.012	0.007	0.005	0.011	0.015	0.030	0.015

*1. The ratio is (the hourly number of events that user locks Mobike in the surrounding area of each metro station) / (hourly outflow populati data of individual metro station).

2. NaN is the result of the hourly outflow population data of individual metro station = 0 and the hourly number of events that user locks Mobi in the surrounding area of each metro station = 0.

3. Inf is the result of the hourly outflow population data of individual metro station = 0.