경영학석사 학위논문

Optimal inventory of Seoul bike-sharing system with static repositioning

2020 년 2 월

서울대학교 대학원

경영학과 생산관리전공

한 유 미

Optimal inventory of Seoul bike-sharing system with static repositioning

지도교수 양 홍 석

이 논문을 경영학 석사학위논문으로 제출함
2020 년 2 월

서울대학교 대학원
경영학과 생산관리전공
한 유 미

한유미의 석사학위논문을 인준함
2020 년 2 월

위 원 장 _____ 박 상 욱 _____ (인)

부위원장 _____ 임 재 현 _____ (인)

위 원 _____ 양 홍 석 _____ (인)

Abstract

Bike-sharing systems are an emerging form of urban mobility, both efficient in terms of reducing carbon emissions and solving the 'last-mile problem' in transportation. This study aims to solve a crucial operational problem of bike-sharing systems that is bike repositioning. This study utilizes the Markov chain to model user dissatisfaction in renting and returning bikes, using actual recorded data for Seoul's bike-sharing system 'Ttareungyi'. Under static repositioning, inventory levels to be set at start of day that minimize the total user dissatisfaction for each station during a day's operation are determined. These results offer managerial aid to bike-sharing system operators in that they can be used as good enough objectives for the repositioning teams throughout operation. The results are analyzed to derive a rather counter-intuitive managerial insight that neither seasons nor days of the week influence the optimal inventory levels for each station. Different penalty ratios are also considered to check the robustness of the model. Moreover, a revised model with loosened capacity constraints show that increased capacity is effective in decreasing user dissatisfaction for all stations.

Keyword : Inventory management, Bike-sharing system (BSS), Static repositioning, Micromobility
Student Number : 2018-25661

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

In light of shared economy and connectivity, today's urban transportation cannot be imagined without its essential component in the form of shared bikes. Municipalities worldwide have adopted bike-sharing systems (BSS) to better address the "last-mile" problem in transportation (DeMaio, 2009).

The definition of bike-sharing is "a short term bicycle rental available at unattended stations (DeMaio, 2009)." Paris bicycle Vélib' and Hangzhou Public Bicycle are just some of the older metropolitan bike-sharing systems, with a respective number of 20,000 and 86,000 bicycles in operation. The city of Seoul has also employed its own public bike-sharing system, 'Ttareungyi', with a fleet size of 20,000 bikes and 1,540 stations. Since its official public launch in 2016, Ttareungyi is comparable to the equally sized Vélib' launched in 2007.

In addition to anticipated public health and tourism benefits, alleviation of traffic congestion, and reduction in CO2 emissions, the Seoul bike system is favorably viewed by citizens (Yoon, 2018). As public attention and favor have shifted towards bike-sharing systems, institutional and academic research is performed on the numerous services worldwide.

The rise of micromobility is another factor contributing to the popularity of research on bike-sharing systems. The term 'micromobility' was coined by tech analyst Horace Dediu in 2017. It is defined as "*personal mobility* whose utility is to move its occupant [with a purpose to] offer maximum freedom of mobility" and with a gross weight of under 500 kg (Dediu, 2019). Micromobility is a recent yet increasingly critical element in urban transportation. However, its volatility and

unmanned nature require systematic control for it to function in a complex transportation environment.

The need for systematic control is what this research aims to address. In particular, finding the initial number of bicycles to stock at each station at start of day that will minimize user dissatisfaction is the main objective. This study utilizes models on static repositioning from prior literature, computes results using Ttareungyi data, and discusses the managerial implications.

The results offer optimal inventory levels that should be attained at start of operation to minimize user dissatisfaction throughout the day. Of course, this cannot be easily executed due to the lack of workforce and the impossible nature of transporting all bikes to desired locations. Nevertheless, neither the repositioning operation status quo can address all stations multiple times a day, as is the intention of dynamic repositioning. This can be attributed to the lack of workforce, the large size of the system, and complex transportation issues.

This study proposes static repositioning levels of inventory so that the dynamic repositioning team can first relocate bicycles when the system is idle, and focus on high-demand stations during operation.

The results are also analyzed to see whether any externalities such as seasons and weekday/holiday factors affect inventory levels. The instances of different penalty costs and capacity are also accounted for. Some implications are discussed regarding the results.

Chapter 2. Literature Review

The bike repositioning problem is dealt with in various literature, mostly in the academic fields of operational research and transportation research (Köchel, Kunze, Nieländer, 2003). The specific topic of bike-sharing systems is relatively new, with traditional subjects including vehicle repositioning (Bruglieri, Colorni, & Luè, 2014) and container repositioning for railroad and maritime transportation as can be seen in Shintani, Imai, Nishimura, & Papadimitriou (2007) and Alan, Juan, & Martin (2009).

DeMaio (2009) and Shaheen, Guzman, & Zhang (2010) have conducted reviews on bike-sharing systems overall, providing an overview of the history and evolution of the systems in general. These two studies remain the most cited work related to bike-sharing systems as of 2019. Reviews on bike-sharing literature include Fishman, Washington, & Haworth (2013), Fishman (2016), Laporte, Meunier, & Wolfler Calvo (2015), and Si, Shi, Wu, Chen, & Zhao (2019), all of which identify related articles.

Laporte et al. (2015) have classified the related literature on shared mobility systems, including that of bicycle sharing. The investigated problems in shared mobility systems are at strategical, tactical, and operational levels. The problems can again be categorized into 5 main headings, based on which problems they aim to solve: Station location, fleet dimensioning, station inventory, rebalancing incentives, and vehicle repositioning. Station inventory, at the operational level, is the focus of this research.

There are also studies related to bike-sharing from a non-operational point of view, such as health benefits (Fuller et al., 2013), (Woodcock, Tainio, Cheshire, O'brien, & Goodman, 2014) and negative aspects of pricing (Goodman & Cheshire, 2014). However, these topics digress from the main focus of this study, which is the initial inventory level at each station to minimize user dissatisfaction.

References to address this problem include operational research studies of Benchimol et al. (2011), Shu, Chou, Liu, Teo, & Wang (2013), Raviv, Tzur, & Forma (2013), Raviv & Kolka (2013), Chemla, Meunier, & Wolfler Calvo (2013), and Schuijbroek, Hampshire, & van Hoeve (2013). These are just but a prominent few of the numerous literature regarding bike-sharing repositioning operations.

Most of the above studies are built upon the static repositioning assumption. Vehicle repositioning can be either static or dynamic. Static repositioning is a method where rebalancing work takes place during the night when demand is low enough for the stations to be considered idle. In dynamic repositioning, rebalancing work occurs throughout the operation, continuously or periodically. A majority of prior literature referenced here concerns the static case, due to the model simplicity and the greater impact of nighttime repositioning (Laporte et al., 2015). This study also attends to static repositioning and the optimal station inventory levels to be reached during the nighttime rebalancing process

This study aims to contribute to the literature by utilizing an existing model for obtaining optimal inventories and applying it to the context of a municipal bike-sharing system. Seoul Ttareungyi, considering its large size and user base, distinctive convenience features such as 'connect-return' and fast synchronization, and unique demand patterns, is characteristically different from other bike-sharing systems that have been studied in the literature. By collecting recorded demand data, proposing

optimal inventory levels to minimize dissatisfaction, and analyzing the results, this study examines Seoul's bike-sharing service Ttareungyi from the viewpoint of operations management.

Chapter 3. Model

3.1. Data

The data used for this research was obtained via the Seoul Open Data Plaza website and information requests to the South Korean Ministry of Public Administration and Security.

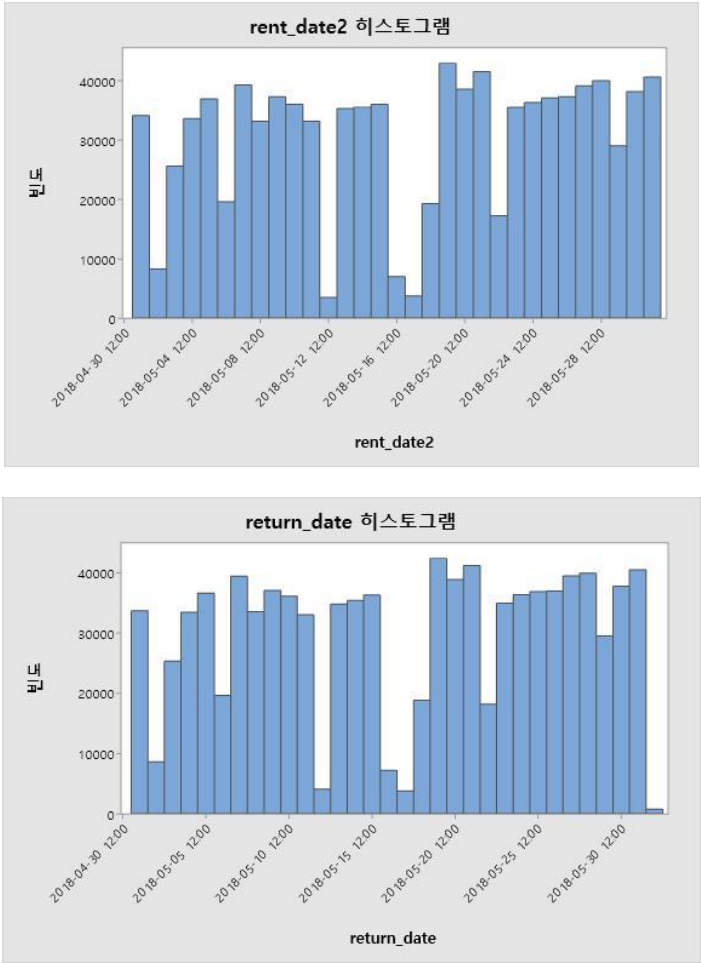


Fig. 1. Histograms for daily rentals (top) and returns (bottom) for all stations during May 2018

The most popular day in May is the 19th, with a total of 42,959 rentals and 42,412 returns. The most popular station, 207, recorded 662 rentals and 773 returns that day.

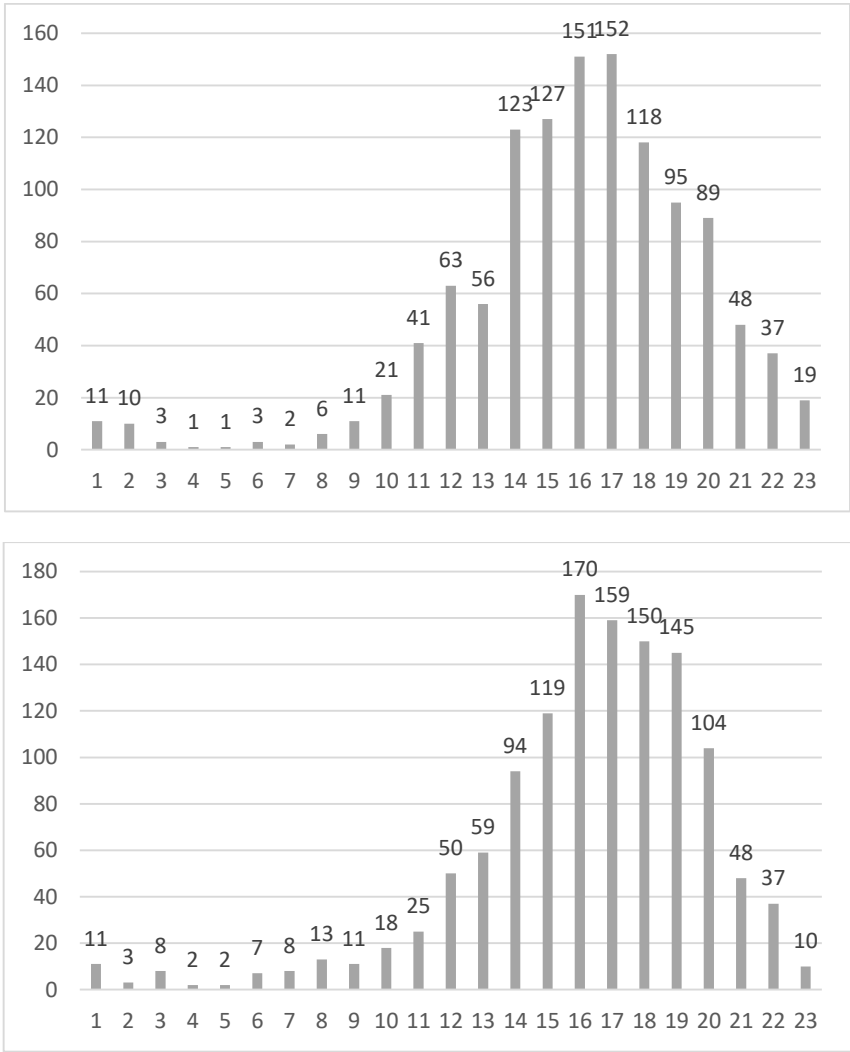


Fig. 2. Hourly rentals (top) and returns (bottom) for 10 stations, May 7th, 2018

It can be observed that there are obvious peak times for both rentals and returns. On the contrary, the demand from 00:00 to 06:00 account for only 2% of the total daily demand. This is the time interval in which the system is considered to be idle and therefore appropriate for static repositioning to take place.

3.2. Model

The key objective of this study is to find the initial inventory levels for each station which will minimize dissatisfied customers throughout the workday. Here, this study makes use of the User Dissatisfaction Function (UDF) from Raviv & Kolka (2013) to calculate the expected number of dissatisfied customers.

A Markov process is a stochastic model of a sequence of possible events in which the probability of the future state of the system depends only on the current state of the system. Since the probability of a station hitting a certain inventory level at time interval $t + 1$ is not dependent on the inventory level of time interval $t - 1$, a Markov process is appropriate in modeling the rentals and returns of a bike-sharing station. Each station is assumed to be independent, which simplifies the model. Nevertheless, this inaccurately represents real-life system behavior, where all stations cannot be independent of each other's demands. This limitation is addressed in the latter part of this section.

3.2.1. Expected User Dissatisfaction Function (UDF)

Raviv & Kolka (2013) introduces a function to calculate user dissatisfaction when customer arrival rates follow a non-homogeneous Poisson process (NHPP):

$$f = \mathrm{p} \cdot \mathrm{E}\big(N_1(I_0)\big) + \mathrm{h} \cdot \mathrm{E}\big(N_2(I_0)\big)$$

Notations:

f = daily user dissatisfaction for each station

p = penalty for bike shortages

h = penalty for docking space shortages

N_1 = number of dissatisfied customers due to bike shortages

N_2 = number of dissatisfied customers due to docking space shortages

I_0 = initial inventory at start of day (number of bikes)

For each station, total dissatisfaction f is measured as the sum of the weighted expected number of dissatisfied customers. $\mathrm{E}\big(N_1(I_0)\big)$ denotes the expected number of customers dissatisfied from shortage of bicycles when initial inventory is I_0. $\mathrm{E}\big(N_2(I_0)\big)$ is the expected number of customers dissatisfied from shortage of return space. The penalty costs p and h represent the weight of each dissatisfaction. Prior literature assumes both to have equal weights of 1 (Raviv & Kolka, 2013). The customer arrival rates are assumed to be Poisson.

Note that this model takes into account only the user dissatisfaction and not the associated operating costs. Raviv & Kolka (2013) mentions that "an important special case of the above bi-objective function is when the weight of the operating costs is zero, expressing a situation in which the marginal operating costs are negligible relative to the importance of the service quality provided to the users."

Ttareungyi indeed fits the description of this “special case.” For many real-life bike-sharing systems, operating costs should be taken into account to ensure sustainable operation and to continue providing profitable service. However, Ttareungyi is not a profitable service although it extrudes effort to be one for the sake of sustainability. Operating at a loss for over 3 years since its launch, it has continuously set goals in its annual reports to make a profit. This proved unsuccessful, with Ttareungyi not disclosing its profits in public financial statements for 2018-2019 (although available upon request).

On the other hand, popularity and customer satisfaction are extremely high, compared to other Seoul city public services (Yoon, 2018). Therefore, as a public welfare policy, Ttareungyi is a special case that holds marginal operating costs as negligible relative to the importance of the service quality (or availability) provided to its users. For this reason, operating costs are not considered in the inventory optimization problem.

Nevertheless, it must be noted that even as a public service, this research aims to provide a solution that can cut unnecessary costs that occur as a result of unorganized rebalancing depending heavily on experience and heuristics. The objective is to find initial inventory levels that satisfy customers and can be readily implemented in the current system, requiring little to no additional cost.

3.2.2. Markov chain

Birth-and-death process

For each station, the probabilities of the inventory level (number of bikes) going from empty to full can be visualized in a birth-and-death process:

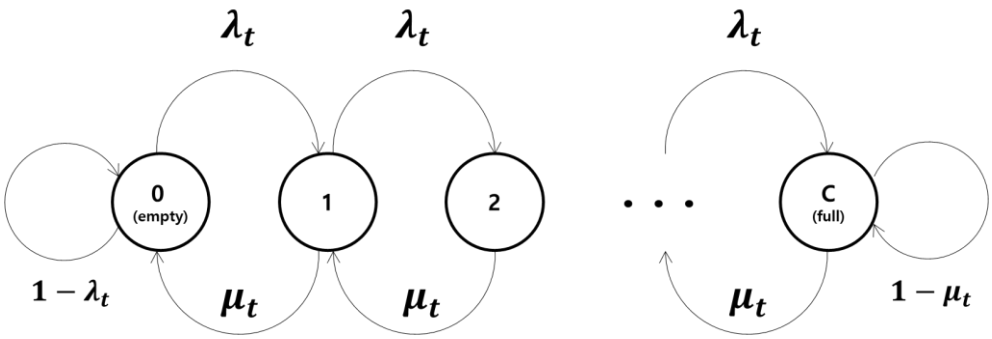


Fig. 3. Birth-and-death process in continuous-time Markov process

Here, the station capacity C is not directly applicable, as Ttareungyi stations have no capacity limit for returns. Bicycles can be connected and returned to an already docked bike in the station ('connect-return'). Therefore, the states of inventory levels are infinite in theory. However, there is the real-world issue of connect-returned bicycles blocking pedestrian paths or entrances and exits.

For the most popular station, station ID 207, the Seoul bike-sharing system authorities were contacted and asked for an estimate of the level of inventory that triggers rebalancing for this particular station. Station 207 has 40 docks, a high number compared to the average 14 for stations in the Yeongdeungpo-gu area.

A Ttareungyi operator has confirmed that there is no system trigger level for rebalancing. The overall real-time inventory levels are monitored by the operations team and the actual inventory levels are observed by the rebalancing team. These two entities continuously determine where and how many bikes to relocate.

The capacity, or space limit, for each station is assumed to be (2*number of docks) for stations with a number of docks under and equal to 20, and (1.5*number of docks) for stations with over 20, rounded to the nearest integer. This calculation

considers that stations are located in easily accessible areas that are prone to blockage when bikes spill out of their designated return spaces. This estimate was confirmed by a Ttareungyi operator to be reasonable. The operators are a credible source of confirmation in that either the system operations team or the rebalancing team decides that there are too many bikes in a particular station.

Station ID	number of docks	capacity
200	20	40
201	15	30
202	30	45
203	15	30
204	13	26
205	20	40
206	35	53
207	40	60
209	12	24
210	21	32

Table. 1. Number of docks and assumed capacity of individual stations

3.3. Probability matrices and steady state approximation

Transition probability matrix P_θ

Arrival rates μ(rentals) and λ(returns) for 75 stations in the Yeongdeungpo-gu area were calculated to form transition probability matrices, based on recorded data for May 7th, 2018. The data from 00:00-06:00 was censored due to the low numbers of rentals and returns during that time (less than 2% of total daily rentals and returns).

To discretize the planning horizon, the 18-hour day was divided into hour-length intervals from 1 to T (T=18). The hour intervals were again discretized into short periods of length δ (δ = 1/60 hours) and the respective per minute arrival rates of rentals and returns were determined. Transition probability matrices were constructed for each hour interval, using the hourly arrival rates and denoted as P_θ, for each time index θ (t = δ, 2δ, …, T).

$$\begin{pmatrix} (1-\lambda) & \lambda & & & & & \\ \mu & (1-\mu-\lambda) & \lambda & & & & \\ & \mu & (1-\mu-\lambda) & \lambda & & & \\ & & & \cdots & & & \\ & & & & \mu & (1-\mu-\lambda) & \lambda \\ & & & & & \mu & (1-\mu) \end{pmatrix}$$

Fig. 4. Transition probability matrix P_θ

The above (C+1) × (C+1) transition probability matrix represents the state transition probability for a single minute within a particular hour for a particular station. Every element $a_{i,j}$ depicts the instantaneous transition probability in which the state will go from i bikes to j bikes within a minute.

Transition rate matrix Q_θ and steady state approximation

The User Dissatisfaction Function, in terms of state transition probabilities, can be stated as:

$$F(I_0) = \int_0^T (\pi_{I_0,0}(t)\mu_t p + \pi_{I_0,C}(t)\lambda_t h)dt$$

$\pi_{i,j}(t)$ denotes the probability of the station being at state *j* at time *t*, given that its initial state at time 0 was *i*. In other words, the first term in the integral is the accumulated expected user dissatisfaction when the station is empty (inventory = 0); the second term is the accumulated expected user dissatisfaction when there is no available return space (inventory = C). Incremental dissatisfaction occurs at rates of μ_t and λ_t for each period (1 minute). $\boldsymbol{\pi}(t)$ denotes the whole transition probability matrix for $t = \theta\delta$. It is computed by:

$$\boldsymbol{\pi}(\theta\delta) = \prod_{\theta=1}^{\theta} P_\theta$$

The recursive relation $\boldsymbol{\pi}(t) = \boldsymbol{\pi}(t-\delta) \times P_{t/\delta}$ is used to calculate all transition matrices $\boldsymbol{\pi}(t)$. Due to the constant arrival rates for each hour, $P_\theta = e^{Q_\theta \delta}$ where Q_θ is the transition rate matrix of the Markov process. In a transition rate matrix, the element $q_{i,j}$ (for $i \neq j$) denotes the rate moving from *i* and arriving in state *j*. Diagonal elements $q_{i,j}$ are defined such that:

$$q_{i,j} = -\sum_{i \neq j} q_{i,j}$$

Therefore, each row of the matrix sums up to 0. The transition rate matrices have negative diagonals that follow $(-\lambda, -\mu-\lambda, -\mu-\lambda, \dots, -\mu-\lambda, -\mu)$.

$$\begin{pmatrix} (-\lambda) & \lambda & & & & & \\ \mu & (-\mu-\lambda) & \lambda & & & & \\ & \mu & (-\mu-\lambda) & \lambda & & & \\ & & & \cdots & & & \\ & & & & \mu & (-\mu-\lambda) & \lambda \\ & & & & & \mu & (-\mu) \end{pmatrix}$$

Fig. 5. Transition rate matrix Q_θ

This is introduced to follow the numerical approximation for a steady state probability matrix introduced in Ross (2009), Section 6.8.:

$$e^Q = \lim_{n\to\infty}\left(1 + Q\frac{1}{n}\right)^n$$

Existing studies have computed the above approximation identity with $n = 2^{10}$, a power large enough to be able to approximate the steady state. The 1 is substituted with the identity matrix I. For every hourly transition probability matrix Q_θ, the above approximation was computed. The end result for each hour will be a (C+1) × (C+1) whole transition probability matrix $\pi_{\theta\delta}$.

$\pi_{\theta\delta}$ is multiplied by itself to the power of 60 (for 60 minutes within an hour). This matrix is recorded and immediately multiplied with the $\pi_{\theta\delta}$ at the beginning of the next hour. This way, the whole transition probability matrix for the next hour can be obtained, with consideration to the inventory state of the hour before. This $\pi_{\theta\delta}$ is again multiplied by itself to the power of 60 and recorded.

State vectors $X_{I_0}^{j}$ and optimal initial inventory levels

At the end of the 18th hour, there will be 18 recorded $\pi_{\theta\delta}$ matrices for each operating hour. Here, this study takes a look at the first and last columns. These columns, when extracted, represent the state vectors that show the probabilities of the station going from initial states i (I_0) to final states j at each hour-end. The first column will be the state vector of the station going empty whereas the last column will be the state vector of the station reaching capacity. An example can be illustrated:

$$\begin{bmatrix} 0.40 \\ 0.25 \\ 0.20 \\ 0.10 \\ 0.05 \end{bmatrix} \quad . \quad . \quad . \quad \begin{bmatrix} 0.05 \\ 0.15 \\ 0.20 \\ 0.25 \\ 0.35 \end{bmatrix},$$

Fig. 6. Example state vectors of a probability matrix, $X_{I_0}^{0}$ and $X_{I_0}^{C}$

The 36 columns are extracted. Then, all 0th and Cth columns are added. The two end product vectors with (C+1) rows show the probabilities of incurring customer dissatisfaction in the form of bike shortage and space shortage, respectively. The rows represent each initial inventory (I_0) from rows 0 to C, or the 'starting point' for the station at 06:00.

The next step is to add the two columns to acquire a state vector of total dissatisfaction probability. This simple addition is possible because penalty costs p and h are identically weighted. Should this not be the case, $X_{I_0}^{0}$ and $X_{I_0}^{C}$ should be weighted first.

$$\begin{bmatrix} 0.45 \\ 0.40 \\ 0.40 \\ \mathbf{0.35} \\ 0.40 \end{bmatrix}$$

Examining the dissatisfaction state vector $X_{I_0}^{D}$, one can easily identify the lowest probability to reach dissatisfaction state *D*. The row of the component with minimum value is the optimal initial inventory level at start of operation, which considers not only customer dissatisfaction at the end of the first hour but at the end of the entire workday. The above processes were repeated for all 75 stations in the Yeongdeungpo-gu area, for 3 selected days of each season of the year. All computation processes were coded in MathWorks MATLAB. Data was refined using Notepad++ and MS Excel. Simple data analyses were executed in Minitab and RStudio. The resultant 12 optimal inventory levels for each station are presented and discussed in later sections.

3.4. Limitations of model

Independence assumption of stations

It would be an inaccurate representation of real life to blindly assume that the stations are independent in terms of demand (rentals and returns of bicycles). This is because the demands of stations are affected by bike or capacity shortage of nearby stations and ensuing demand spillovers. However, Raviv & Kolka (2013) show that even with this simplifying assumption, the model used in this study prescribes good decisions regarding initial inventory.

Endogeneity concerns of available data

Concerns can be addressed to the endogeneity issue of the available data, which was collected under the current practice of dynamic repositioning. However, the current dynamic repositioning operation used for Ttareungyi eliminates most of the shortages through a trial-and-error procedure of the experienced repositioning team. As a result, the recorded data fairly well represents true rent/return demands. This argument echoes that of Raviv & Kolka (2013), which acknowledges the above concern.

If the current repositioning eliminates most shortages, why introduce another strategy? The main objective of static repositioning in Ttareungyi is to reduce effort put towards relocation. This could enable the current repositioning operation to focus on busier stations and make better use of limited resources. In other words, this static repositioning method can be easily implemented to the current dynamic repositioning approach. It can lessen the rebalancing workload throughout the day and thus eliminate the need to hire more workers, which is a direct expense charged to taxpayers and one the operators could ill afford in the long run.

Chapter 4. Results

4.1. Optimal inventory results

The results did not fail to show optimal initial inventory levels that minimize daily customer dissatisfaction.

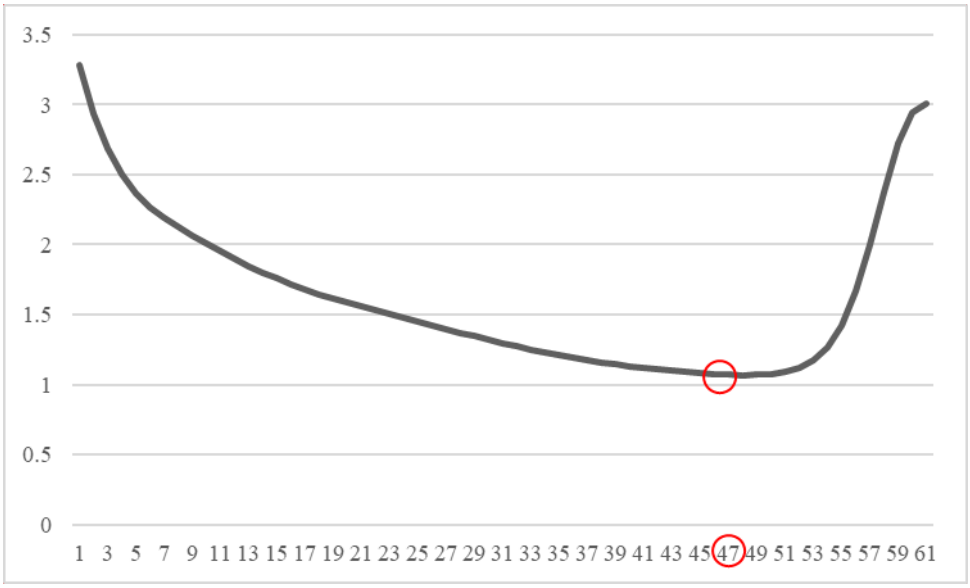


Fig. 7. User Dissatisfaction Function for Station 207, May 7th 2018

It can be seen that the UDF is unimodal, allowing a minimal value to be identified. However, there are some instances where unimodality is not too apparent.

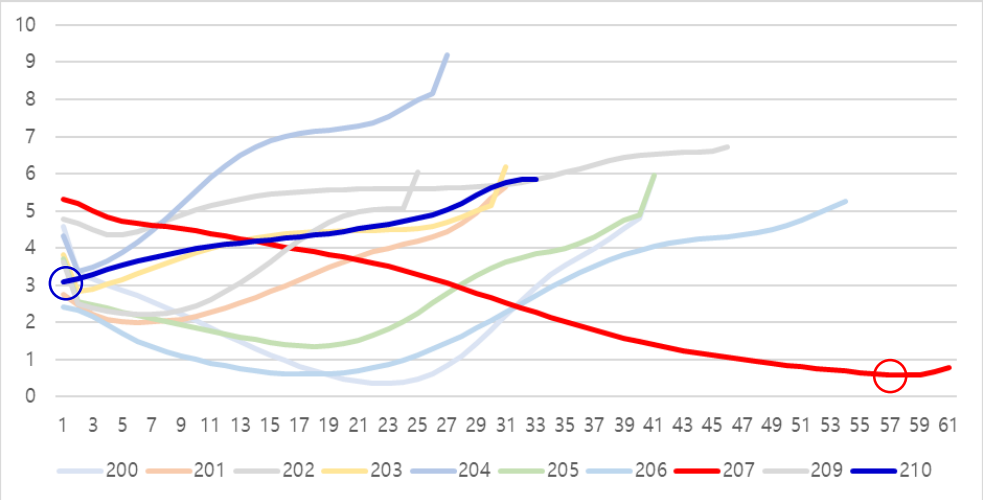
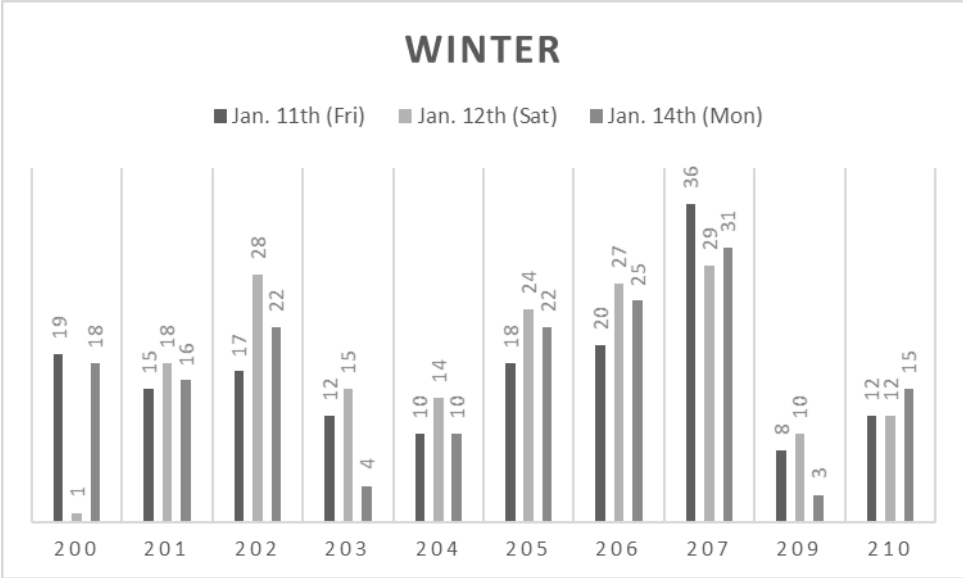
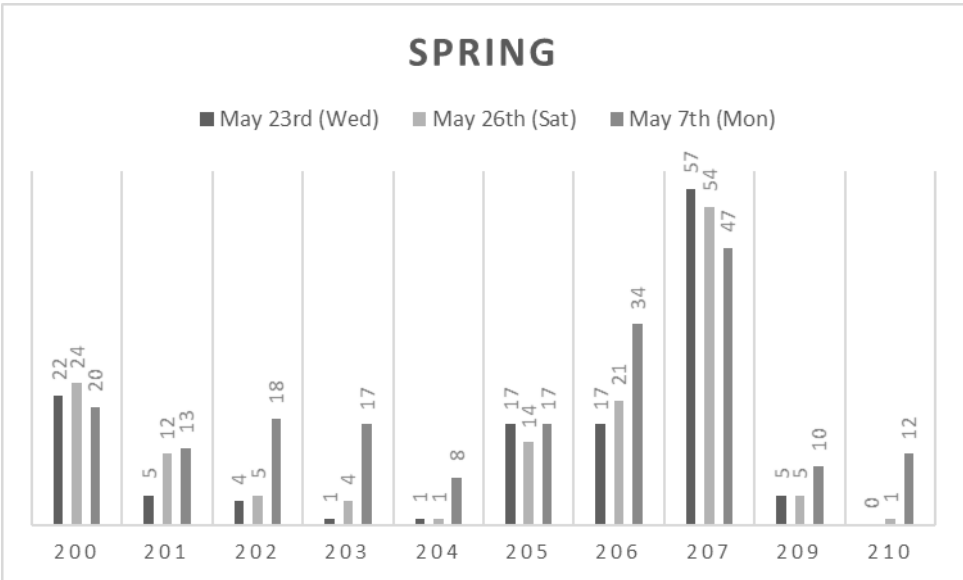


Fig. 8. User Dissatisfaction Function for 10 stations, May 23rd

Note that the functions for stations 207 and 210 do not seem unimodal to the eye. Although the optimal levels are computed (at 57 and 0, respectively), they are very close to each stations' capacity and empty states.

This is not due to the imbalance of numbers of rentals and returns in each station. The overall ratio of rentals/returns for the above 10 stations on May 23rd is 0.95. The rentals/returns ratio for stations 207 and 210 are 0.96 and 0.89. It can be inferred from this that each station will have an optimal inventory level that is irrelevant to the overall daily number of rentals and returns.


WINTER
Jan. 11th (Fri)
Jan. 12th (Sat)
Jan. 14th (Mon)
19 1 18
15 18 16
17 28 22
12 15 4
10 14 10
18 24 22
20 27 25
36 29 31
8 10 3
12 12 15
200
201
202
203
204
205
206
207
209
210


SPRING
May 23rd (Wed)
May 26th (Sat)
May 7th (Mon)
22 24 20
5 12 13
4 5 18
1 4 17
1 1 8
17 14 17
17 21 34
57 54 47
5 5 10
0 1 12
200
201
202
203
204
205
206
207
209
210

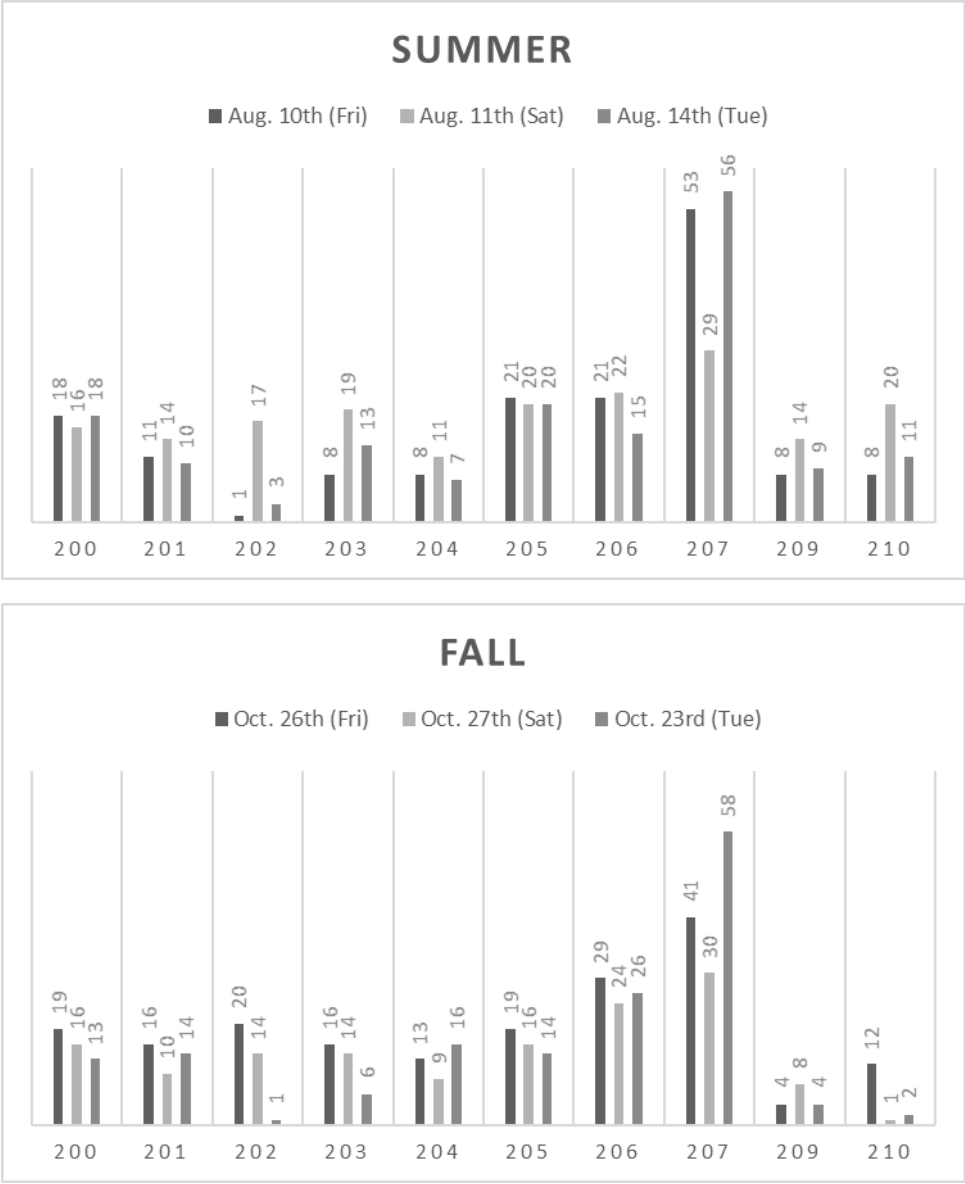


Fig. 9. Optimal inventory levels for 10 stations across 4 seasons

Above are the inventory levels for 12 dates for each season, from the spring of 2018 to the winter of 2019. All inventory levels were determined for 75 stations in the Yeongdeungpo-gu area.

Comparison and analyses will be performed on the inventory level results to find implications regarding repositioning. The findings are discussed in the following.

4.2. Comparison with recorded inventory levels

Actual inventory data was obtained and compared with the results of the calculated optimal inventory.

station	actual	optimal	difference	station	actual	optimal	difference	station	actual	optimal	difference	station	actual	optimal	difference
200	12	22	**10**	221	13	5	**-8**	242	10	21	**11**	265	9	18	**9**
201	11	5	**-6**	222	15	2	**-13**	243	9	19	**10**	266	19	6	**-13**
202	12	4	**-8**	223	11	19	**8**	244	8	18	**10**	267	2	11	**9**
203	0	1	**1**	224	22	20	**-2**	245	11	17	**6**	268	2	10	**8**
204	3	1	**-2**	225	18	31	**13**	247	8	22	**14**	270	0	6	**6**
205	16	17	**1**	226	19	20	**1**	249	13	13	**0**	271	9	14	**5**
206	15	17	**2**	227	11	12	**1**	250	3	11	**8**	272	21	29	**8**
207	40	57	**17**	228	17	11	**-6**	251	1	7	**6**	274	13	15	**2**
209	5	5	**0**	229	18	11	**-7**	252	5	14	**9**	275	13	17	**4**
210	17	0	**-17**	230	11	16	**5**	253	10	9	**-1**	276	5	11	**6**
211	9	20	**11**	231	6	13	**7**	254	8	11	**3**	277	6	10	**4**
212	10	48	**38**	232	7	20	**13**	255	4	10	**6**	278	12	19	**7**
213	6	18	**12**	233	10	13	**3**	256	2	9	**7**	279	4	12	**8**
214	8	18	**10**	234	4	10	**6**	257	9	16	**7**				
215	6	10	**4**	235	7	11	**4**	258	6	14	**8**				
216	2	10	**8**	236	8	7	**-1**	259	20	34	**14**				
217	1	3	**2**	238	5	10	**5**	260	0	14	**14**				
218	8	18	**10**	239	4	18	**14**	262	4	11	**7**				
219	2	10	**8**	240	7	15	**8**	263	3	10	**7**				
220	16	32	**16**	241	7	12	**5**	264	8	16	**8**				

Table. 2. Recorded and calculated optimal inventory for 73 stations, May 23rd

For May 23rd, 2018, recorded inventory level data for 73 stations at 06:00 was compared to that of the calculated optimal inventory levels. The actual total user dissatisfaction derived by the UDF was 175.04, compared to the total dissatisfaction of 83.78 with the optimal inventory levels. This is an impressive reduction of 52.13% for 73 stations.

It should be noted that this does not accurately represent the actual user dissatisfaction that has occurred that day, as the actual system practices dynamic repositioning. Nevertheless, it indicates that following such demand reflected in the

arrival data, setting arbitrary initial inventory levels without insufficient attention (in the form of repositioning) throughout the day could lead to greater dissatisfaction. This is speculated to be quite common, as visiting all 1540 stations throughout the day even only once is a burden to the 3 repositioning teams that operate for each half-day shift. Therefore, a good enough initial inventory level that can act as a 'goal level' will lessen the repositioning workload and user dissatisfaction.

4.3. Analysis of variance (ANOVA)

Two-way ANOVA was conducted to examine the effects of season and the day of the week on individual station initial inventory levels. The analyses showed counterintuitive results which indicate that neither seasons nor day of the week affects the initial inventory levels.

There are some managerial implications to be derived from these results. Ttareungyi employs different rebalancing teams for peak and off seasons, in the form of contract workers. Since there need not be significant changes made to initial inventory levels according to season, repositioning teams should focus more on individual stations rather than seasonal and/or holiday effects. A suggestion may be made to task the current 2-shift 3-team system with geographical clusters of stations, regardless of peak and off seasons.

Two-way ANOVA with replications

Source of Variation	*SS*	*df*	*MS*	*F*	*P-Value*	*F crit*
Seasons	86.18111	3	28.72704	1.606258	**0.186762719**	2.619754
Stations	46198.6	74	624.3053	34.90773	**7.3656E-173**	1.309243
Interaction	5529.902	222	24.90947	1.392801	**0.001073915**	1.195528
Within	10730.67	600	17.88444			
Total	62545.35	899				

α = .05

Table. 3. Two-way ANOVA results for seasons and stations

Seasons are not a source of variation whereas stations are. Interaction between seasons and stations is observed.

Two-way ANOVA with replications

Source of Variation	*SS*	*df*	*MS*	*F*	*P-Value*	*F crit*
Day of the week	18.72667	1	18.72667	1.094842	**0.295962531**	3.862206
Station	27358	74	369.7027	21.61442	**2.1217E-108**	1.317218
Interaction	2648.773	74	35.79423	2.092686	**2.44697E-06**	1.317218
Within	7697	450	17.10444			
Total	37722.5	599				

α = .05

Table. 4. Two-way ANOVA results for day of the week and stations

Days of the week are also not a source of variation. Stations remain to be a source of variation for inventory levels.

4.4. Sensitivity analysis for different penalty costs

In this study, the penalty costs for user dissatisfaction p and h were weighted equally. However, in real life, the penalty for bike shortage and the penalty for return space shortage will be different in terms of actual user dissatisfaction.

Seoul Ttareungyi has employed a system of 'connect-return' in all of its stations. This loosens the capacity restraint of stations in that extra returns may be returned by simply connecting the used bicycle to an already docked (or returned) bicycle. This allows the stations to have an infinite capacity in theory. In this study, the stations were assumed to have capacities of 1.5 or 2 times the number of docks. Although this was confirmed by a Ttareungyi operator to accurately portray the space limitation of stations, it still is a greatly generalized, rule-of-thumb method of measuring station capacity.

There are two possible user scenarios concerning the connect-return system. The first is in which there are no empty docks but still plenty of space available to connect-return a used bicycle. This available space may easily exceed the capacity constraint this study has assumed. In this case, there will be no return space shortage penalty h and therefore it may be considered irrelevant to the user dissatisfaction.

The second scenario is when there are no empty docks nor space available to return a used bicycle. As the stations are mostly located in busy city centers, near subway station entrances, buildings, and traffic hubs, the availability of space is a real issue. Many stations have been shut down due to civil complaints of connect-returned bicycles blocking pedestrian paths and entrances or exits. This is in line with the capacity constraint assumption used in this study. However, there is some additional dissatisfaction that may occur to the user in this case. Ttareungyi charges its users a relatively large fine for late returns or bicycle theft. There are two types of vouchers for all membership and pay-per-use: 1-hour and 2-hour vouchers. Should the respective durations be exceeded, users are charged an extra 200 KRW for every 5 minutes. Even involuntary 'theft' may occur when users fail to return bikes after 4 hours or 6 hours, depending on the voucher.

Moreover, when a user arrives at her destination but fails to find return space, she may have to go out of her way to find another station to return the bicycle. This will be especially frustrating as such micromobility transportation exists to solve the last-mile problem, yet it will be defeated of its purpose in this situation. It can be seen that in the above second scenario of no available return space, users may experience dissatisfaction in terms of extra charge and wasted time, and therefore contribute to a higher penalty cost h.

For such considerations, a sensitivity analysis was performed for different penalty costs p and h. Here, h was held constant at 1 with the p/h ratio adjusted for 5 instances. The optimal inventory levels are shown in the following:

200	**19**	221	**18**	241	**11**	263	**16**
201	**15**	222	**9**	242	**19**	264	**12**
202	**17**	223	**15**	243	**14**	265	**17**
203	**12**	224	**18**	244	**22**	266	**6**
204	**10**	225	**23**	245	**9**	267	**10**
205	**18**	226	**18**	247	**23**	268	**10**
206	**20**	227	**12**	248	**12**	270	**9**
207	**36**	228	**12**	249	**10**	271	**12**
209	**8**	229	**23**	250	**12**	272	**15**
210	**12**	230	**7**	251	**13**	274	**9**
211	**11**	231	**13**	252	**6**	275	**12**
212	**47**	232	**21**	253	**11**	276	**14**
213	**1**	233	**8**	254	**11**	277	**8**
214	**16**	234	**12**	255	**10**	278	**13**
215	**9**	235	**9**	256	**13**	279	**21**
216	**14**	236	**13**	257	**10**	**Penalty costs**	
217	**1**	237	**24**	258	**13**		
218	**21**	238	**12**	259	**31**	p=1, h=1	
219	**12**	239	**26**	260	**13**		
220	**28**	240	**12**	262	**3**		

200	**18**	221	**18**	241	**10**	263	**15**
201	**15**	222	**7**	242	**19**	264	**11**
202	**16**	223	**14**	243	**13**	265	**16**
203	**10**	224	**17**	244	**22**	266	**6**
204	**9**	225	**23**	245	**8**	267	**9**
205	**17**	226	**18**	247	**22**	268	**9**
206	**19**	227	**11**	248	**11**	270	**8**
207	**34**	228	**11**	249	**10**	271	**12**
209	**7**	229	**22**	250	**12**	272	**15**
210	**10**	230	**5**	251	**12**	274	**8**
211	**10**	231	**12**	252	**5**	275	**10**
212	**47**	232	**20**	253	**10**	276	**13**
213	**1**	233	**8**	254	**10**	277	**7**
214	**14**	234	**12**	255	**9**	278	**12**
215	**9**	235	**9**	256	**12**	279	**20**
216	**13**	236	**12**	257	**9**	**Penalty costs**	
217	**1**	237	**23**	258	**12**		
218	**21**	238	**10**	259	**29**	p=0.5, h=1	
219	**11**	239	**25**	260	**13**		
220	**27**	240	**11**	262	**2**		

200	**18**	221	**18**	241	**10**	263	**15**
201	**15**	222	**7**	242	**19**	264	**11**
202	**16**	223	**14**	243	**13**	265	**16**
203	**10**	224	**17**	244	**22**	266	**6**
204	**9**	225	**23**	245	**8**	267	**9**
205	**17**	226	**18**	247	**22**	268	**9**
206	**19**	227	**11**	248	**11**	270	**8**
207	**34**	228	**11**	249	**10**	271	**12**
209	**7**	229	**22**	250	**12**	272	**15**
210	**10**	230	**5**	251	**12**	274	**8**
211	**10**	231	**12**	252	**5**	275	**10**
212	**47**	232	**20**	253	**10**	276	**13**
213	**1**	233	**8**	254	**10**	277	**7**
214	**14**	234	**12**	255	**9**	278	**12**
215	**9**	235	**9**	256	**12**	279	**20**
216	**13**	236	**12**	257	**9**	**Penalty costs**	
217	**1**	237	**23**	258	**12**		
218	**21**	238	**10**	259	**29**	p=0.66667, h=1	
219	**11**	239	**25**	260	**13**		
220	**27**	240	**11**	262	**2**		

200	**19**	221	**19**	241	**12**	263	**17**
201	**16**	222	**10**	242	**19**	264	**13**
202	**18**	223	**15**	243	**14**	265	**17**
203	**13**	224	**19**	244	**23**	266	**7**
204	**10**	225	**23**	245	**10**	267	**10**
205	**18**	226	**19**	247	**24**	268	**10**
206	**20**	227	**12**	248	**13**	270	**10**
207	**36**	228	**12**	249	**10**	271	**13**
209	**9**	229	**23**	250	**13**	272	**15**
210	**14**	230	**9**	251	**13**	274	**10**
211	**12**	231	**13**	252	**7**	275	**13**
212	**48**	232	**21**	253	**11**	276	**14**
213	**1**	233	**8**	254	**11**	277	**8**
214	**17**	234	**13**	255	**10**	278	**13**
215	**9**	235	**9**	256	**13**	279	**21**
216	**15**	236	**13**	257	**11**	**Penalty costs**	
217	**1**	237	**24**	258	**13**		
218	**22**	238	**13**	259	**32**	p=1.5, h=1	
219	**12**	239	**26**	260	**14**		
220	**28**	240	**13**	262	**3**		

200	**19**	221	**19**	241	**12**	263	**17**
201	**16**	222	**10**	242	**20**	264	**13**
202	**18**	223	**15**	243	**14**	265	**17**
203	**13**	224	**19**	244	**23**	266	**7**
204	**11**	225	**24**	245	**10**	267	**11**
205	**18**	226	**19**	247	**24**	268	**10**
206	**20**	227	**12**	248	**13**	270	**10**
207	**37**	228	**12**	249	**10**	271	**13**
209	**9**	229	**23**	250	**13**	272	**16**
210	**15**	230	**10**	251	**13**	274	**10**
211	**13**	231	**13**	252	**7**	275	**14**
212	**48**	232	**22**	253	**11**	276	**15**
213	**1**	233	**8**	254	**11**	277	**8**
214	**17**	234	**13**	255	**11**	278	**14**
215	**9**	235	**9**	256	**13**	279	**21**
216	**15**	236	**13**	257	**12**	**Penalty costs**	
217	**1**	237	**24**	258	**13**		
218	**22**	238	**14**	259	**33**	p=2, h=1	
219	**13**	239	**26**	260	**14**		
220	**28**	240	**14**	262	**3**		

Table. 5. Inventory levels for different penalty costs

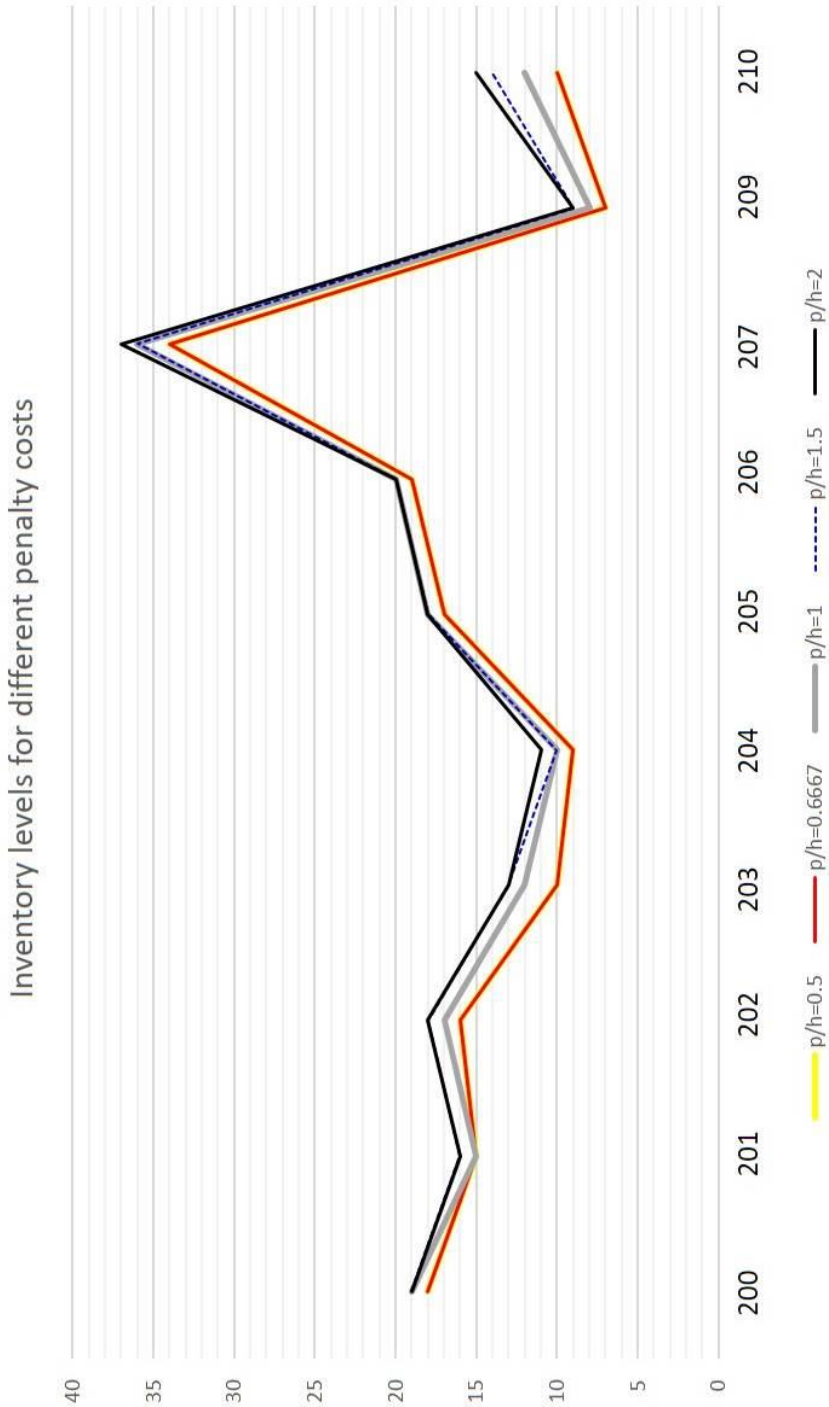


Fig. 10. Inventory levels for different penalty costs

It can be observed that the changes in inventory levels are rather small for all instances. Fig. 10 indicates that the inventory levels are unchanged when the bike shortage penalty to return space shortage penalty ratio p/h is adjusted from 0.5 to 0.6667. It can be inferred that a marginal change in the penalty ratio is negligible.

p/h	p	h	Variance of 75 station inventory levels
0.5	1	2	**54.1128**
0.666667	1	1.5	**54.1128**
1	1	1	**54.1398**
1.5	1.5	1	**54.1557**
2	2	1	**54.7939**

Table. 6. Variances of inventory levels for different penalty costs

Table. 6 shows the variance of inventory levels for different penalty ratios. Here, the penalty ratios seem to have little to no effect on the overall variance of the station inventory levels. This suggests that this model can provide robust results regardless of the change in penalty ratios.

4.5. Model with increased capacity

In this section, the capacity assumption of the model is addressed again. Here, the capacity constraints are relaxed to allow for more bicycles to be returned after use. This is either an accurate representation of the current Ttareungyi operation with its connect-return system or a portrayal of what could be should Ttareungyi install more docks or secure additional space for existing stations. Note that not only the station space but the number of docks is crucial in determining station capacity, due

to its significance as a reference point for operators and users to monitor inventory levels.

The capacity for each station was increased by 5. The inventory levels for 75 stations in Yeongdeungpo-gu for the identical 12 dates were calculated. The results were that almost every station showed increased levels of optimal inventory. It showed an increased daily average of 186 bikes for 75 stations. This roughly translates to an average of 2.5 additional bikes to be allocated to each station every day.

Such results can intuitively be understood, as loosening the capacity constraints means that the system can focus on addressing the bike shortage dissatisfaction more so than return space shortage. Should the capacity constraints be relaxed completely, so that there is infinite space available for returns, the results will be not too different from when there is no bike shortage penalty h.

What is interesting is that the total dissatisfaction for the loosened capacity constraint instance is 36.11% lower than the base case scenario. This implies that Ttareungyi should secure more docks or space for their existing stations if possible, to lower user dissatisfaction.

To explore this implication, the optimal inventory levels for the base case scenario were examined. For certain stations, the inventory levels were equal to their capacity levels.

Station	Date(s)	Capacity	Inventory levels with relaxed capacity constraints
216	Aug. 14th	20	**25**
241	Oct. 23rd	20	24
251	Oct. 23rd	20	22
258	Aug. 10th	28	32
259	May 23rd Aug. 10th Oct. 23rd	34	35 35 38
275	Oct. 23rd	20	24
276	Aug. 10th	20	23

Table. 7. Station inventory levels at capacity levels

For these stations, when capacity constraints were loosened by an additional 5, most stations showed inventory levels below the new capacity. For Station 216, the inventory level was yet again at capacity. However, seeing that Station 216 does not have similar issues for other dates, it can be considered as less urgent of needing extra capacity than Station 259. Station 259, out of 12 dates, has 3 instances where the inventory levels reach its capacity. It can be inferred that adding space of 5 more additional bikes can effectively reduce user dissatisfaction in this case.

Chapter 5. Conclusion

Bike-sharing is intended to provide users with transportation, leisure, and added environmental and health benefits. With both the public and the private sectors investing in shared micromobility schemes, research for achieving operational efficiency is in demand.

Research pertaining to bike-sharing and bike-sharing operations, although relatively new, is widely studied by various academics. This study emphasizes the repositioning issue of bike-sharing operations, with attention to the static repositioning method.

The rental and return rates of each station for each operating hour were calculated from Ttareungyi data. For 75 stations within the Yeongdeungpo-gu area, a popular city hub with high bicycle demand that roughly translates to 10% of total daily Ttareungyi use, optimal inventory levels to be set at start of day were determined. A Markov chain model was used to calculate the probability of a station reaching certain states during the day. As per the User Dissatisfaction Function, probabilities of reaching empty states and full-capacity states were recorded and multiplied with respective bike shortage and return space shortage penalties.

This study has analyzed the results to extract meaningful implications that may be of use to operators. First, the base case scenario was compared to that of actual recorded inventory data under the status quo dynamic repositioning. The base case yielded improved results in terms of decreased user dissatisfaction. It should be noted that the user dissatisfaction for the recorded inventory levels is not accurate in portraying actual dissatisfaction that has occurred. Nevertheless, considering that the

dynamic repositioning team lacks the workforce to visit every station multiple times throughout the day, actual dissatisfaction may not be too different from what this study has estimated it to be.

Analysis of variance (ANOVA) was performed to determine the effects of seasons and day of the week on inventory levels. The purpose of ANOVA was to see if Ttareungyi's employment of different teams for peak and off seasons are justifiable. The results indicated that neither seasons nor day of the week but only individual stations, or the geographical location, affect inventory levels. Consequently, Ttareungyi should focus more on the geographical elements and not the seasonal factors for bike relocation.

Since this model relies heavily on the assumption that de facto capacities exist for the theoretically infinite return spaces, some what-if scenarios were considered.

Penalty costs for bike shortages and return space shortages were controlled to see how the inventory levels change with respect to different penalty ratios. Marginal changes in inventory levels were observed for a range of penalty ratios.

Capacity constraints were loosened by theoretically adding return space of 5 additional bicycles for each station. This resulted in an overall increase in allocated inventory levels for most stations. Moreover, it decreased the total user dissatisfaction by more than 30%. Although it is not realistic to suggest additional docks for all stations, for some stations that have optimal inventory levels that reach capacity levels, acquiring extra space may decrease user dissatisfaction.

This study can be further extended to a dynamic repositioning model in which the optimal inventories for certain time windows during a day are determined. Here, the inventory levels will be updated for each repositioning visit for real-life portrayal. A traveling salesperson problem (TSP) or vehicle routing problem (VRP) may be

incorporated into the extended model to provide the operator and repositioning teams an accurate guideline for relocation.

There is also the possibility of applying the static repositioning model to other forms of micromobility, such as scooter sharing systems (SSS) and electric bike-sharing systems (e-BSS). These systems are characteristically different from simple bike-sharing in that the vehicles must be recharged regularly in order to provide mobility. Moreover, in most cases, the systems are free-floating, as opposed to the traditionally docked system of bike-sharing. These may present the need for additional assumptions in determining optimal relocation inventory of stations or locations. Nevertheless, the basic foundation upon which this study is formed, using customer arrival data to establish a Markovian model of state transition, will remain effective in modeling dissimilar systems.

References

Alan, L. E., Juan, C. M., & Martin, S. (2009). Robust Optimization for Empty Repositioning Problems. *Operations Research, 57*(2), 468-483. doi:10.1287/opre.1080.0650

Benchimol, M., Benchimol, P., Chappert, B., De La Taille, A., Laroche, F., Meunier, F., & Robinet, L. (2011). Balancing the stations of a self-service bike hire system. In F. Meunier (Ed.), (Vol. 45, pp. 37-61).

Bruglieri, M., Colorni, A., & Luè, A. (2014). The relocation problem for the one-way electric vehicle sharing. *Networks, 64*(4), 292-305. doi:10.1002/net.21585

Chemla, D., Meunier, F., & Wolfler Calvo, R. (2013). Bike sharing systems: Solving the static rebalancing problem. *Discrete Optimization, 10*(2), 120-146. doi:10.1016/j.disopt.2012.11.005

DeMaio, P. (2009). Bike-sharing: History, Impacts, Models of Provision, and Future. In: Scholar Commons.

Dediu, H. (2019, February 23). The Micromobility Definition [Blog post]. Retrieved from https://micromobility.io/blog/2019/2/23/the-micromobility-definition

Fishman, E. (2016). Bikeshare: A Review of Recent Literature. *Transport Reviews, 36*(1), 92-113. doi:10.1080/01441647.2015.1033036

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

Fuller, D., Gauvin, L., Kestens, Y., Daniel, M., Fournier, M., Morency, P., & Drouin, L. (2013). Impact evaluation of a public bicycle share program on cycling: a case example of BIXI in Montreal, Quebec. *American journal of public health, 103*(3), e85. doi:10.2105/AJPH.2012.300917

Goodman, A., & Cheshire, J. (2014). INEQUALITIES IN THE LONDON BICYCLE SHARING SYSTEM REVISITED: IMPACTS OF EXTENDING THE SCHEME TO POORER AREAS BUT THEN DOUBLING PRICES. *J. Epidemiol. Community Health, 68*(s1), A75-A75.

Köchel, P., Kunze, S., & Nieländer, U. (2003). Optimal control of a distributed service system with moving resources: Application to the fleet sizing and

allocation problem. *International Journal of Production Economics, 81*(82), 443-459. doi:10.1016/S0925-5273(02)00287-6

Laporte, G., Meunier, F., & Wolfler Calvo, R. (2015). Shared mobility systems. *A Quarterly Journal of Operations Research, 13*(4), 341-360. doi:10.1007/s10288-015-0301-z

Raviv, T., & Kolka, O. (2013). Optimal inventory management of a bike-sharing station. *IIE Transactions, 45*(10), 1077-1093. doi:10.1080/0740817X.2013.770186

Raviv, T., Tzur, M., & Forma, I. (2013). Static repositioning in a bike-sharing system: models and solution approaches. *EURO Journal on Transportation and Logistics, 2*(3), 187-229. doi:10.1007/s13676-012-0017-6

Ross, S. M. (2009). *Introduction to Probability Models* (10 ed.): Elsevier Science.

Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., & Tarantola, S. (2010). Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. *Computer Physics Communications, 181*(2), 259-270. doi:10.1016/j.cpc.2009.09.018

Schuijbroek, J., Hampshire, R. C., & van Hoeve, W. J. (2017). Inventory rebalancing and vehicle routing in bike sharing systems. *European Journal of Operational Research, 257*(3), 992-1004. doi:10.1016/j.ejor.2016.08.029

Shaheen, S. A., Guzman, S., & Zhang, H. (2010). Bikesharing in Europe, the Americas, and Asia Past, Present, and Future. *Transp. Res. Record, 2143*(2143), 159-167. doi:10.3141/2143-20

Shintani, K., Imai, A., Nishimura, E., & Papadimitriou, S. (2007). The container shipping network design problem with empty container repositioning. *Transportation Research Part E, 43*(1), 39-59. doi:10.1016/j.tre.2005.05.003

Shu, J., Chou, M., Liu, Q., Teo, C.-P., & Wang, I. L. (2013). Models for Effective Deployment and Redistribution of Bicycles Within Public Bicycle-Sharing Systems. *Operations Research, 61*(6), 1346-1359. doi:10.1287/opre.2013.1215

Si, H., Shi, J.-G., Wu, G., Chen, J., & Zhao, X. (2019). Mapping the bike sharing research published from 2010 to 2018: A scientometric review. *Journal of Cleaner Production, 213*, 415-427. doi:10.1016/j.jclepro.2018.12.157

Woodcock, J., Tainio, M., Cheshire, J., O'brien, O., & Goodman, A. (2014). Health effects of the London bicycle sharing system: health impact

modelling study. *BMJ : British Medical Journal*, *348*(7946). doi:10.1136/bmj.g425

Yoon, G. (2018, December 16). '따릉이', 시민이 뽑은 '서울시 10 대 뉴스' 2 년 연속 1 위. Yonhap News Agency,

Abstract in Korean

이 연구는 공유 자전거 시스템 운영의 자전거 재배치 문제를 다룬다. 대중 교통과 공유 경제의 혼합 형태인 공유 자전거 시스템은 연구자와 시민을 비롯한 세간의 이목을 받고 있다. 교통의 '라스트 마일(last-mile)' 문제 해결은 물론 시민 건강 증진과 탄소 배출량 저감의 이점을 가진 공유 자전거 시스템은 일상에서 빠질 수 없는 교통 요소로 자리매김하고 있다. 이 연구의 목적은 정적 재배치 가정 하 하루 동안 발생할 고객 불만족을 최소화하는 기초 재고량을 구하는 것이다. 이를 위해 서울시 '따릉이'의 자전거 대여/반납 정보를 활용해 대여소 별 시간당 고객도착률을 구하고, 마코프 체인에 기반한 확률적 모형을 만들었다. 상태 전이 확률로써 영등포구 75 개 자전거 대여소의 최적 기초 재고량을 구했으며, 이에 대한 계절과 요일 요인의 이원분산분석을 진행했다. 또한 비용 함수의 계수 비율에 대한 민감도 분석을 진행했으며 대여소 자전거 보관 대수에 대한 제약을 느슨하게 하여 최적 재고량의 변화를 관찰하였다. 사용자의 원활한 이용을 위한 대여소 별 최적 재고량 그리고 분석에 기반한 정적 재배치 운영 방안을 제시함으로써 이 논문은 의의를 지닌다.

주요어 : 재고관리, 공유 자전거 시스템, 정적 재배치, 마이크로모빌리티
학　번 : 2018-25661