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A dynamic allocation model for bike sharing system; the sharing economy concept

Katayut Kamano[1)], Patchanee Patitad[2)] and Woramol C. Watanabe*[2)]

[1)]Department of Industrial Engineering, Faculty of Engineering, Kasetsart University, Bangkok 10900, Thailand
[2)]Faculty of Logistics and Digital Supply Chain, Naresuan Univeristy, Phitsanulok 65000, Thailand

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Abstract

The problem of allocating bikes in bike sharing is well known and involves balancing the number of bikes in a station to avoid having too many or too few. Distributing the bikes incurs costs, such as maintenance, distribution, staff, insurance, office space, and others, which are borne by the organization. To maintain the same level of service while reducing operational costs, the sharing economy concept has been introduced. In this study, we assume that every bike user is willing to move the bike to a nearby station, and we propose a dynamic model that allows for bike allocation during operation time. Our mathematical model for dynamic allocation aims to determine the maximum number of transfer bikes needed by the users. Additionally, we compare our proposed model with the traditional model in terms of the number of insufficient bikes, distance, and CO_2 emissions. Our results demonstrate that the proposed model ensures that there are no unbalanced bikes at every station, similar to the traditional model. Even the total distance covered by the proposed model is longer than that of the traditional model. However, our findings indicate that applying the sharing economy concept also benefits the environment by reducing CO_2 emissions.

Keywords: Optimization, Sharing economy, Taiwan, Bike allocation

1. Introduction

With concerns about global warming, oil prices, green logistics, and traffic congestion, many cities are encouraging their citizens to use public transportation instead of private vehicles for their journeys. Bike sharing, or public bike sharing, has been increasing in popularity in recent years. The next generation of bike sharing systems, the 4th generation, aims to improve efficiency, sustainability, and usability [1]. The bike sharing system is a sustainable transport solution for short distances, leading to a reduction in greenhouse gases and an improvement in local air quality [2]. This system is usually implemented in urban areas to provide alternative modes of transport, especially for short routes. It provides bikes for users who need to make a short journey, and the rental bike stations are usually located near MRT stations, public parks, schools, residential areas, business centers, etc. A bike sharing system (BSS) is designed for users to pick up and return their bikes within the city.

One of the fundamental problems in operating a BSS is allocating bikes to bike stations in order to minimize the cost of allocation while still meeting customer needs. Since the current generation of bike sharing systems allows users to pick up a bike for their journey and return it at either the same or a different station, this causes an unbalanced demand and supply of bikes at some stations. For example, at a station where there are many users, the number of bikes may not be sufficient, while at a station where users usually end their journey at the same time (e.g. at the MRT station during peak hours), the parking lots may not be sufficient. Another difficulty in managing a BSS is the difference in bike demand depending on the time of day; for example, during peak hours, the demand for bikes is higher. Inappropriate allocation of the provided bikes can lead to customer complaints and affect the viability of the system. BSS providers usually avoid these issues by redistributing the bikes after a planning horizon (e.g., every hour, every 10 minutes, or once a day).

To redistribute the bikes, BSS providers need to invest in trucks, labor, and a system for bike redistribution. This process incurs costs for maintenance, distribution, staff, insurance, office space, etc. The current bike redistribution process is still performed by BSS providers, resulting in high operation costs. To decrease the operation cost while maintaining the same service level, the concept of sharing economy is introduced. This concept aims to redistribute existing goods and/or capacity across the population in order to maximize functionality [3]. This concept is linked with sustainability, for example, as a more sustainable form of utilization [4]. One concern of sharing economy is that it allows the transfer of power from a few large firms to many connected actors, which can lead to social revolution [5]. For this reason, applying this concept to bike redistribution can improve the system's efficiency while reducing costs and keeping positive benefits for society and the environment.

This paper aims to improve the efficiency while maintaining the sustainability of bike redistribution in the bike sharing system. The paper proposes a mathematical model for dynamic allocation to determine the smallest number of transfer bikes with the time-dependent aspects of a system. The sharing economy concept is also included in the model to show the consequences of applying this concept to the bike sharing system. To demonstrate the advantages of the concept, the results from the proposed model are compared with the results from a previous study.

*Corresponding author.
Email address: woramolc@nu.ac.th; woramol.ch@gmail.com
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The remainder of the paper is organized as follows. The next section provides background on BSS rebalancing research. Subsequently, the paper introduces the problem description and the proposed bike allocation model. Afterwards, the case study of Zhongshan district, Taipei city, Taiwan, is presented. Finally, the conclusions and suggestions are summarized in the last part of the paper.

2. Background

The problem of allocating resources in bike-sharing systems is commonly referred to as the Bike Sharing Rebalancing Problem (BRP). The BRP can be modeled as either a static or dynamic optimization problem. In static environments, redistribution usually occurs when the system is not in use and there is low demand for bicycles. In dynamic environments, real-time data is considered, and the redistribution plan can be updated as soon as the system requires a decision to be made [6]. Since 2010, more than a hundred research papers have been published on various aspects of bike-sharing systems, such as operational development, bicycle rebalancing, and demand prediction, both in static and dynamic contexts.

The rebalancing problem can be further classified into static rebalancing and dynamic rebalancing. In a static environment, users cannot interact with the bikes during the rebalancing process [7]. Many research papers have presented different objectives for investigating the new flow by considering the need to collect bicycles that require repair [8], minimizing the number of lost demands [9], reducing the scale of the static bike rebalancing problem [10], and determining minimum-cost routes for a fleet of homogeneous vehicles to redistribute bikes among stations [11].

In contrast, dynamic rebalancing can be performed throughout the day to address imbalances during rush hours and handle varying demand [12]. Various research papers have focused on dynamic rebalancing for bike-sharing systems, such as minimizing the operational cost of rebalancing while maximizing user satisfaction [12], including historical data to predict network conditions and take prompt action as necessary [13], predicting future demand at bike stations using live data [14], achieving higher service quality for lower cost [15], and reducing CO_2 emissions [16].

Despite the considerable research into rebalancing problems in bike-sharing systems, the main objective has only been to optimize resources for managing the system. To apply the sharing economy system to this problem, no research has yet been conducted. According to this concept, the bike-sharing system could notify users who need to travel along a route from a sufficient bike station to an insufficient one, or a nearby station, and incentivize them with rewards to transfer the bike.

To propose a system that can allocate bikes dynamically, we chose a dynamic allocation model. As a result, we propose applying the sharing economy concept to the BRP in this paper. We present a comparison of our proposed approach with the previous model to demonstrate its advantages.

3. Dynamic allocation model with the sharing economy concept

3.1 Problem description

A bike sharing system enables customers to rent and return bicycles at any station located conveniently for them to get to their destination. Customers can simply pick up the bike at the station, travel to their destination, and return the bike either to the same station or a different one where they picked it up. This paper addresses a problem that has the following characteristics:

- Customers can pick up the bike at any located station and return it at any station.
- Customers can rent only one bicycle for each journey.
- If no bicycle is available at the rental station at the time customer arrives, the customer will leave the system immediately.
- The arrival rate of a customer who needs to return a bicycle and the departure rate of a customer who needs to pick up a bicycle follows a Poisson process. The arrival and departure rate of each station is divided into 3 categories [1].

A. Arrival rate > Departure rate
B. Arrival rate = Departure rate
C. Arrival rate < Departure rate

This study is motivated by the ideas of peer-to-peer; in other words, allowing customers who have idle resources (time and ability to distribute bikes) to operate the allocation of bicycles in the system instead of the system owner. To avoid confusion, customers who are actual users who want to rent a bike are defined as customers, while people who operate the bike allocation are defined as operators. In this research, we use the "Ubike" Taipei bike sharing system as a case study to demonstrate the bike allocation model and strategic policy. Figure 1 shows the bike stations in the system.

There are three types of stations in this figure: A, B, and C. Inadequate stations (C) are depicted by circle symbols ($q_j < q_{min}$), while stations with enough bicycles (A) are shown as rectangular symbols (($q_j > q_{min}$)). Stations with an exact number of bicycles that meets the minimum requirement (B) are depicted as triangle symbols

3.2 Notation

In this section, the notation which used in mathematical model is presented. This paper, the objective of the proposed model is to maximize the number of transferred bicycles from sufficient rental stations to stations that bikes is inadequately to customers' need. The notation for the proposed allocation model is given as follows.

k_i The capacity of the parking lot at station i
y_i Number of bicycles at station i
y_j Number of bicycles at station j
s_i Number of bicycles at station i allowing to supply to insufficiency station (Supply station i)
q_j Number of insufficiency bicycle at station j (Insufficiency station j)
d_{ij} Geometric approximate distance from station i to station j
d_{max} Maximum distance of allocation
q_{min} Minimum number of bicycle at stations
λ_i Arrival customers who need to return a bicycle at station i
μ_i Departure customers who pick-up a bicycle at station i
x_{ij} The number of allocation of bicycle from stations i to stations j

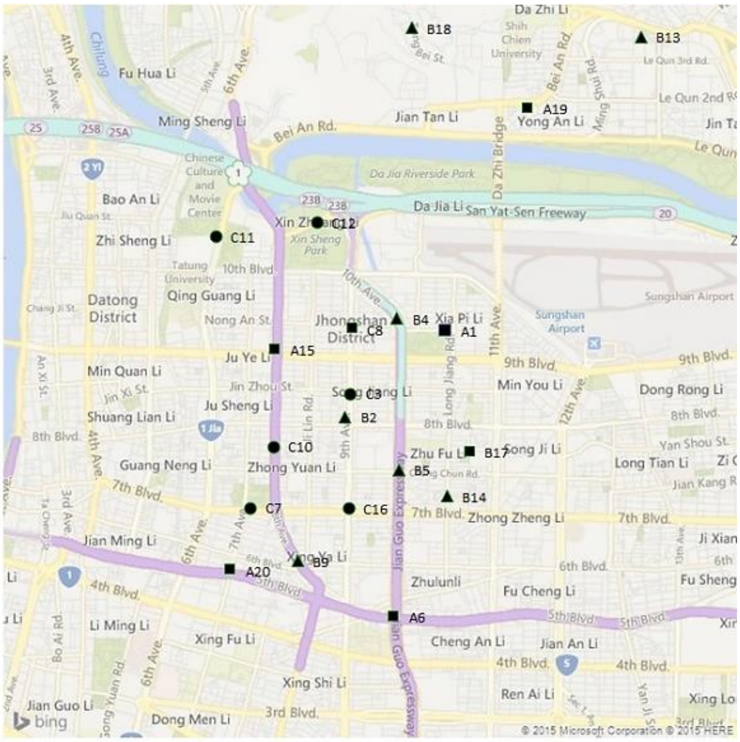


Figure 1 Bike station at Zhongshan district, Taipei city, Taiwan

3.3 Mathematical model

In this section, the operational execution of the system is evaluated in a dynamic setting using simulation. A continuous stream of customer arrivals and departures is generated based on a Poisson process for each bike station. Each station has arrival and departure rates for customers, and the allocation of bicycles depends on the forecasted arrival and departure of bicycles in the current period. Transfers occur in the next period, and the simulation covers two time periods: t=0 and t=1. For each station, the relationship between the current and next periods is shown in Eq. (1).

$$\mathcal{Y}_i(t) = \mathcal{Y}_i(t-1) + (\lambda_i(t) - \mu_i(t)) \tag{1}$$

$\mathcal{Y}_i(t-1)$: The current stock of bicycle in time period $t-1$
$\mathcal{Y}_i(t)$: The number of bicycle needed in time period t

$$\max C = \sum_j \sum_i x_{ij} \tag{2}$$

$$\text{s.t.} \sum_i x_{ij} \le q_i, \forall A_j \qquad \text{(Demand constraint)} \tag{3}$$

$$\sum_j x_{ij} \le s_i, \forall A_i \qquad \text{(Supply constraint)} \tag{4}$$

$$\text{If } \mathcal{Y}_j \le q_{min}, then\ q_j = q_{min} - \mathcal{Y}_i, \text{ otherwise } q_i = 0, \forall A_j \qquad \text{(Demand at station } j\text{)} \tag{5}$$

$$\text{If } d_{ij} \ge d_{max}, then\ x_{ij} \le 0, \forall A_{ij} \qquad \text{(Allocation distance must less than } d_{max}\text{)} \tag{6}$$

$$\text{If } \mathcal{Y}_i \ge q_{min}, then\ s_i = \mathcal{Y}_i - q_{min}, \text{ otherwise } s_i = 0, \forall A_i \qquad \text{(Supply at station } i\text{)} \tag{7}$$

$$x_{ij} = 1 \text{ or } 0 \tag{8}$$

The simulation was started in period 1 using the set of inputs for allocation, which is the set $y_i(t)$. To apply the peer-to-peer concept, if there are bicycle allocation requests, the operation will transfer bicycles in the current time period to fulfill customers' needs in the next time period. A Mixed Integer Linear Programming (MILP) model is used to determine the optimal number of bicycles to allocate. The MILP model for allocation is described in equations 2-8.

The objective of the proposed model is to maximize the number of allocated bicycles from the supply station located within the maximum distance (d_{max}) from the insufficient station, as shown in Line 2. Constraint (3) ensures that the number of allocated bicycles does not exceed the number of insufficient bicycles. Similarly, on the supply side, the number of allocated bicycles must not exceed the number of bicycles at the supply station (Line 4). The constraints for the sharing economy concept are shown in lines 5, 6, and 7. Line 5 checks if there are enough bicycles at station j. If there are enough bicycles, the number of insufficient bicycles (q_j) is zero. Line 6 imposes a distance constraint, inspecting the distance between the supply and insufficient stations. If the distance is greater than d_{max}, no allocation is made. Line 7 assigns a supply constraint to examine whether the supply station has enough bicycles to supply to the insufficient station or not. Line 8 sets the number of allocations as an integer.

4. Mechanism comparison between the traditional and the proposed model

4.1 The traditional model

The allocation occurred at the beginning of the time horizon. In the mechanism, the classical Vehicle Routing Problem (VRP) model is used. The Microsoft Excel work- book "VRP Spreadsheet Solver" [17] is used to determine the optimal route. The Solver is an open-source unified platform for representing, solving, and visualizing the results of Vehicle Routing Problems. It unifies Excel, public GIS, and metaheuristics to solve VPR with up to 200 customers with multiple couriers. The characteristics for allocation with VPS are shown as follows.

1. A truck processes reallocation with the city government worker.
2. Allocation is processed only 1 time at the beginning of the time horizon.
3. The start point of the trip (hub) is located at the first station.
4. A truck is visited only insufficient station.

4.2 The proposed model

To apply the concept of sharing economy to the allocation problem, the proposed mechanism assumes that allocation occurs when there are not enough bicycles at a given station and customers are in need of a bicycle. If the number of bicycles at a station falls below the minimum required amount, nearby customers are expected to move the bicycles from stations with a surplus to those with a shortage. Station j refers to the location that can provide bicycles to the insufficient stations, while station i represents the stations with an insufficient number of bicycles. For the allocate mechanism, the allocation is processed when the station j adopts the following characteristic.

1. Station which has the number of bicycles (y_i) less than or equal to the minimum bicycle (q_{min}).
2. The supply station s_i that is located at less than or equal to the distance d_{max} from insufficient station q_i and has the number of bicycles more than qmin.
3. Allocation is operated every 10 minutes.

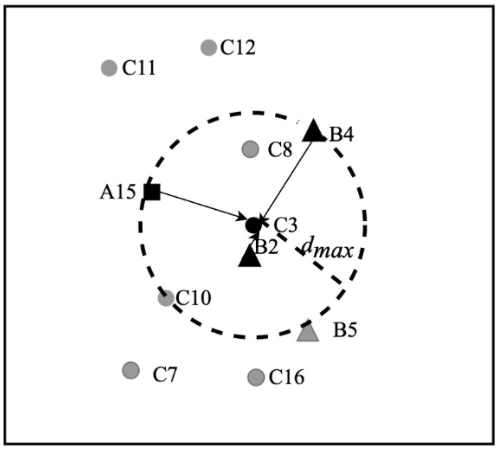


Figure 2 The candidate supply station

Figure 2 displays the potential supply stations for bicycles, which can provide bicycles to those that are insufficient. If a potential supply station (A or B) is within the maximum distance (d_{max}) or falls within the dashed circle, it is eligible to provide bicycles to an insufficient station. For example, the station C3 can receive bicycles from stations A15, B2, and B12. It cannot receive any bicycles from station B5 because it is farther than the maximum distance.

5. Case study

In this research, the proposed model is applied to the case study of Zhongshan district, Taipei city, Taiwan to demonstrate its merit. The duration period used in this study is one hour during rush hour, from 5:00 p.m. to 6:00 p.m. Bicycle allocation occurs every 10 minutes, and data collection was conducted 30 times to estimate the numbers used in the simulation. The parameter settings used in this study are shown below.

$q_{min} = 3$
$d_{max} = 0.8$ km.

The arrival and departure rate are different base on the station categories. These parameters are shown as follows. The rates for the A category are shown below.

$\lambda_i = 4$
$\mu_i = 1$
The rates for the B category are

$\lambda_i = 2$
$\mu_i = 2$

And the rates for the C category are as follows.

$\lambda_i = 1$
$\mu_i = 4$

To create the data, actual data was collected and analyzed, revealing that it had a poison distribution. Subsequently, the simulation data for customer arrival and departure rates was generated using the Poisson process and random number generation. The results are displayed in Table 1. The first row of the table displays the names of each station, while the second row lists the category of each station. The remaining rows in the table show the number of customers who arrive at and depart from each station.

Table 1 The arrival and departure rate of the case study

Station		**1**	**6**	**15**	**19**	**20**	**2**	**4**	**5**	**9**	**13**	**14**	**17**	**18**	**3**	**7**	**8**	**10**	**11**	**12**	**16**
Category		**A**	**A**	**A**	**A**	**A**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**C**	**C**	**C**	**C**	**C**	**C**	**C**
5:10 p.m.	λ	2	2	2	1	4	2	0	0	3	3	1	3	1	0	1	1	1	1	0	3
	μ	1	0	1	0	0	1	2	0	3	1	1	2	0	2	5	4	3	2	4	4
5:20 p.m.	λ	1	3	6	4	1	2	1	0	2	2	2	2	2	2	1	1	0	1	1	2
	μ	0	1	2	1	1	2	2	2	1	1	0	0	0	2	3	8	3	6	3	4
5:30 p.m.	λ	3	4	4	3	3	1	3	3	3	2	4	3	0	0	0	2	2	1	1	1
	μ	0	0	1	1	0	1	1	1	4	2	2	1	3	3	6	3	6	2	3	3
5:40 p.m.	λ	3	2	6	2	3	4	1	2	2	1	2	2	2	1	0	0	0	0	1	0
	μ	0	0	0	0	3	2	0	1	0	2	2	1	0	3	6	3	6	3	4	2
5:50 p.m.	λ	5	2	4	6	6	5	3	1	2	3	2	2	1	3	0	2	3	1	1	3
	μ	2	0	1	0	0	2	3	1	2	2	2	4	3	5	7	3	3	5	5	4

To demonstrate the mechanism of the proposed model, Table 1 shows the data for each station at each time. The number of bicycles arriving and departing at each station is listed in Table 2. For example, at 5:00 PM, there are 14 bicycles at Station 1. At 5:10 PM, two bicycles arrive and only one bicycle departs, resulting in a total demand of -1 (1-2). This means that there is no need for any bicycles and one bicycle remains at the station. As a result, the number of bicycles at the station increases to 15 (14-(-1)). No allocation is required at this station. At the end of this time period, the number of bicycles after allocation is 15, which becomes the beginning number for the 5:20 PM time period.

Table 2 Number of bicycles of each station (Bicycle stock)

Station		**1**	**6**	**15**	**19**	**20**	**2**	**4**	**5**	**9**	**13**	**14**	**17**	**18**	**3**	**7**	**8**	**10**	**11**	**12**	**16**	**Allocation**
Category		**A**	**A**	**A**	**A**	**A**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**C**	**C**	**C**	**C**	**C**	**C**	**C**	
5:00 PM	Number of bicycle	14	2	18	22	20	4	18	22	33	33	47	59	13	4	18	4	21	1	14	33	0
5:00 PM	λ	2	2	2	1	4	2	0	0	3	3	1	3	1	0	1	1	1	1	0	3	6
	μ	1	0	1	0	0	1	2	0	3	1	1	2	0	2	5	4	3	2	4	4	
	Total demand of bicycle	-1	-2	-1	-1	-4	-1	2	0	0	-2	0	-1	-1	2	4	3	2	1	4	1	
	Number of bicycle	15	4	19	23	24	5	16	22	33	35	47	60	14	2	14	1	19	0	10	32	
	Allocation Direction	0	0	-3	0	0	0	-2	-1	0	0	0	0	0	1	0	2	0	3	0	0	
	Number of bicycle after allocation	15	4	16	23	24	5	14	21	33	35	47	60	14	3	14	3	19	3	10	32	
5:20 PM	λ	1	3	6	4	1	2	1	0	2	2	2	2	2	2	1	1	0	1	1	2	12
	μ	0	1	2	1	1	2	2	2	1	1	0	0	0	2	3	8	3	6	3	4	
	Total demand of bicycle	-1	-2	-4	-3	0	0	1	2	-1	-1	-2	-2	-2	0	2	7	3	5	2	2	
	Number of bicycle	16	6	20	26	24	5	13	19	34	36	49	62	16	3	12	-4	16	-2	8	30	
	Allocation Direction	0	0	-5	0	0	0	-7	0	0	0	0	0	0	0	0	7	0	5	0	0	
	Second allocation	16	6	15	26	24	5	6	19	34	36	49	62	16	3	12	3	16	3	8	30	
5:30 PM	λ	3	4	4	3	3	1	3	3	3	2	4	3	0	0	0	2	2	1	1	1	5
	μ	0	0	1	1	0	1	1	1	4	2	2	1	3	3	6	3	6	2	3	3	
	Total demand of bicycle	-3	-4	-3	-2	-3	0	-2	-2	1	0	-2	-2	3	3	6	1	4	1	2	2	
	Number of bicycle	19	10	18	28	27	5	8	21	33	36	51	64	13	0	6	2	12	2	6	28	
	Allocation Direction	0	0	-1	0	0	0	-1	-3	0	0	0	0	0	3	0	1	0	1	0	0	
	Third allocation	19	10	17	28	27	5	7	18	33	36	51	64	13	3	6	3	12	3	6	28	
5:40 PM	λ	3	2	6	2	3	4	1	2	2	1	2	2	2	1	0	0	0	0	1	0	11
	μ	0	0	0	0	3	2	0	1	0	2	2	1	0	3	6	3	6	3	4	2	
	Total demand of bicycle	-3	-2	-6	-2	0	-2	-1	-1	-2	1	0	-1	-2	2	6	3	6	3	3	2	
	Number of bicycle	22	12	23	30	27	7	8	19	35	35	51	65	15	1	0	0	6	0	3	26	
	Allocation Direction	0	0	-3	0	0	0	-3	0	-3	0	0	0	0	2	3	3	-2	3	0	0	
	Fourth allocation	22	12	20	30	27	7	5	19	32	35	51	65	15	3	3	3	4	3	3	26	
5:50 PM	λ	5	2	4	6	6	5	3	1	2	3	2	2	1	3	0	2	3	1	1	3	18
	μ	2	0	1	0	0	2	3	1	2	2	2	4	3	5	7	3	3	5	5	4	
	Total demand of bicycle	-3	-2	-3	-6	-6	-3	0	0	0	-1	0	2	2	2	7	1	0	4	4	1	
	Number of bicycle	25	14	23	36	33	10	5	19	32	36	51	63	13	1	-4	2	4	-1	-1	25	
	Allocation Direction	0	0	-8	0	0	-1	-2	0	-7	0	0	0	0	2	7	1	0	4	4	0	
	fifth allocation	25	14	15	36	33	9	3	19	25	36	51	63	13	3	3	3	4	3	3	25	
																					Total bicycles	52

Conversely, at stations where the number of bicycles is insufficient, such as Stations 3, 8, and 0, bicycles are supplied from other stations. For example, at Station 3 at 5:10 PM, there are four bicycles at the beginning. There are no bicycle arrivals, but two bicycles depart, resulting in a total demand of 2 (2-0). The number of bicycles is updated to two (4-2), but since the minimum number of bicycles required at the station is three, Station 3 is now insufficient. Bicycle allocation is required, and Station 5 is identified as the supply station since it is within the maximum distance. The allocation direction for Station 5 will be -1, and Station 3's allocation direction will be 1, indicating that one bicycle is allocated from Station 5 to Station 3. The number of bicycles after allocation at Station 5 is updated to 21 (22+(-1)), and the number of bicycles after allocation at Station 3 is 3 (2+1).

At 5:10 PM, the stations with insufficient bicycles are highlighted in grey: stations 3, 8, and 11. Station 3 has 2 bicycles, station 8 has 1 bicycle, and station 11 has no bicycles. Since the minimum requirement for bicycles is 3, station 3 needs 1 more bicycle, station 8 needs 2 more bicycles, and station 11 needs 3 more bicycles. Therefore, the total number of bicycles allocated at 5:10 PM is 6 (1+2+3) which shown in the last column of Table 2.

6. Result and discussion

Table 3 displays the bicycle shortages for the traditional and proposed models. In the traditional model, there are bicycle shortages in all time periods. However, in the proposed model, every station has the number of bicycles equal to the minimum requirement (q_{min}). This indicates that by using the proposed model, there are no insufficient stations. The comparison indicates that the proposed model reduces the bicycle shortage quantity from 55 to 3, or by 94.55%.

Table 3 the bicycle shortages for the traditional and proposed models

Station		1	6	15	19	20	2	4	5	9	13	14	17	18	3	7	8	10	11	12	16	Shortage
The traditional model	5:00 PM	14	2	18	22	20	4	18	22	33	33	47	59	13	4	18	4	21	1	14	33	3
	5:10 PM	15	4	19	23	24	5	16	22	33	35	47	60	14	2	14	1	19	0	10	32	6
	5:20 PM	16	6	20	26	24	5	13	19	34	36	49	62	16	3	12	-4	16	-2	8	30	12
	5:30 PM	19	10	18	28	27	5	8	21	33	36	51	64	13	0	6	2	12	2	6	28	5
	5:40 PM	22	12	23	30	27	7	8	19	35	35	51	65	15	1	0	0	6	0	3	26	11
	5:50 PM	25	14	23	36	33	10	5	19	32	36	51	63	13	1	-4	2	4	-1	-1	25	18

Station		1	6	15	19	20	2	4	5	9	13	14	17	18	3	7	8	10	11	12	16	Shortage
The proposed model	5:00 PM	14	2	18	22	20	4	18	22	33	33	47	59	13	4	18	4	21	1	14	33	3
	5:10 PM	15	4	16	23	24	5	14	21	33	35	47	60	14	3	14	3	19	3	10	32	0
	5:20 PM	16	6	15	26	24	5	6	19	34	36	49	62	16	3	12	3	16	3	8	30	0
	5:30 PM	19	10	17	28	27	5	7	18	33	36	51	64	13	3	6	3	12	3	6	28	0
	5:40 PM	22	12	20	30	27	7	5	19	32	35	51	65	15	3	3	3	4	3	3	26	0
	5:50 PM	25	14	15	36	33	9	3	19	25	36	51	63	13	3	3	3	4	3	3	25	0

Table 4 Number of bikes allocated and distance

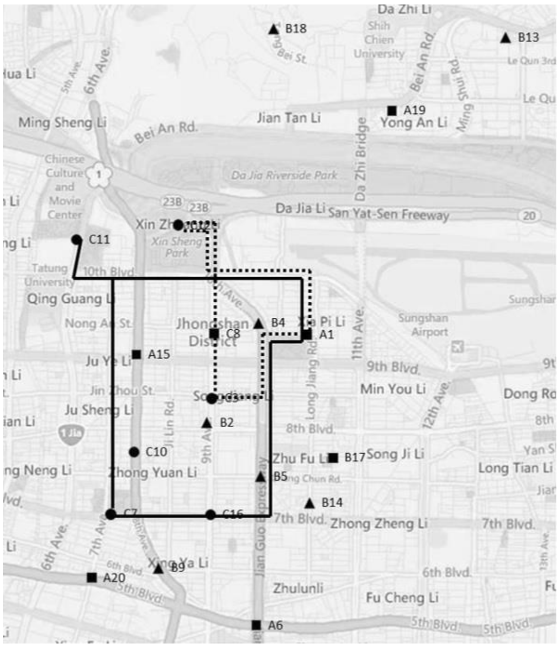
Supply Station	Demand Station	Number of bike allocation	Distance (km.)	Total distance (km.)
2	8	1	0.35	0.35
4	8	9	0.37	3.31
4	12	4	0.77	3.06
4	3	2	0.49	0.98
5	3	4	0.49	1.94
9	7	10	0.45	4.50
10	3	2	0.68	1.35
15	11	12	0.61	7.32
15	8	4	0.65	2.59
15	12	4	0.61	2.44
		52		27.84

The total bike allocation, the distance traveled, and the supply (origin) and demand (destination) stations are shown in Table 4. The total distance (the last column) is calculated by multiplying the number of bike allocations (column 2) with the distance from the supply station to the demand station (column 4). The total distance traveled for the bike allocation in the case study is 27.84 km. The highest number of bike allocations is from station 15 to station 11, which is 12 bicycles, followed by 10 bikes from station 9 to station 7.

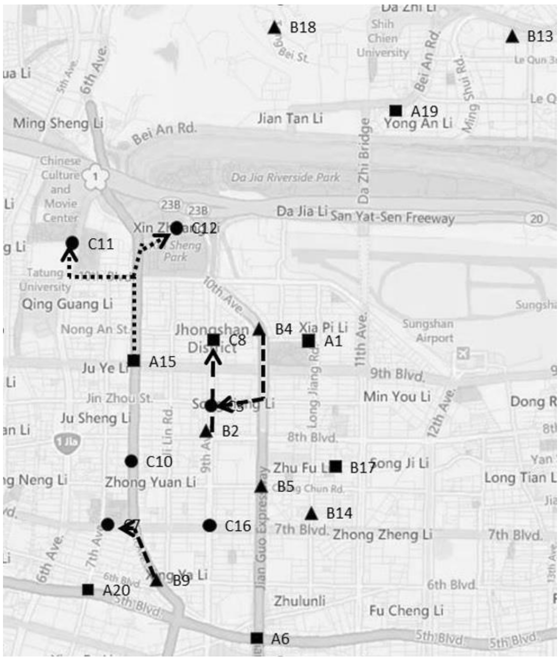
To compare the effectiveness of the proposed method, the traditional model developed by the author [16] was utilized. Figure 3 displays the bike allocation of both models at 5:40 p.m. On the left-hand side (Figure 3(a)), the bicycle allocation by the traditional VRP model is shown, while the right-hand side (Figure 3(b)) displays the bicycle allocation of the proposed model. The traditional model utilizes a truck to allocate bicycles, which travels along the optimal route without exceeding its capacity. At the end of the day, 37 bicycles are allocated. Due to the limited capacity of the truck, it needs to make two trips along the insufficient stations, shown as solid and dashed lines in Figure 3(a).

In contrast, the proposed model assumes that every customer will allocate the bike they can allocate, and bicycles are distributed to insufficient stations every 10 minutes. A total of 52 bicycles are allocated. The dashed line in Figure 3(b) displays the movement of the customers, and it is evident that customers will only allocate bicycles near the station. By comparing the two models, it is evident that the proposed model effectively reduces the shortage of bicycles from 37 to 3, which is a reduction of 94.55%.

Although the proposed model requires more bicycles to be relocated compared to the traditional model, it has an advantage in terms of sustainability and reducing carbon dioxide emissions. For instance, urban delivery trucks emit 307 grams of CO_2 per kilometer (gCO_2/km) [18], whereas bicycles only generate 21 grams of CO_2 emissions per kilometer [19]. By considering the concept of sustainability, the proposed method seems to be more beneficial.



(a) The traditional model



(b) The proposed model

Figure 3 Bike allocation at 5:40 p.m.

Table 5 The comparison of CO_2 emission between the traditional and the proposed model

	Number of bikes allocated	**Number of allocation**	**Total distance (km.)**	**CO_2 emission (gCO_2/km)**
The traditional model	37	2	7.55	2,317.85
The proposed model	52	52	27.84	584.64

Table 5 presents a comparison of the number of bikes allocated number of allocations, distance, and CO_2 emissions. In the traditional model, bikes were allocated only twice using a truck, resulting in a CO_2 emission of 2,317.85 gCO_2/km (7.55 * 307). On the other hand, the proposed model allocated bikes a total of 52 times over 27.84 km, resulting in a CO_2 emission of 584.64 gCO_2/km (27.84 * 21). In terms of the number of bikes allocated and number of allocations, the proposed model allocated 52 bicycles 52 times, which is higher than the traditional model. This is because the proposed model allocates bikes every time there is a shortage, and the distance between locations is short enough to make frequent allocations feasible. Although the total distance of allocation in the proposed model is longer than in the traditional model (as shown in column 4), the proposed model generates 24.49% less CO_2 emissions than the traditional model.

7. Conclusion

In conclusion, the proposed dynamic allocation model for bike sharing systems based on the sharing economy concept offers a sustainable solution for managing the distribution of bicycles. The model assumes that all bike users are willing to allocate bikes by themselves and uses a Mixed Integer Linear Programming (MILP) to maximize the number of allocations while ensuring that each station meets the minimum bike requirement. A case study of the Zhongshan district in Taipei City, Taiwan is used to demonstrate the value of the model. The results reveal that the proposed model can avoid bicycle shortages, successfully ensuring that every station contains the required number of bicycles. Additionally, the model leads to lower carbon dioxide emissions when compared to traditional methods involving delivery trucks. Overall, this model offers an effective solution for managing bike sharing systems and promoting sustainability in urban transportation.

A limitation of this study is that the proposed model is based on the assumption that all users of the bike-sharing system are willing to allocate a bicycle by themselves. In practice, this assumption may not hold true, and additional factors, such as the characteristics of users who will use the system, the cost of incentivizing users to participate, and the maximum distance users are willing to travel to allocate bicycles, must be explored to make the model applicable in real-world situations. This topic could also be considered as a further area for work as well.

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