A Research on The Redistribution Strategy of Bicycle Sharing System Through Historical Usage Pattern Analysis

Civil and Environmental Engineering Urban Transport Engineering and Planning laboratory
Nayli Nazurah Binti Norhalim

1. INTRODUCTION

Bicycle sharing system (BSS) are expanding rapidly worldwide as sustainable urban mobility solution, contributing to reduced traffic congestion, provide affordable last-mile connectivity, and lower greenhouse gas emissions (O'Brien et al., 2014; Mateo-Babiano, 2015; Fishman, 2016). There are currently over 1,917 BSS in operation worldwide, with Japan ranked 8th hosting 57 systems (Meddin, 2022). Despite their benefits, BSS face operational challenges, particularly related to station imbalances leading to service disruptions such as empty stations, which compromise user satisfaction and in the worst case, may loss a potential customer.

Niigata City7s 24-hour BSS, "Niigata 2km Share-Cycle", was launched in 2022 face the same issues as empty station still occur despite their redistribution efforts (Fig.1).

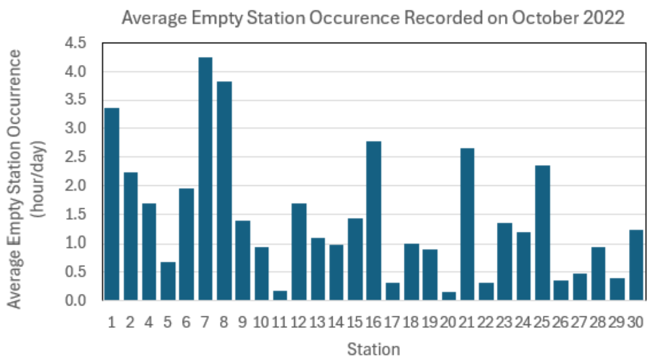


Fig. 1 Average empty Station Occurrence Recorded in October 2022

Station imbalances, characterized by surpluses or shortages of bicycle are a significant concern in BSS operations (Wong et al., 2015) Surveys by the Taipei YouBike system report over 36% of issues stemming from these imbalances, where users cannot pick up or return bikes due to station capacity constraints (Taipei Friendly Environment Association) and Barcelona's BSS similarly experiences similar challenges (Kaltenbrunner et al., 2010). Addressing these imbalances is crucial for ensuring reliable service, particularly in cities like Niigata, where empty station occurrence persist despite active redistribution.

2. LITERATURE REVIEW

Research has explored various methods for optimizing bicycle redistribution. Studies have applied static redistribution strategies, like the Capacitated Vehicle Routing Problem (CVRP), to minimize operational costs (Dell 'Amico et al., 2014; Erdoğan et al., 2014). These static strategies focus on minimizing costs through predefined redistribution routes during low-demand periods. Dynamic models have also been explored to handle fluctuating demand patterns (Chen et al., 2024; Brinkmann et al., 2015; Shi et al., 2024).

However, while demand prediction models are well-established, many studies focus on optimizing redistribution without considering real-world budgetary constraints and resource limitations.

This research contributes to addressing gaps in existing literature by proposing an optimized static redistribution model for Niigata's BSS, focusing on historical usage data with flexible demand coverage level where operators can set targets for bicycle demand coverage, balancing resource constraint and service performance.

3. OBJECTIVE & METHODOLOGY

(1) Research Objective

Our main objective is **to develop a cost-effective redistribution plan with a model considering buffer and historical usage pattern analysis** to ensure the availability of bicycles at stations even during limited bicycle resources while also at reasonable cost. Particularly, the study has the following sub-objectives:

i. To identify usage patterns.
ii. To determine the required number of bicycles for each station, along with buffer levels.
iii. To develop cost-effective redistribution

strategies that optimize available resources.

(2) List of data

With cooperation with "Niigata 2km Share-Cycle", below are lists of data obtained;

- **Bicycle GPS Tracking Records:** GPS logs are analyzed to identify demand variations and usage patterns, including outflow and inflow of each station.
- **Empty & Full Station Logs:** to verify station activity patterns, station imbalances, and comparison of the redistribution results with the proposed model.
- **Manual Redistribution Logs:** to verify station activity patterns, station imbalances, and the comparisons of the redistribution steps compared to the proposed model.
- **Weather Data:** Historical weather data of Niigata city, sourced from the Japan Weather Association is used to analyze demand variations caused by weather conditions (https://tenki.jp/past/2022/10/weather/4/18/).

(3) Research Process and Methodology

Overall research is divided into two phases to answer the subobjectives (Fig. 2).

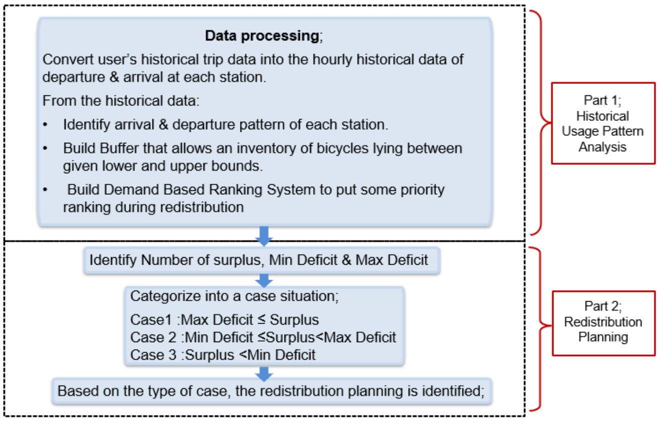


Fig. 2 Research Process

- **First phase:** Historical data on bicycle GPS tracking records, empty & full station logs, and manual redistribution patterns are analyzed to identify usage patterns and its station-wise demand variation. The optimum number of bicycles required at each specified station is then determined based on its coverage levels to prevent empty station occurrence.
- **Second phase:** a capacitated static redistribution model is developed with buffer to allocate number of inventories within predefined bounds set by the operator and apply scenario-based modeling to optimize redistribution path even under limited number of bicycle resources.

Phase One: Historical Usage Pattern Analysis

Historical usage data forms the foundation to analyze required number of bicycles to prevent empty station occurrence. In Niigata2kmSharecycle BSS system, each bicycle is equipped with a GPS logger that records its location (latitude and longitude) at three-minutes intervals. The GPS position data is used to identify the starting, and ending station of the trips, as well as the departure and the arrival times. Empty station history records are matched with GPS data timestamps to improve precision in hourly arrival and departure pattern analysis. This process allows hourly arrival and departure patterns at each station to be identified.

The data categorized based on four temporal conditions: weekday (clear), weekday (rain), weekend (clear), and weekend (rain). Using arrival and departure data of each station, cumulative fluctuation was calculated to identify patterns in bicycle availability. A cumulative density function of negative fluctuations was developed to estimate the probability of station imbalances occurring. These fluctuation patterns were further analyzed to determine bicycle requirements and buffer levels needed to ensure consistent availability at each station. These results were used to estimate bicycle requirements and buffer levels to ensure consistent availability at each station.

Phase Two: Redistribution Planning

In our study, the model determines optimal redistribution strategies, including the stations to serve and the number of bicycles to redistribute based on bicycle allocations derived from historical data and predefined buffer levels. The redistribution process follows these steps;

1) **Identify surplus station and its number of surplus stations:** Stations exceeding upper buffer thresholds are classified as surplus stations, and the model calculates the number of bicycles available at surplus stations without reducing their inventory below the maximum buffer level.
2) **Address deficit stations:** The models allocate the number of bicycles to be redistributed to the deficit stations, prioritizing minimum buffer requirements at deficit stations. If surplus bicycles remain after meeting minimum requirements, high-demand stations will receive additional bicycles until reaching the maximum buffer threshold. It continues until all surplus bicycles are distributed, or all maximum buffer requirements are met.
3) **Optimize vehicle routing:** Using the shortest-path algorithm, the model determines the most efficient routes for collection and redistribution. Routes are optimized while adhering to vehicle capacity constraints to minimize travel distance and operational costs.
4) **Output redistribution plan:** The model generates a detailed redistribution plan specifying the number of bicycles to be collected, number of bicycles to be redistributed, step-by-step station visit with the visual map, total predicted costs and the summary of the number of bicycles at each station before and after the redistribution operation.

For redistribution, Network X was employed to model and plan the most efficient routes. Buffers are implemented that allows an inventory of bicycles lying between lower and upper bounds given based on the minimum and maximum target coverage level selected by the operator. Model will conduct the redistribution based on identified three case scenarios based on varying levels of surplus and deficits to dynamically allocate bicycles as efficiently as possible (Fig. 3).

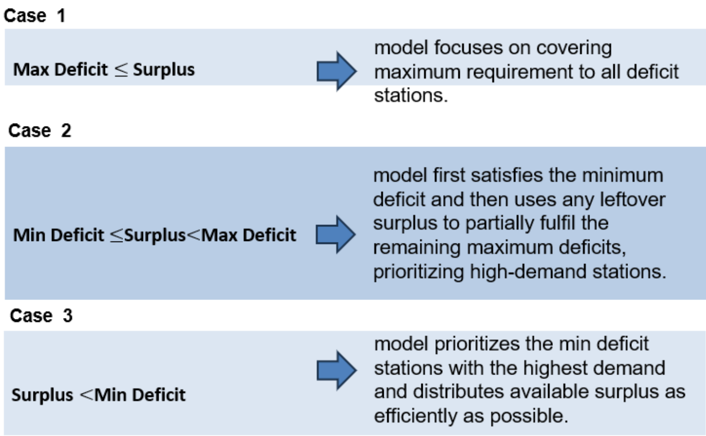


Fig. 3 Case-Scenarios and its Redistribution Plan

Case 1; Maximum deficit ≤ Total Surplus

Case 1 is when the system has enough bicycles to meet the maximum demand at all stations. The goal here is to avoid unnecessary pickups and minimize operational costs by only covering essential demands.

Case2; Minimum deficit ≤ Surplus < Maximum deficit

Case 2 is a situation when the system can meet only the minimum demand requirement at each station but cannot reach the maximum demand requirement. In this case, the model reassigns the number of bicycles to be allocated to each deficit stations. It first satisfies the minimum buffer levels first, and any remaining surplus bicycles are then allocated to high-demand stations to partially meet their maximum demand requirements.

Case3; Surplus < Minimum deficit

Case 3 is a situation where the system cannot even meet the minimum demand across all stations. Redistribution prioritizes high-demand stations first, ensuring the most critical deficits are resolved while lower-priority stations may receive limited to no support.

4. RESULTS AND DISCUSSIONS

(1) First Phase: Historical Usage Pattern Analysis

As of October 2022, Niigata's BSS comprised one depot, 29 stations, and 252 parking docks, with capacities ranging from 5 to 12 slots per station. A total of 150 bicycles were in operation, serving 1,923 users and 196,248 trips. Trip lengths ranged from 1.2km to 2.1km, averaging 2km. It was assumed that users traveled directly from departure to arrival stations without intermediate stops.

Stations located near transportation hubs and convention center exhibited higher levels of usage, where the circle sizes in Fig. 4 proportional to the rental amounts. This observed usage pattern serves as the foundation for a station priority in this study, guiding redistribution efforts to optimize resource allocation by prioritizing stations with high usage demands when only the bicycles are limited to comply to all demands.

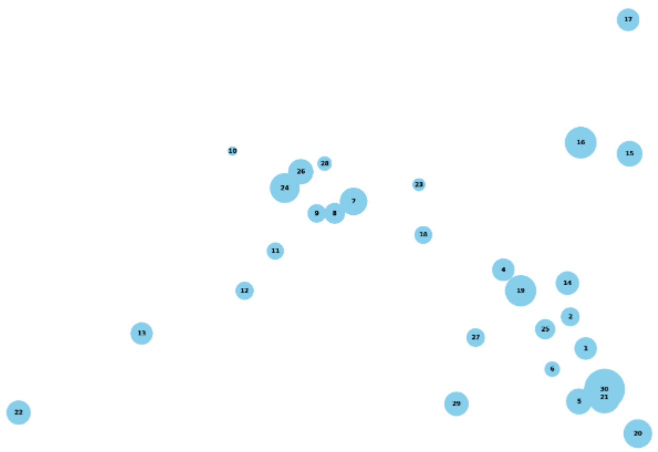


Fig. 4 circle sizes proportional to the usage demands

Historical data revealed that weather conditions significantly influenced usage patterns. On clear days, an average of 179 trips per day was recorded, while rainy days saw a 27.93% decline, with only 129 trips per day. Similarly, activity levels varied by the day of the week, with weekdays averaging 135 trips per day and weekends experiencing a 57% increase to 212 trips per day.

Spatially activity patterns also varied across stations based on their geographic characteristics. Stations near hotels exhibited prolonged periods of low bicycle activity excepts on the weekends, reflecting their role as first/last-mile transit points on weekends. Conversely, stations located near transportation hubs or shopping districts maintained consistent activity throughout the day, accommodating a diverse range of trip purposes.

Further analysis highlighted nuanced differences in temporal patterns (Fig. 5).

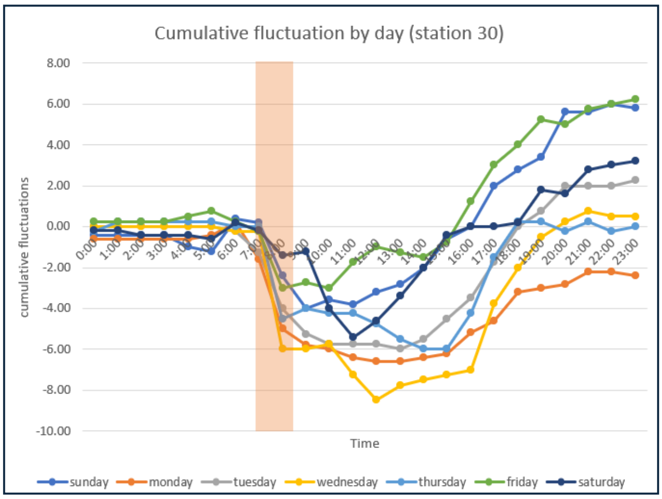


Fig. 5 Average Cumulative Fluctuations By Day (Station 30)

On weekdays, station activity fluctuations were more pronounced due to a mix of commuting and leisure trips. In contrast, weekends exhibited more stable patterns, likely driven by users engaging with similar activities, such as shopping or recreation. Negative fluctuations, where departures exceeded arrivals, were more prevalent during daytime hours on both weekdays and weekends and often persisted until evening. This highlights the need for redistribution efforts to maintain adequate bicycle availability.

Peak activity periods were identified between 7:00 and 8:00 am on both weekdays and weekends, aligning with typical commuter behavior. This observation supports the feasibility of static redistribution strategies, allowing bicycles to be pre-positioned before anticipated peak usage. Weekday fluctuations were sharper due to mixed trip purposes, while weekend patterns remained stable, driven by recreational activities. Negative fluctuations during daytime during daytime hours on weekdays underscored the importance of timely redistribution to prevent station depletion.

In identifying the minimum number of bicycles need to be stationed at each specific station, we first differentiate each day of the data into week of the day (weekend, weekday) and the weather (clear, rain). Then, the data is divided into category of weekend clear, weekend rain, weekday clear, and weekday rain to specifically identify the demand patterns based on is conditions. For each station we evaluated the net flow of bicycles on a daily basis, computed as the difference between the inflow and the outflows throughout the day. This gives the difference between the bicycles available at the beginning of the day and the and those left at the end of the day in each station. We then plotted the redistribution of the net flows over the period.

Fig. 6 shows the distribution graph in station 30 during weekend clear where the x axis gives the cumulative fluctuations; which is the difference between arrivals and departures in a station per day, and the y axis is a cumulative probability; where it gives the percentage of occurrence this number appears in a day throughout the period that we studied. This shows that majority of the days over the observations of the stations ended up with a number of bicycles different from that available at the beginning of the day. This graph of the PDF and the CDF will support the choice of performing redistribution operations. As we are focusing on preventing empty station occurrence, we only consider the negative fluctuations where departures exceeded arrivals, and removed the positive cumulative fluctuations.

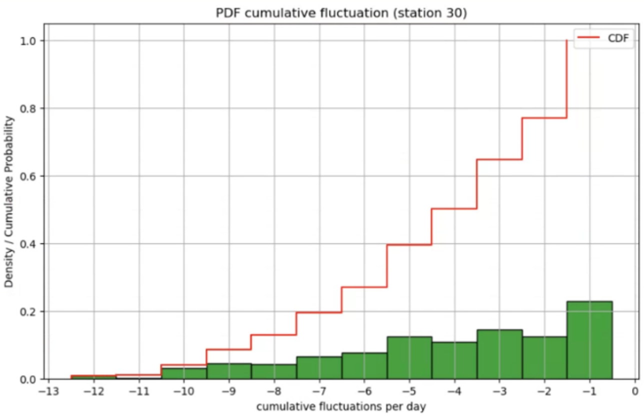


Fig. 6 PDF and CDF (Station 30)

Table 1 shows the optimum number of bicycles at each station based on its target coverage level. Operators have the option to select coverage levels that best align with their budget constraints. leveraging these insights, operators can forecast bicycle shortages in advance, allowing for proactive redistribution. This ensures an expected continuous availability of bicycles across the station thus reducing the risk of empty stations.

Table. 1 Number of Bicycle Required Based on Probability of Occurrence (Weekend-clear)

STATIONS	0%	5%	10%	15%	20%
1	6	5	5	4	4
2	5	4	4	3	3
4	5	5	4	4	3
5	6	5	4	4	3
6	4	4	4	3	2
...					
26	9	7	4	4	3
27	6	5	4	4	3
28	4	4	3	3	2
29	7	6	4	4	3
30	12	10	9	8	7
SUM	189	152	126	117	96

(2) Second phase: redistribution planning

Niigata BSS has single depot, where the redistribution truck is stationed. the system includes 29 nodes (starting from station 1 to station 30, excluding station 3 as in the historical data, station 3 was being temporarily closed), representing the station locations based on October 2022. The geographical distribution of the station is illustrated in Fig. 7.

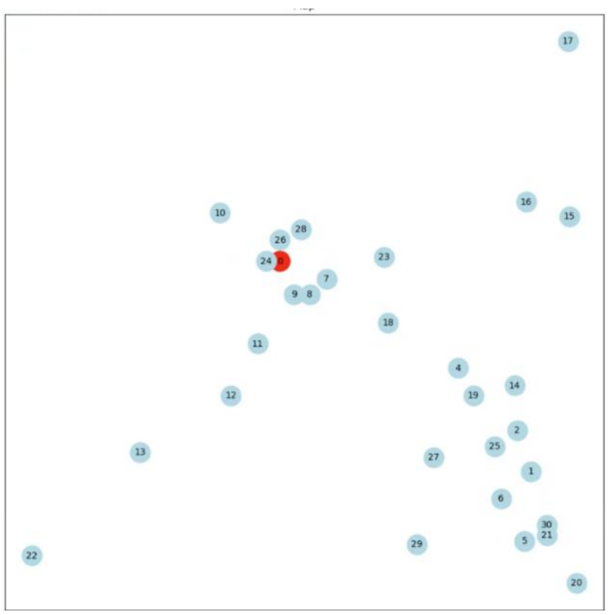


Fig. 7 Location of the Depot and The Station Nodes

It was considered that 2 staff were conducting the manual redistribution with wage per hour of 1,000yen, truck average speed of 20km/h, and the gasoline cost per km of 20yen. In addition, for the research discussion purposes and our attempt to solve real-world instances, initial number of bicycles at each station before the redistribution are set based on historical data, specifically on 11th October 2022 (Table 2) with minimum coverage level set 95% (probability of satisfying at least 95% of the demand) and maximum coverage level set as 100% (probability of satisfying at most 100% of the demand). The details of inter-station node position coordinates and the initial number of bicycles before the redistribution operation are provided in table 4.1 for clarity purposes. with set number of bicycle in operation of 170 bicycles

Table. 2 Position Coordinates and Its Initial Number of Bicycles Before Distribution

Station	Coordinate	Initial number of bicycles before distribution (bicycle)
0 [depot]	(139.044132,37.9221741)	0
1	(139.0598182,37.91503299)	4
2	(139.0590157,37.91644145)	2
4	(139.0555256,37.91853535)	8
5	(139.0594708,37.91267667)	8
6	(139.0580734,37.91411355)	3
7	(139.0477174,37.92157842)	2
8	(139.0467311,37.92104756)	8
9	(139.0457961,37.92104351)	8
10	(139.0414051,37.92381902)	8
11	(139.0436379,37.91936825)	10
12	(139.0420371,37.91760259)	6
13	(139.0366695,37.91570026)	7
14	(139.0588651,37.91794196)	4
15	(139.0621078,37.92369821)	8
16	(139.0595599,37.92419258)	10
17	(139.0620342,37.92965834)	8
18	(139.0513544,37.92008714)	6
19	(139.0564291,37.91760135)	2
20	(139.0625362,37.91124416)	8
21	(139.0607885,37.91286432)	5
22	(139.0302563,37.91217876)	3
23	(139.0511232,37.92232405)	8
24	(139.044132,37.9221741)	5
25	(139.0577059,37.91588886)	5
26	(139.044964,37.92289772)	6
27	(139.0540806,37.91551765)	7
28	(139.0462085,37.92326164)	5
29	(139.0530801,37.91256726)	3
30	(139.0608,37.91322)	3

Based on the target minimum coverage level, target maximum coverage level, and current number of bicycles at each station before redistribution keyed in by the operator, the model will identify the case-scenario and its distribution approach.

Fig. 8 shows that the model identifies the redistribution to be a case 2, where the system can meet the minimum demand requirement at each station but does not have sufficient resources to fulfill all the maximum demand requirement at each station. Thus, the model will reassign the number of bicycles to be allocated to each specific deficit station. For this case scenario, the surplus bicycle first allocated to cover all the minimum requirement first. Since there is more remaining surplus (4 bicycles), the model then allocates the remaining bicycle to cover maximum requirement based on the station demand priority until all the surplus is used. Then, the model will made the summary of the redistribution plan, showing the selected deficit station and its numbers of bicycles to be redistributed.

```
Case 2: Total surplus is between min deficit and max deficit. Covering minimum requirements first.
Station 1: Min deficit covered = 1, Remaining surplus = 31
Station 2: Min deficit covered = 2, Remaining surplus = 29
Station 6: Min deficit covered = 1, Remaining surplus = 28
Station 7: Min deficit covered = 4, Remaining surplus = 24
Station 14: Min deficit covered = 1, Remaining surplus = 23
Station 19: Min deficit covered = 3, Remaining surplus = 20
Station 21: Min deficit covered = 2, Remaining surplus = 18
Station 22: Min deficit covered = 3, Remaining surplus = 15
Station 26: Min deficit covered = 1, Remaining surplus = 14
Station 29: Min deficit covered = 3, Remaining surplus = 11
Station 30: Min deficit covered = 7, Remaining surplus = 4
Station 30: Additional deficit fulfilled = 2, Remaining surplus = 2
Station 21: Additional deficit fulfilled = 2, Remaining surplus = 0
Final distribution plan: {1: 1, 2: 2, 6: 1, 7: 4, 14: 1, 19: 3, 21: 4, 22: 3, 26: 1, 29: 3, 30: 9}
```

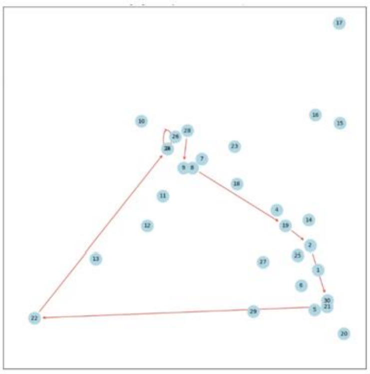
Fig. 8 Location of the Depot and The Station Nodes

Then, the model will identify the shortest path for the collection and redistribution process. Table. 3 shows the step-by-step redistribution procedure; including the station need to be visited in order, the number of bicycles needed to be collected or distributed at specific station, and the expected distance in meters for each steps taken. For an example at the first row of table 4.2, it shoes that redistribution vehicles first need to travel from station 0 (depot) to station 28. At station 28, 1 bicycle need to be collected. And the summary for the distance taken from station 0 to station 28 is 240 meters. Table 16 shows that in total, 32 bicycles had been redistributed for this redistribution process.

Table. 3 Result Showing Redistribution Procedure from The Model

	From Station	To Station	Collect	Distribute	Truck Inventory	Distance (meters)
0	0	28	1	0	1	240
1	28	9	1	0	2	240
2	9	8	1	0	3	130
3	8	11	5	0	8	460
4	11	12	1	0	9	250
5	12	13	1	0	10	600
6	13	22	0	3	7	750
7	22	13	2	0	9	750
8	13	10	1	0	10	1100
9	10	26	0	1	9	180
10	26	10	1	0	10	180
11	10	7	0	4	6	440
12	7	23	4	0	10	400
13	23	19	0	3	7	1020
14	19	4	3	0	10	120
15	4	1	0	1	9	620
16	1	2	0	2	7	180
17	2	6	0	1	6	350
18	6	5	2	0	8	300
19	5	27	1	0	9	980
20	27	29	0	3	6	500
21	29	10	3	0	9	1910
22	10	23	1	0	10	840
23	23	14	0	1	9	1570
24	14	30	0	9	0	790
25	30	17	2	0	2	2380
26	17	16	2	0	4	700
27	16	21	0	4	0	1960
28	21	0	0	0	0	2670
29	Total		32	32		22610

Fig. 9 shows the highlighted redistribution trip (left), and the summary of before and after the redistribution procedure, including the list of minimum required bicycles at each specific station, maximum required bicycles at each specific station, number of bicycles at each station before and after the redistribution.



	Station	Min Required Bicycles	Max Required Bicycles	Before Distribution	After Distribution
0	0	0	0	0	0
1	1	5	6	4	5
2	2	4	5	2	4
3	4	5	5	8	5
4	5	5	6	8	6
5	6	4	4	3	4
6	7	6	7	2	6
7	8	5	7	8	7
8	9	5	7	8	7
9	10	3	3	8	3
10	11	3	5	10	5
11	12	4	5	6	5
12	13	4	4	7	4
13	14	5	6	4	5
14	15	7	9	8	8
15	16	8	8	10	8
16	17	5	6	8	6
17	18	4	7	6	6
18	19	5	9	2	5
19	20	8	14	8	8
20	21	7	10	5	9
21	22	6	9	3	6
22	23	3	3	8	3
23	24	5	6	5	5
24	25	4	6	5	5
25	26	7	9	6	7
26	27	5	8	7	6
27	28	4	4	5	4
28	29	6	7	3	6
29	30	10	12	3	12
30	Total	152	195	170	170

Fig. 9 Highlighted redistribution trip (left) and Highlighted station (Right)

Lastly, the model will identify the total cost taken for the redistribution process. Fig. 10 shows the summary of the total distance travelled, total cost; which includes labor wage, and the fuel costs, and the total estimated trip duration.

```
Total distance traveled: 22.61 km
Total cost: 11289 yen (Wage: 10837 yen, Gasoline: 452 yen)
Total trip duration: 5.42 hours
```

Fig 10. result showing estimated operational cost from the model

Results of the model by implementing 95% coverage level into the simulation and comparing the expected empty station occurrence result with the recorded empty station occurrence shows 20% to 100% reduction with station 1, 10, 16, 23, 26, and 27 shows 100% reduction and station 15 showing least reduction at 20% (Fig.11).

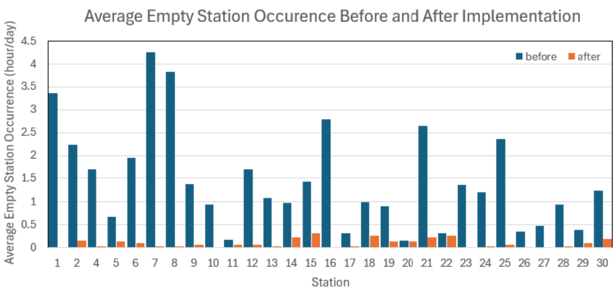
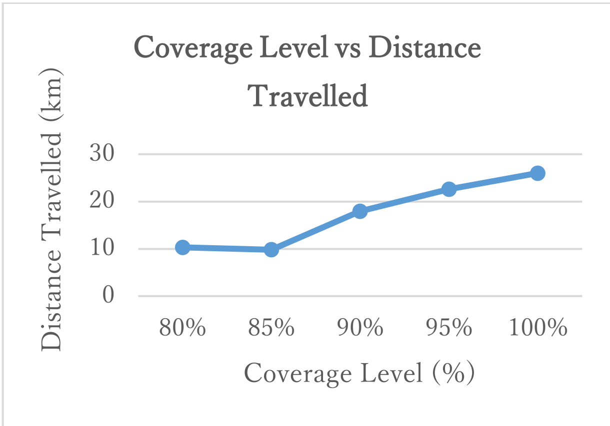


Fig. 11 Predicted Average Empty Station Occurrence After Implementation

To comprehensively investigate the influence of coverage on the outcomes generated by the model presented in this research, the demand coverage level from 100%, 95%, 90%, 85%, and 80%. The sensitivity analysis showed decreasing coverage levels reduced costs and distances proportionally. 100% coverage require to 26.02km redistribution trip, with operation cost of 8,750yen (8,230yen and 520 gasoline price). When the coverage is changed to 95%, the trip distance decreased by to 22.61km, and the cost of operation decreased to about 8,341yen. When the coverage is changed to 90%, the trip distance decreased to 17.95km, and the cost of operation decreased to about 7,782yen. When the coverage is changed to 85%, the trip distance decreased to 9.8km, and the cost of operation decreased to about 6,608yen (Fig. 12). Therefore, we believed that it was important to consider the percentage of coverage.



100% coverage level

- Total distance : 26.02km
- Total cost : 8,750yen (wage: 8,230yen Gasoline: 520yen)
- Total trip: 4.12hours

95% coverage level

- Total distance : 22.61km
- Total cost : 8,341yen (wage: 7,889yen/ Gasoline: 452yen)
- Total trip: 3.94hours

90% coverage level

- Total distance : 17.95km
- Total cost : 7,782yen (wage: 7,423yen Gasoline: 359yen)
- Total trip: 3.71hours

85% coverage level

- Total distance : 9.8km
- Total cost : 6,804yen (wage: 6,608yen Gasoline: 196yen)
- Total trip: 3.30hours

Fig. 12 Sensitive Analysis on The Coverage Level

5. CONCLUSION

This paper has proposed a cost-effective static redistribution model leveraging historical demand data to optimize BSS efficiency while balancing resource allocation and service quality. Using the Capacitated Vehicle Routing Problem (CVRP), the model efficiently solves redistribution challenges, considering truck capacity, demand coverage thresholds, and station priorities. Sensitivity analysis validated its responsiveness to changes in demand and bicycle availability, demonstrating how coverage levels impact trip distance and operational costs. Phase One revealed spatial and temporal demand variations, emphasizing the importance of timely redistribution to prevent station depletion. Phase Two optimized redistribution by identifying shortest paths, calculating bicycle movements, and analyzing cost trade-offs. Overall, this research provides a data-driven framework to enhance Niigata's BSS, offering adaptable strategies to improve resource allocation, reduce costs, and enhance user experience.

6. LIMITATIONS & FUTURE WORKS

This study is subject to certain limitations. Firstly, it ignoring the possibility of demand when there is event occurring at the specific locations. Thus, finding is limited to the demands at one season. Secondly, the research focusing on reducing the empty station occurrence and neglecting the station capacity, which may cause the probability of full station occurrence.

In the future, this model can be extended to address these limitations by incorporate longer historical BSS data to capture seasonal demand variations (spring, summer, autumn, & winter). Event-related demand surges should also be considered by integrating data on location-specific local events to develop more adaptive redistribution models. While this study focuses on empty station reduction, future work on full station should account for enhanced operational efficiency.

REFERENCES

1) O'Brien, O., Cheshire, J., & Batty, M. (2014). Mining bicycle sharing data for generating insights into sustainable transport systems. Journal of Transport Geography, 34, 262–273. https://doi.org/10.1016/j.jtrangeo.2013.06.007
2) Mateo-Babiano, I. (2015). Public bicycle sharing in Asian cities. Journal of the Eastern Asia Society for Transportation Studies/Journal of the Eastern Asia Society for Transportation Studies, 11(2015), 60–74. https://doi.org/10.11175/easts.11.60
3) Fishman, E., & Schepers, P. (2015). Global bike share: What the data tells us about road safety. Journal of Safety Research, 56, 41–45. https://doi.org/10.1016/j.jsr.2015.11.007
4) Meddin R., DeMaio P., O'Brien O., Rabello R., Yu C., Gupta R., et al. 2022. The meddin bike-sharing world map.
5) Wong, J., & Cheng, C. (2015). Exploring activity patterns of the Taipei Public Bikesharing system. Journal of the Eastern Asia Society for Transportation Studies/Journal of the Eastern Asia Society for Transportation Studies, 11, 1012–1028. https://doi.org/10.11175/easts.11.1012
6) Kaltenbrunner, A., et al., (2010) Urban Cycles and Mobility Patterns: Exploring and Predicting Trends in a Bicycle-Based Public Transport System. Pervasive and Mobile Computing, 6, 455-466. https://doi.org/10.1016/j.pmcj.2010.07.002
7) Dell'Amico, M., Hadjicostantinou, E., Iori, M., & Novellani, S. (2013). The bike sharing rebalancing problem: Mathematical formulations and benchmark instances. Omega, 45, 7–19. https://doi.org/10.1016/j.omega.2013.12.001
8) Erdoğan, G., Laporte, G., & Calvo, R. W. (2014). The static bicycle relocation problem with demand intervals. European Journal of Operational Research, 238(2), 451–457. https://doi.org/10.1016/j.ejor.2014.04.013
9) Brinkmann, J., Ulmer, M. W., & Mattfeld, D. C. (2015). Short-term strategies for stochastic inventory routing in bike sharing systems. Transportation Research Procedia, 10, 364–373. https://doi.org/10.1016/j.trpro.2015.09.086