Simulation for Operation and Cost Optimization in Bike Sharing Rebalancing to Balance Supply and Demand

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Abstract: The bike sharing service is an alternative to urban transport. One of the greatest challenges of the bike sharing system is a shortage of bikes due to an imbalance in the bike distribution. An analysis is carried out in this paper using data mining to determine bike activity patterns and gain insights into the complex bike activity patterns at station. The activity model revealed an imbalance in the bike distribution. The data mining process supports operating decisions of bike sharing systems to know the critical point of the system and makes it easier to resolve the issue. This case study uses a simulation based on the arrival rate; this method assists in managing a bike sharing rebalancing system with the most profitable objective and meets the users' needs. The simulation results showed that rebalancing the number of bikes before rush hour is an optimal solution for bike sharing systems.

Keywords: Alternative Mode, Simulation, Data Mining, Green Vehicles, Mobility Service

1. INTRODUCTION

Nowadays, bike sharing services are gaining worldwide popularity. Numerous countries in Europe and Asia have been using the bike sharing system for decades. City residents often use bike sharing to go to work or on trips, as bikes are convenient to use in cities and allow users to ride rented bikes from one bike station to another. Bike sharing services are also a good option for urban transportation in smart cities (Rani and Vyas, 2017). Even though a bike sharing system can use various technologies such as sensor devices to make it smart, a user simply uses a smartphone to assess the location of available bikes and docks that can be used for daily mobility. This system facilitates the use of rentals that can be picked up and dropped off at any station. Moreover, bike sharing also reduces the need to travel by car or other modes of transport for shorter distances, thereby reducing congestion. Further, bike sharing can assist in decreasing vehicle emissions, including carbon dioxide. Thus, it can also reduce fuel costs.

Bike sharing relocation is a method that can improve bike sharing systems. This method is commonly referred to as rebalancing. Owing to various demands, bike usage can suffer an imbalance. Some stations have a high demand for bike renting, which can result in bike shortage at such stations; whereas, at some stations, users like to return the bike, which might result in a space shortage for the users which are next in line. To balance the network, operators can plan truck routing to maintain the bike supply by refilling the bikes at each station and to manage bike availability in docks by picking them up at each station (Chiariotti *et al.,* 2018). Here, the operation trucks can depart from the same station or different stations depending on the network and operating costs of the service of each provider.

There is a lot of competition in the current situation. In order to operate the business, profits and customer satisfaction are the main aspects to be considered. Bike sharing service business is one that, in addition to providing people with a mode of transport, affects the world in terms of reducing carbon dioxide emissions from non-motorized vehicles or electric power vehicles. To make this business sustainable, it is necessary to improve the quality of the service system that can meet the needs of customers while considering the operating costs that affect the profits for the organization incurred.

Several previous research works have conducted studies to solve bike sharing rebalancing problems: Forma *et al.* (2015) proposed a 3-step mathematical program based on a heuristic algorithm for solving large-scale instances of a static bike rebalancing problem, which aims to minimize the total traveling distance. Lin and Liang (2017) presented a model on the Arena simulation software to obtain the optimal number of relocations for minimizing the waiting time by using the O-D probability matrix, arrival time, and rental time. Chen *et al.* (2020) presented the pricing strategies of bike sharing to adjust the price and demand based on users' travel behavior, which may increase their participation in using bikes. Soriguera *et al.* (2018) proposed a tool to support the decision-making regarding daily operation of planning. They implemented a MATLAB programming code to access and relocate adjustments. The simulator assesses the performance of a bike sharing system before use or for those in performing the analysis of some aspects that are particularly difficult to measure; others can be analyzed from simulations. The simulator can also be used as a productivity tool in the planning process of the bike sharing system.

There are several methods such as truck routing or pricing strategies that can solve bike unbalancing problems. However, there is only one solution that can solve the virtual bike balancing problem: the simulation method that is widely used in various fields. It can also solve complex problems. This research proposes to solve the problem of bike rebalancing using a simulation method that can meet customer needs and obtain the most profitable authorized provider.

2. LITERATURE REVIEW

The literature related to this work concerns bicycle sharing. The researchers propose that the system is characterized with a flexible system using GPS and smartphones (Fishman and Christopher, 2016; Gu *et al*., 2019) in the real time of movable docking station. Daniel *et al*. (2013), Hsu *et al*. (2018), and Martin and Shaheen (2014) have presented in their studies that the bike sharing systems have the potential to create modal shifts, thereby affecting public transport and promoting active mobility. In transit, as a bike-sharing scheme, it may improve the quality of urban environments in terms of reducing pollution (Cerutti *et al*., 2019).

Previous research has proposed a method for improving service quality of the bikes sharing systems. This can be classified into two aspects (Liu *et al*., 2019). The first category is qualitative research: a focus on development of bike sharing systems by analyzing its strengths and weaknesses. Guo *et al*. (2017) proposed the bivariate ordered probit (BOP) model to consider factors associated to bike sharing usage and satisfaction. Moreover, Fishman *et al*. (2015) analyzed factors influencing bike share predictors to maximize and achieve the goal to quantify walking and cycling's contribution. Zhang *et al*. (2015) proposed a second category: quantitative research. This creates a layout of the station and resolves the bike relocation problem. This is similar to Ban and Hyun (2019) adopting the novel simulation method with the use of a tree-dimensional (3D) to improve truck route as a visual analysis for rebalancing bike sharing system. Furthermore, Chen *et al*. (2018) proposed the mathematical programming model to maximize the interval between relocation activity and

satisfaction of demands. Ghosh *et al*. (2017) conducted a study to rebalance the bike sharing system operators. A mixed linear model was used to estimate the influence the infrastructure and the characteristics of land-use. Faghih-Imani *et al*. (2017) developed the binary logit model to identify rebalancing time and used the regression model to predict the number of bikes required for rebalancing. Alvarez-Valdes *et al*. (2016) analyzed the unsatisfied demand and guide redistribution algorithm. Moreover, Schuijbroek *et al*. (2016) presented a new cluster-first route-second heuristic to consider the account service level and route cost.

However, engineering design systems is an important part of making the system run more efficiently. This consists of the various models such as the mathematic model, diagram model and schematics, etc. The simulation model is also a type of the model that can be support of the complex systems (Raymond and Daniel, 2018) and help decision-making by experimenting with different policy approaches. The disadvantage of the simulation modeling is the cost may appear high when designing or planning among alternative with trial implementation for decision the outcomes. Simulation is the process of designing a situation or behavior of a real system by using computer programs. It is carried out in order to study the flow of various activities and analyze the appropriate model before it is put into practice. The simulation process consists of 3 steps as follows:

Step 1: Define the problem or system of interest and create a mathematical model of the system. The simulator must have a good understanding of the system in order to create a model that must adhere to its definition. In the event that the simulator does not own the problem but is no longer assigned as the problem solver, the owner of the problem must participate in the modeling and closely supervise the model creation.

Step 2: Simulate the system on the computer. The mathematical model of the system needs to be simulated on a computer. It will use mathematical knowledge, such as statistical probability, along with information technology to create a model on a computer that can be efficiently processed (run). The advantage of a powerful computer model is that it allows the simulator to repeat an increased amount of processing in the same amount of time. Statistically, having a large amount of data allows for more accurate analysis of results.

Step 3: Analysis of the results. Since the simulation is random, the results obtained from the simulation are also random. Therefore, statistical techniques are needed to analyze the results for the correct interpretation of the results.

Resource limitation is the area in urban affect that cannot improve the service by building new stations or redesigning stations for supporting demand. Increasing the number of bikes in the system to meet the demand could affect investment and maintenance costs. Therefore, this research proposed the management the currently utility. This work considers the sustainability of the proportion of the initial number of bike available in the system for balancing demand and supply to maximize profit. This is undertaken in order to satisfy customers, reduce the number of customers lost, return to the use of the bike sharing service, and improve quality of service then became to mouth word. Thus, for cost optimization and improved resource allocation that is intended to balance demand and supply in the bike sharing system, this paper proposes a simulation that represents the system and support of complex problem.

3. DETERMINING BIKE SHARING TRAVEL PATTERNS

High dynamic movements of users cause an imbalance between demand and supply of bikes. The bike sharing provider could operate the systems to satisfy users. Data mining is a decision-making method used for the operation of bike sharing systems. It is the process of analyzing large amounts of data to discover hidden patterns and relationships. Several

research works have applied data mining to many cases. For instance, it has been applied to the business that supports the decision-making of executives regarding this subject. Moreover, data mining is the process of defining patterns and correlation in a large dataset using statistical techniques and artificial intelligence; this helps to explore and analyze raw data and convert it into potential information. Citi Bike has been providing the historical data since 2013 (Citi Bike, 2021). This paper uses trip data from Jersey City's Citi Bike in 2020. The datasets consist of the trip's start day and time, trip duration in seconds, trip's stop time and date, name of the station of departure, name of the station of arrival, station ID, station latitude and longitude, bike ID, user type, gender, and year of birth of the user.

This paper explores various parameters for improving bike sharing services. In particular, the information provided is essential in understanding critical points of the system and bike activities on the operation (Vogel *et al.,* 2011; Xu *et al.*, 2018). The station activities were identified by analyzing the travel pattern on the system during rush hour. First, activity patterns of the dataset were determined. The Citi Bike data facilitated the in-depth analysis of trip patterns. The data helped investigate the changes in daily usage based on season and time. The usage of bike stations and the bike rental demand for each month were analyzed. Furthermore, we analyze different cycle lengths as a month and a day.

Figure 1 shows the pattern of daily bike usage in 2020. The difference in weekday and weekend patterns can be clearly seen from the figure. On weekdays, the demand is high during morning, and there is a lower demand pattern during the afternoon, which is accompanied by a higher demand during the rush hour in evening. On weekends, the trend shows a high demand at around 9 AM, and the demand continues to rise until 5 PM, and then gradually reduces until prime time.

A monthly bike usage analysis was conducted to reflect the needs of customers' monthly bike use. This is beneficial for planning in accordance with demand and supply. In Figure 2, the results show the pattern of monthly bike usage in 2020. It can be seen that the period from June to October was highly active. This was found during summer, which may affect the demand for travelling (Corcoran *et al.,* 2014) where the environment is suitable for the use of bikes. Winters and rainy seasons may not be convenient for a heavy bike use; this may reduce its use as compared with summer.

An analysis of the customer's bike usage characteristics in term of distance and time was made using a frequency distribution with a graph. Figure 4 shows that most of the users traveled short distances, within 2 miles and Figure 3 shows with the most ravel time of less than 20 minutes. This means that most customers use the bike for short distances and shorter periods of time.

To find out patterns in data, we used circles for each station on the map. The radius corresponds to the number of trips at a particular station. We applied logarithmic scaling to the total number of trips. Set the exact radius size color represents the ratio of inbound and outbound journeys per station is a gradient station with all incoming travel are stations with all incoming travel, as shown in Figure 5. Following that, we analyzed the number of users for each station in order to provide resource management to suit user needs. Figure 6 shows the stations that are frequently used.

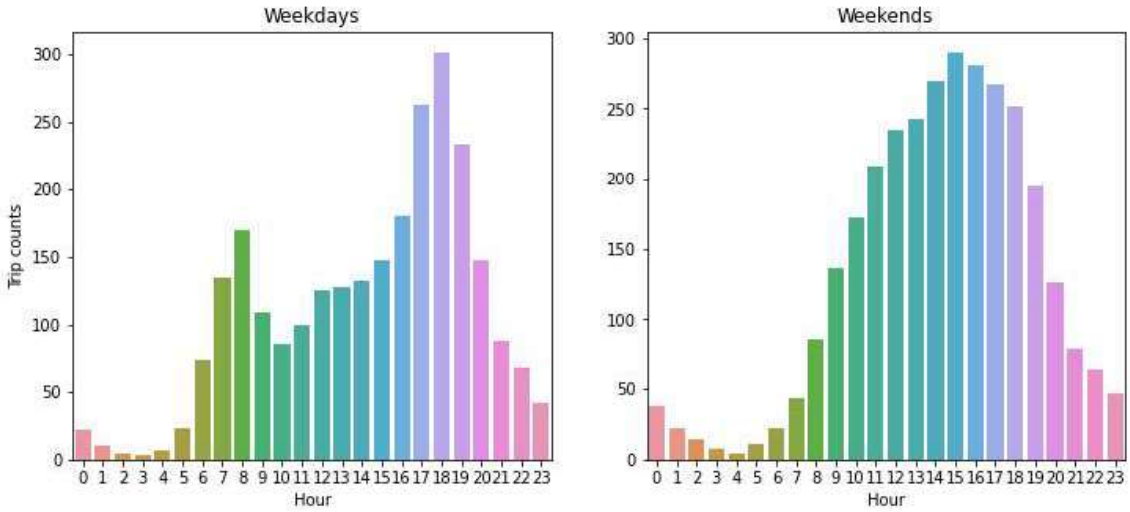

Figure 1. Trip count by hour

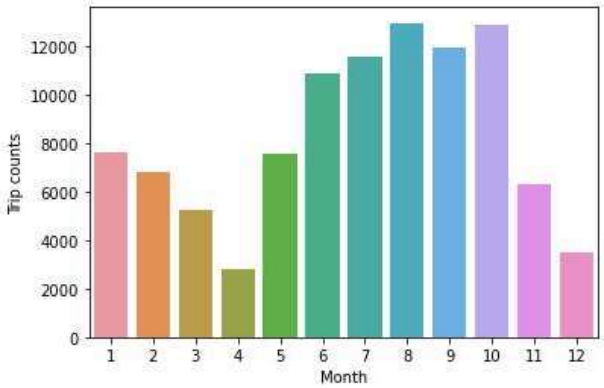

Figure 2. Trip count by month

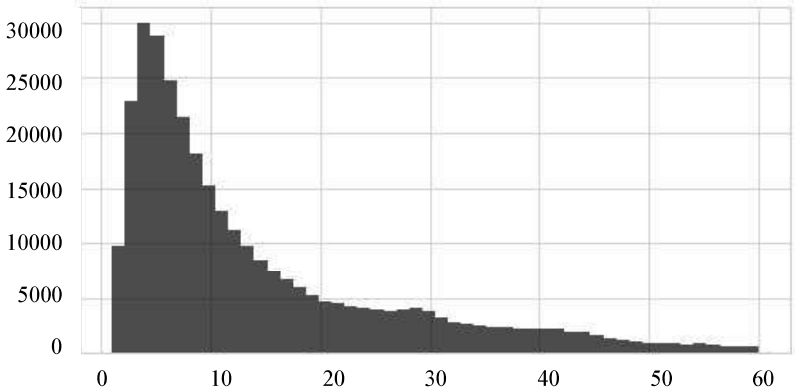

Figure 3. Customer usage cumulative frequency in trip duration (minutes)

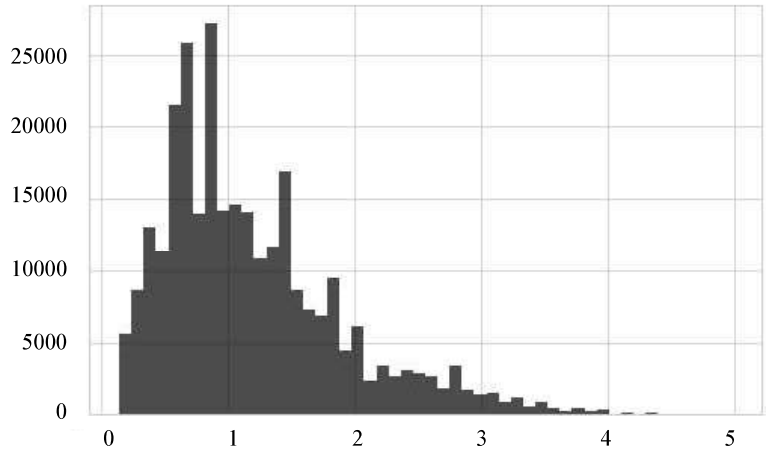

Figure 4. Customer usage frequency in distance trip (miles)

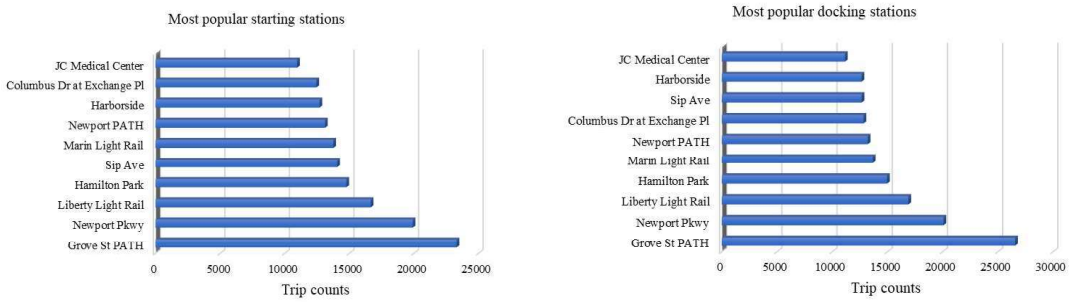

Figure 5. Most popular starting stations (left) and docking stations (right)

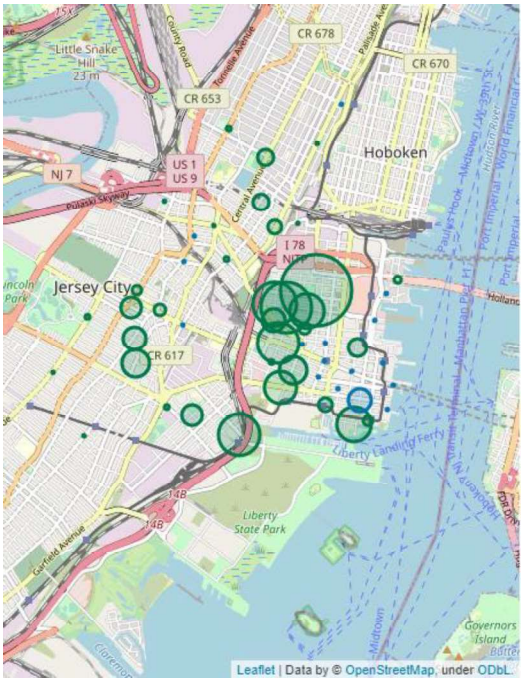

Figure 6. Map of bike sharing station; green color shows high demand, and blue color shows low demand

4. SIMULATION

A simulation was used to solve the problem of the bike sharing service; it focused on cost value by simulating bike balancing and parking spots to meet user needs. During the morning rush hour where each station earns the highest amount of customer needs. Generally, there is a greater demand for rental bikes during rush hour, thereby making users unable to find an available bike or dock, which reduces user satisfaction and results in a company losing the opportunity to generate more revenue (Bullock *et al.*, 2017). This allowed us to make decisions, for example, to determine the most efficient handling of each station to suit the overall system requirements and to assess where the bikes should be placed at the beginning of each day.

4.1 Data Set

We used the user trip data to simulate users and real user travel data based on the location information, from where the real user wants to start the trip or where the docking station is located. To best reflect the actual situation, we used station coordinates. By analyzing the previously mentioned data, we found 7 AM to 10 AM to be the peak hours. Owing to these reasons, this period was used for simulation. Using real data from the Jersey City's Citi Bike in 2020, we calculated the inter-arrival rate of demand at each station (Kim and Whitt, 2013; Kuo *et al.,* 2006), as shown in Figure 8, along with calculating the destination's demand rate and when the user wants to return the bikes, as shown in Figure 8.

4.2 Validate Input Data.

The verification that ensures the implementation and model are correct (Roungas, B. *et al*., 2018). The distribution fitting by Kolmogorov-Smirnov Goodness-of-fit Test was used to test for exponential distribution (Maio and Schexnayder, 1999) by using the SPSS Program for testing. We choose the represented data from Grove St PATH station on 1st January 2020 to test whether the input data is correct. The results show that the analysis of the renting bike rate and the return rate of bikes seen in the probability distribution of the data shows that the data characteristics are exponentially distributed at a significance level of 0.01 as shown in Table 1.

Table 1. Analysis of the data's distribution model.

			Renting	**Return**
Exponential parameter.	Mean		13.3006	12.6261
Most Extreme Differences	Absolute		0.444	0.292
	Positive		0.230	0.157
	Negative		-0.444	-0.292
Test Statistic			0.444	0.292
Monte Carlo Sig. (2-tailed)	Sig.		0.000	0.000
	99% Confidence Interval	Lower Bound	0.000	0.000
		Upper Bound	0.000	0.000

4.3 Simulation Model

The simulation model's objective is to assist in making decisions regarding balancing bike sharing, revenue, operation costs, and opportunity costs, as well as the key variables that need to be observed when calculating profitability. In this research, we used discrete-event simulation programming with Python. The balancing event has attributes that specify the queue station, response terminal, and number of bikes ordered for rebalancing. Conversely, it may be more than one station to track all of them without specifying which station is being simulated. The simulation began by recording the changes in the value of the interest variables.

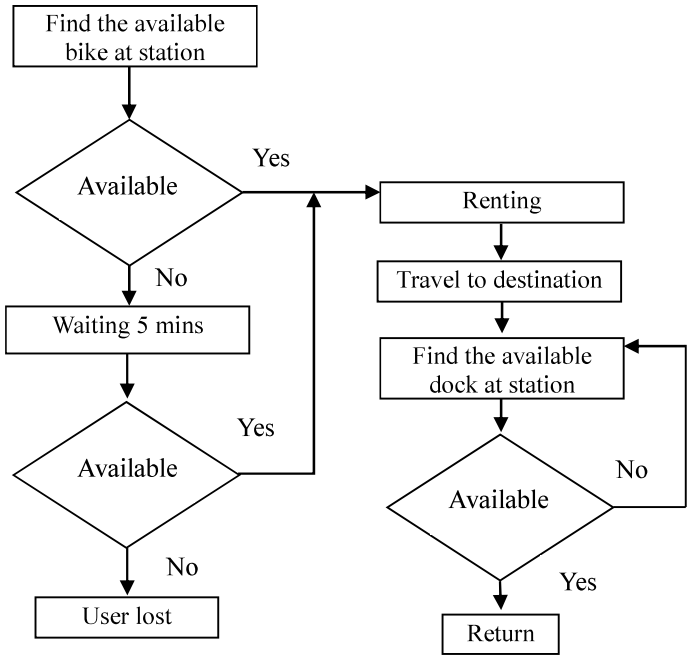

Figure 7. The flow of customers through the bike sharing process for renting

Consider bike sharing event for a station. A bike sharing system needs to check if someone is present or not. If users have to wait too long to return their bikes, they get a money refund, but if no one is in the queue, the bike's presence or absence is checked. If there is an idle bike, the user pays to rent the bike. When the number of bikes is less than two, a balancing act is conducted to transport bikes from depot to station. The system calculates the wait time and checks if the user has left due to a high waiting time and then creates a time between the time the bike is rented and till it's returned. When the user finishes the trip and arrives at the station, the system needs to check if another user is waiting to rent the bike, as there are no bikes at the station, or the dock is available for the user to return. This is done in order to retain users since costs increase due to loss of business opportunities.

The rebalancing policy is simple. This model dynamically distributes the bike to avoid the station being full or empty. We assumed that there is a centralized control: When no port is available, a station sends a signal to transport the bike back to the center. In organizing the balancing event, operating and fuel cost are calculated.

The number of bikes that can be refilled at the station before the rush hour is a problem to optimize for each station. For this calculation, the expected number of bikes coming in and

going out of the station during each minute of peak hours, capacity, and number of bikes can be used. The model for simulating bike rebalancing aims to maximize the profit and is defined as follows:

$$Max\,Z = \sum_{i,j \in N} R_i x_{ij} - \sum_{i,j \in N} C_i x_{ij} - \sum_{i \in N} pl.y_i \tag{1}$$

subject to

$$\sum_{i,j \in N} x_{ij} \le Q \tag{2}$$

$$W_{ij} \le T \tag{3}$$

$$x_i \le q_i \tag{4}$$

$$x_{ij}\,,\ w_{ij} \ge 0 \ \ for\, i, j \in \{1, ..., N\} \tag{5}$$

where,

R_i : revenue,

C_i : operating cost,

pl : loss-of-opportunity cost,

W_i : waiting time,

q_i : capacity of each station,

Q : bikes in system,

N : number of bike stations,

T : acceptable waiting times for the available bike or docking,

x_{ij} : when bikes travel at station i in the interval j, the value is 1; otherwise it is 0, and

y_i : when user cannot wait for an available bike or docking, the value is 1; otherwise it is 0.

We selected the five most popular stations for simulating bike pickups and returns for each station. Following that, the data was analyzed for distribution, which is scheduled to the arrival time and returns bike time rate, as shown in Figure 8. The nonstationary Poisson arrival process (NSPP) (Goldenshluger and Koops, 2019) was used for arrival rate by modeling real data. The interval time was calculated to be 20 minutes from the data analysis which highlights that the almost every trip duration is 20 minutes. This is shown in Figure 4.

This research work assumed that the revenue cost is \$3, operating cost is \$2, W$\in$ {41, 13, 21, 26, 33}, opportunity cost is \$3, and acceptable waiting time is 5 minutes. The first process began at 7:00 AM and ended at 10:00 AM, with the number of replications being 100 cycles. The result obtained is shown in Table 2-3, which indicates that refilling bikes before rush hour can maximize profit.

5. RESULTS AND DISCUSSIONS

In this simulation, bike management options that suited the customer's needs were created. This was done by simulating the results with the help of the proportion of bikes in the system and the number of dock bike parking spaces that meet the needs of each station with different usage requirements. From the analysis of the data in Figure 8, it was found that the traffic of bike users renting the bike and the return rate of those who wish to return bikes at each station have different needs. Some stations require a lot of bikes for renting; however, some stations require more bikes to be returned at different times. This is an essential factor that impacts the imbalance including the available number of bikes available and the docks available which are supplied and demanded in the systems. This does not take into account the route allocation method or pricing strategies or analyzed factors influencing bike share systems. This paper proposed the factors that influence the profit for operator rebalance bike sharing systems and customer satisfaction. We simulated the trial and error by varying the proportion of bikes available per available dock bike in systems as shown in Table 2-3.

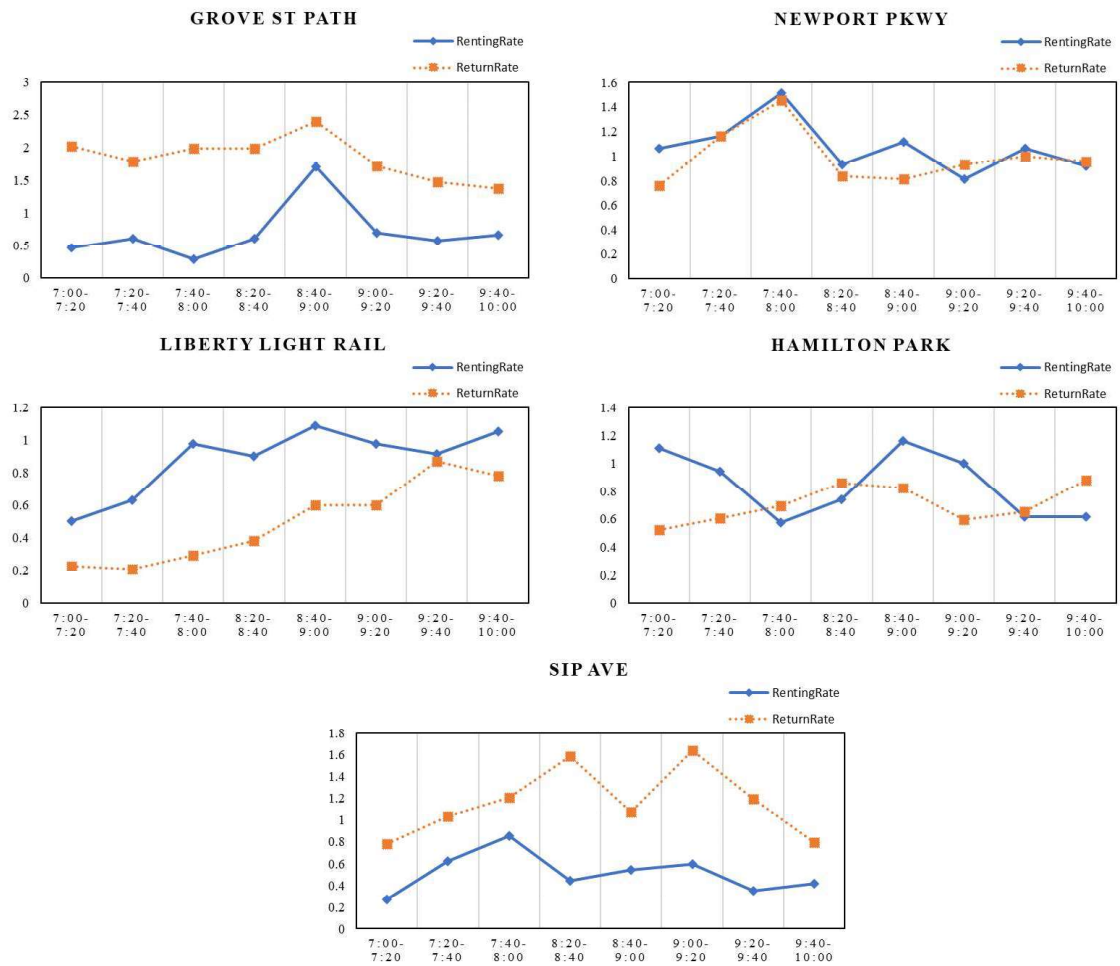

Figure 8. Arrival time rate and return bike time rate for each station

Table 2. Results of simulation: Optimal number of bikes at each station

Proportion of bikes available / available dock bike in systems	Grove St PATH	Newport Pkwy	Liberty Light Rail	Liberty Light Rail	Sip Ave
90/10	35	12	19	25	30
85/15	28	12	19	25	30
80/20	36	10	12	25	24
75/25	34	12	18	20	17
70/30	32	9	14	11	28
65/35	29	6	13	18	21
60/40	24	12	14	15	15
55/45	21	5	11	17	20
50/50	16	11	12	13	15

Table 3. Results of simulation carried out to find the optimal the proportion of number of bikes and available dock in systems

Proportion of bikes available / available dock bike in systems	Cost ($)	Customers lost	Number of bikes to be moved	Profit ($)
90/10	80	15	20	135
85/15	74	19	21	135
80/20	82	22	11	120
75/25	59	25	14	131.25
70/30	88	19	13	142.5
65/35	42	29	8	116.25
60/40	66	24	10	127.5
55/45	66	24	10	127.5
50/50	60	19	8	116.25

Table 3 displays the scenario of bikes' proportion in systems for yielding the best profit with 70 percent of the bikes in the system and 30 percent of the vacant parking spaces in the system. A profit of 142.5 dollars can be found with only 19 customers lost, which is a small number. This implies that a loss of customers can be avoided without affecting customer satisfaction. The proportion of bikes available in systems and the available dock to return have also influenced the system profit. The amount of bikes available at each station is the high level that affects the current customer, rather than customers that are lost. Thus, the number of available bikes is low at each station that affects the current number of bikes is not enough for renting then lost customer.

In addition, this simulation can also optimize the number of bikes at each station to be filled at each station for meeting the needs of customers, maximizing the profits and avoiding a loss of the customer. We propose that the providers should be concerned with the proportion between the number of bikes available and number of available docks in the systems. When there is a high amount of bikes or a smaller number of bikes, it affects the quality of bike sharing systems for responsible customer and, consequently, total profit.

At times, the provider ignores to modify the solution for customer satisfaction because it increases the cost in the operation systems. However, customer satisfaction should be one of the top goals of an organization. This is because of the long-term benefits of having satisfied customers such as positive word-of-mouth reviews, customer loyalty, and sustainable profitability in the service sector (Greenwell *et al*., 2002; Liu and Jang, 2009).

6. CONCLUSION

This research provides simulations to solve the balancing problem of bike sharing in order to meet consumer needs and obtain more revenue. Based on data analysis for knowing critical points of the process in the system, it can be concluded that rental vehicles users' travel distances as short as 2 miles, travel time of less than 20 minutes, and the time pattern of use differs on weekdays and weekends. The imbalance problem between the demand and supply that arises in finding available bikes till renting, and finding available dock to return the bike can be solved by assessing user satisfaction based on arrival time rate and return bike time rate from historical data; this would also help to determine profitable benefits to the authorized provider by helping the provider to calculate the number of bikes to refill at each station before the rush hour. This research presents the solution to the problem by conducting simulation to maximize the profit. In this simulation, a reasonable number of bikes were presented that had to be refilled before the rush hour in terms of ratio of bike in the systems to allocation levels that might be required to find balance between demand and supplies of the bike sharing systems.

Since this simulation is a short-term simulation and does not present the number of times bikes can be refilled at a station, in the future, we aim to analyze the number of appropriate bike or how many times should refill per day that would benefit both users and providers.

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