MODELING AND SIMULATION OF A BIKE RENTAL COMPANY

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Abstract

Bicycles usage is on a rise across the globe in order to decrease the greenhouse gas emissions, traffic congestion and to improve the overall health of the people. The rise of bicycles usage calls for more and more bike-renting companies in various parts of the world.

When starting-up a new bike-rental company, there are lots of questions entrepreneurs have that need to be answered such as setting the profit margins, determining the inventory of bikes required, determining the average time that customers need to wait in queue before the company provides them a redemption of the booking amount and the loss-incurred to the company on account of customers returning without renting the bike and hence getting the refund of their booking amount.

In our project, we have addressed the above queries by modeling and simulating a real-world bike renting company in SIMIO® wherein people can rent bikes from 5 different types of locations such as Street Corners, Railway Stations, Bus Stops, Shopping Malls, Places of Attraction for duration of upto 24 hours. Customers can pre-book the bikes and pay beforehand. Once they reach the location and a bike is available, they can rent the bike immediately. If no bike is available then they can chose to wait till maximum of 15 minutes before they are allowed to get reimbursement of 1.5 times their booking amount. Upon the end of rental duration, they can return the bikes to the same location where they picked up the bike or at a different location.

The results of our model assist the company in 1) determining the number of bikes that should be deployed to realize a minimum 50% profit 2) daily revenue to the company, 3) daily profit to the company 4) daily average customer wait time and 5) loss incurred to the company due to customers returning without renting a bike. The model also provides the optimized number of bikes to be deployed to make a minimum 50% profit and yet maintaining minimum wait time to achieve highest level of customer satisfaction and target profits.

The findings from our model suggest that it is best to deploy 500 bikes daily to achieve minimum 50% profit with the least amount of wait time for the customers.

Keywords

Rental Duration, Wait Time, Profit, Simulation, Simio®

1. Introduction

The usage of bicycles has shown an increasing trend in the last few years particularly since the last decade. The environmental damage has been happening years over years due to various actions of mankind. Air pollution caused by automobile emissions and exhausts from factories and water pollution due to the dumping of waste in rivers, lakes etc is deteriorating our environment. The nature in last couple of years has become very unpredictable with so many natural calamities happening worldwide. This behavior of nature has started to make people cautious of how their individual actions is damaging the environment gradually and making earth an unsafe place to live in. People slowly are becoming more environments friendly and hence want to do their bit by reducing their carbon footprint. Thus, they are opting to maximize the use of environment friendly modes of transport amongst which obviously bicycles come to mind first.

As more and more people want to use as much as bicycles as possible in different places such as schools, universities, tourist attractions, crowded areas/streets, small neighborhoods, shopping malls, railway stations, bus stops, it has opened up doors for many people to start-up businesses to rent the bikes in these kind of areas.

So the first challenge for the new entrepreneurs is to decide what is the total number of bicycles that they should deploy at various types of locations? Which locations should the highest number of bicycles to be deployed? If the entrepreneurs want to realize a minimum amount of profit, what should be the number of bicycles that they should work with that would give them their expected profit. Making the business a profitable business is a challenge but more than that is to get the best customer satisfaction and obtain long-term customer retention. So in order to achieve high customer satisfaction, the bike-rental company has to make sure that customers don't have to wait long in queues to get a bike. They need to decide suitable provisions to provide them a bike immediately upon arrival or with the least waiting time. If not, they need to have provisions to reimburse the customers with their payment amounts plus some more incentive since they had to return without getting a bike on time.

The company will be successful only when there is a perfect balance between the profit the company makes and at the same time it is able to meet the demand of the bicycles without neglecting the customer satisfaction. Though it is very important to obtain customer satisfaction to get long-term customer retention and add new customers, however, deploying extra bicycles will have a negative impact on the profitability of the company. In this paper, we focus mainly on the above queries that new entrepreneurs face and try to address these questions using our modeling and simulation of a bike-rental company.

2. Literature Review

Literature available regarding bike renting and redistributions is very large as it provides a wide variety of conceptual and mathematical information of how the bikes could be shared or rented. Different sources show the simulation models for sharing and re-distributing bikes.

Paul DeMaio (2009) focuses on the history and real-life applications of bike sharing system. It provides an overview of different generations of bike sharing programs and the parameters that will be considered while modeling future generation bike sharing program.
It covers information on history of bike sharing and how the 1st generation, 2nd generation and 3rd generation bike sharing models work. He talks about the benefits and disadvantages of each generation of bike sharing models and how the future generation bike sharing program would look like and how it would operate. He also talks about the capital and operational expenses incurred by the bike sharing programs.

Shu, Chou, Liu, Teo and Wang (2011) provide very good coverage on the models for effective deployment and redistribution of bicycles within Public Bicycle-Sharing Systems. They show how to estimate the flow of bikes within a network and the number of trips that would be supported based on the initial allocation of bikes at every station by developing a network flow model with proportionality constraints. They have also examined the effectiveness of periodic redistribution of bicycles in the network to support greater flow, and the impact on the number of docks needed.

2.1 Paul De Maio(2009)

A brief look into the history of bike sharing programs-
1st generation bike sharing program was introduced in Amsterdam in 1965. A person took a bike, rode to his/her destination and left it there for the next user. However, the bikes got thrown into the canals and people kept them for personal use. 2nd generation bike sharing program was introduced in

Denmark in 1991. The bikes were designed to be robust with solid rubber tires and advertising plates and could be picked up and returned at specific locations throughout the Central City in Copenhagen with coin deposits. However, the bikes were stolen in this model.

3rd generation bike sharing program called "Bikeabout" was introduced in Portmouth University in England in 1996 which used more sophisticated methods such as magnetic swipe card to rent a bike, which further emerged into advanced 3rd generation bike sharing programs operated using electronically locking racks/bike locks, telecom systems, smartcards, fobs, mobile phone access and onboard computers.

The cost of the bike sharing program depends upon the system, population density, service area and fleet size. Capital costs include fabrication of the bikes and stations, license or purchase of the back-end system used to operate the equipment, member access cards (if necessary), purchase or rental of maintenance and distribution vehicles, and installation.

For example- estimates for capital costs are $3,600 per bicycle for Clear Channel Outdoor's SmartBike system, $4,400 per bicycle for JCDecaux's Cyclocity system and $3,000 per bicycle for Bixi. These costs are the yearly costs/bicycle.

Operating Costs of bike sharing program comprises of maintenance costs, distribution, staff, insurance, office space, storage facilities, website hosting and maintenance and electricity.

For example – operating costs for New York city's several bike sharing programs comes to about $1,600 per bicycle per year.

Based on the study, the 4th generation program would have improved efficiency, sustainability and usability by way of improving bike distribution, installation, and tracking, offering pedal assistance bikes and using new business models.

Improved bike distribution at various stations will be implemented by having "push" and "pull" stations which will either encourage trips to leave or arrive, respectively, at these stations based on the demand for bikes. Incentives will include free time, credit, or cash.

This has been implemented by "Velib" (A bike share program in Paris) which give extra 15 min for example if the rider has to go on a route which has an uphill or upslope ride. Also, giving extra credit to riders for future use or giving them instant discounts motivates for appropriate distribution of bikes at stations.

So basically when customers are given extra credit/incentives for distribution of bikes to stations where there is more need increases distribution efficiency at a much lesser cost than having the bike company staff do the distribution work.

Costs for installation of bike stations will be reduced by utilizing a "technical platform" which is basically a stand-alone platform placed over the ground. This technical platform has in-built system for docking and locking the bikes and has an inbuilt payment system too. So this platform can just be bolted to the ground without having an expensiveaaasneed of excavating the ground and doing underground wiring and electrical connections which leads to skyrocketing of prices.

Tracking of bikes will be improved by implementing GPS in the bikes which will help understand the favorite routes, pick-up points and destinations based on which stolen bikes could be tracked and also the miles travelled could be tracked.

Pedal assistance provided in the bikes will help ride the bikes in hilly areas or would help people who do not have enough leg strength to pedal the entire distance of their journey. Therefore, electric pedal assistance would be a great help for these people and hence would motivate more people to adopt bike sharing programs.

Powering stations for bikes are expensive since they have to be close to the nearest electrical source and limits the place where bike stations will be located. Therefore, implementing solar panels will be a cheaper and cleaner option to charge/power the bikes and will remove the need for underground wiring. This has been implemented by Bixi.

System	VELIB	BICING	BIXI	Beijing	Hangzhou	Nanchang	Wuhan
Operator	JCDecaux	ClearChannel Adshel	Staonnement de Montréal	Fortune	Bicycle service	Xinfeida	Xinfeida
City	Paris	Barcelona	Montréal	Beijing	Hangzhou	Nanchang	Wuhan
Start Date	Jul-07	Mar-07	Spring 2009	Aug-05	May-08	Aug-09	Nov-08
Bicycles	20,600	6,000	5000	10,000	50,000	1000	20,000
Bike Stations	1451	400	400	1000	2000	30	718
Rentals/bike-day	12.5	16	15	2.32	8	4	5

Table 1: Statistics for Bicycle Sharing System

2.2 Model for effective deployment and redistribution of bikes (Shu, Chou,Liu, Teo and Wang 2011)

Shu et al (2011) have created models which help to predict the utilization rate of the bikes. Their models mainly focus on how the deployment and distribution of bikes in the network affect the utilization of the bikes and how it affects the service level experienced by the users.

They have assumed that the number of stations is known. Considering the number of stations to be known, they have computed the number of bikes that will be needed to be deployed in the network. The numbers of bikes in network in turn affect the number of bicycle trips made and that has eventually aided in computing the utilization rate of the bikes in the network.

Shu et al have also designed the strategy for redistribution of bikes by studying the flow of bikes which is dictated by the customers' travel patterns and also the time of the day at which the bikes are being used. For example – in the morning hours travel patterns are from home to office or interchange and usage of bicycles is highest during peak morning hours. So the redistribution of bikes completely depends upon the demand of bicycles on a day/time and number of bicycles that have been deployed in the network.

They conclude that a small number of daily redistribution of bikes suffices since more frequent redistribution of bikes will not add much benefit to total supported bicycle trips.

Lastly, Shu et al also computed the number of bike docks needed to be installed at every station so that the bicycles can be returned by customers upon arrival at their destination and it shows that the number of docks required at a station depend on the bike utilization and how the bikes are flowing between stations in the bike network. The number of docks also depend upon the fact whether periodic bike redistribution is matching the supply and demand of bikes at the stations.

They conclude that daily redistribution of bikes can help in lowering the number of bike docks required at each station since it prevents the surplus bikes to be gathered at the stations. They also concluded that more bikes should be deployed in stations in congested areas which in turn will cause more docks to be installed there.

3. Simulation Model

A modeling software Simio® was used to model the bike rental system. Below is a screenshot from the simulation software which shows an overview of the model.

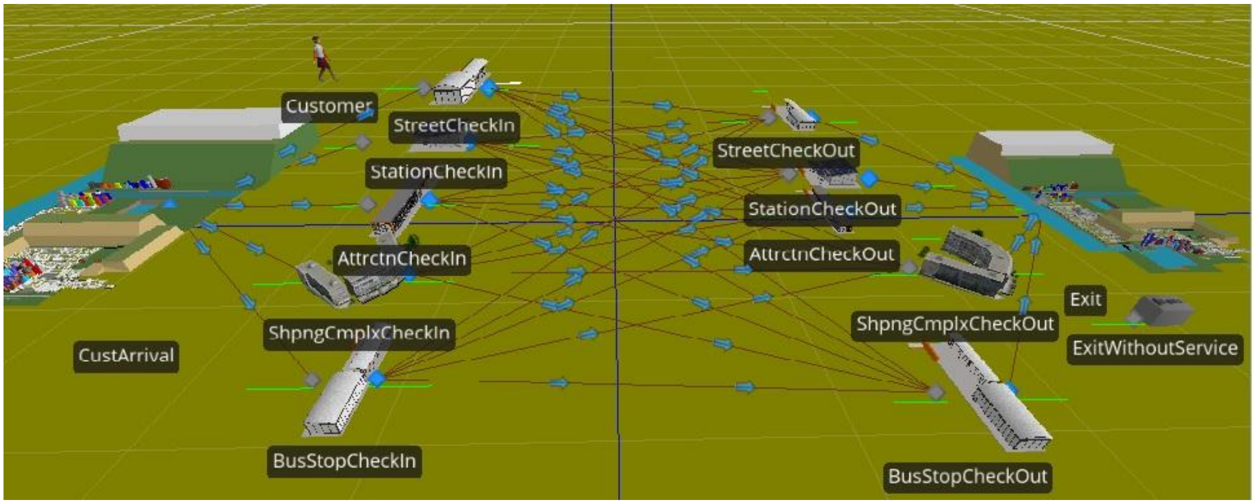

Figure 1: Simio® Model

This aligns with the below flowchart of the model where bike renters pre-book a bike for any of the five locations – namely Street Corners, Railway Stations, Places of Attractions, Shopping Complexes and Bus Stops and also for a particular trip duration which ranges from minimum 30 minutes to maximum of 24 hours. On arrival at the rental location, the customer checks in and checks out

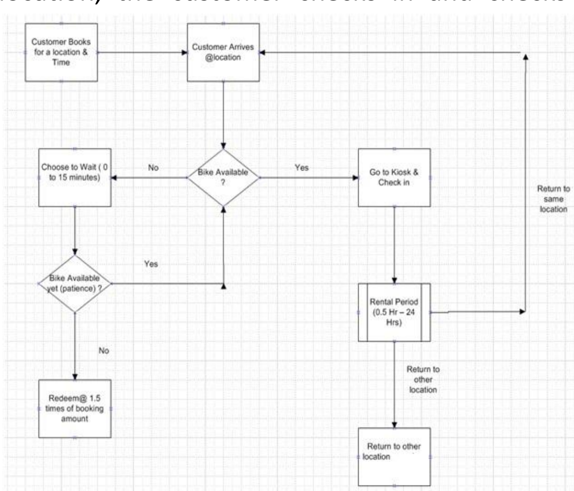

Figure 2: Flowchart of the Model

3.1 Input Data

This simulation uses input data from an actual bike renting company named 'Capital Bike Share', which is based around Washington DC area. The bike stations are located in Alexandria (VA), Arlington (VA), Rockville/Shady Grove (MD), Rest of Montgomery County (MD) and Washington (DC).

with a bike for the booked duration. If the customer does not find a bike within 15 minutes of check in, he/she can get a refund of 150% of the booking amount. After the completed trip duration, the customer can return the bike in the same location from where the bike was rented or to any other 4 locations.

These five locations are mapped to Places of Attractions, Shopping Complex, Bus Stop, Railway Stations and Street Corners correspondingly. In the company website data for Number of bikes deployed, trip origination & destination, trip duration etc. are available from calendar year 2010 to 2015.Input data for this model actually has been taken from calendar year 2014 only. The company data being referred here can be viewed and downloaded from http://www.capitalbikeshare.com/system-data

Arrival Data: Arrival pattern throughout the year for all of the five locations is very similar. Summer is the peak season and winter is the slowest season and the arrival pattern follows a typical bell curve for all the locations as below example (Washington, DC in the example here):

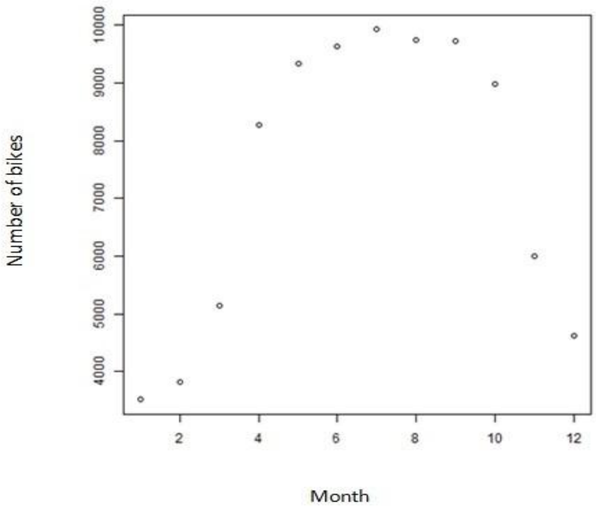

Figure 3: Yearly Arrival Pattern – Street Corners

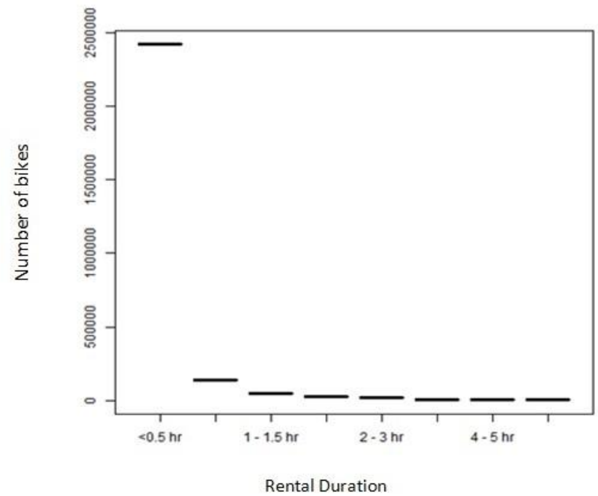

Figure 4: Pattern of Trip Duration

As this is a yearly pattern, we cannot find a consistent input for daily rate unless we do an average based on 365 days of the year. In a typical day again the arrival pattern will be more like a normal distribution where during the noon there will be peak demand and midnight the lowest demand. Taking that into account the daily arrival was distributed using a normal distribution rate table and this is done for all the locations.

Location	Number of Yearly Arrivals	Number of Daily Arrivals	Percentage	Mapped Loca
Washington,DC	2662459	7294.41	90.37	Street Corners
Arlington,VA	213393	584.64	7.24	Shopping Com
Montgomery,MD	33088	90.65	1.12	Railway Statio
Alexandria,VA	30932	84.75	1.05	Places of Attr
Grove,MD	6236	17.08	0.212	BusStop
Total	2946108	8071.53	100	

Table 2: Percentage of Bike Distributions/Customer Arrivals

Trip Duration: Trip duration data for the various locations for year 2014 can be found from the company data. Daily, monthly, yearly and even for five years the pattern looks like an exponential curve as shown in **Figure 4**. This is same for all the locations.

In the model, trip durations are calculated using 'Random. Discrete' distribution pattern and the probabilities of each trip duration have been entered. Below is an example of probability of the trip duration for 'Street Corner' location.

Duration (Minutes)	Street Corners	Shopping Complex	Railway Stations	Places of Attraction	Bus Stops
< 30	90.984	89.945	80.685	83.667	87.556
30 – 60	5.282	6.216	10.977	8.338	6.366
60 – 90	1.715	1.775	4.503	3.766	2.951
90 – 120	0.938	0.92	1.683	1.869	1.299
120 – 180	0.722	0.734	1.303	1.416	0.914
180 – 240	0.182	0.194	0.405	0.424	0.401
240 – 300	0.08	0.097	0.127	0.188	0.16
300 - 1440	0.095	0.119	0.317	0.333	0.353

Table 3: Percentage Distribution of Rental Duration

Return Probability: The company data does have the 'trip originated' and 'trip ended' information for each type of location, but that does not give a probability of an originated bike being returned to the same location or to a different location. So, for the purpose of this model, the percentage of returning a bike at a particular location was assumed same as the arrival percentage of customers for that location.

Location	Number of Yearly Arrivals	Number of Daily Arrivals	Percentage	Mapped Loca
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Total	2946108	8071.53	100	

Table 4: Percentage of Bike Returns at various locations

Cost To Company & Revenue: Cost to the company includes fixed capital cost(constant), operating cost of $5/bike for repairs and maintenance and a daily parking cost which is linked to a location. This data was not available in the company data, so this data was assumed. **Table 5** shows the cost to company per location.

We considered street corners to be the most frequented by customers in terms of picking up and dropping-off a bike hence the cost/bike at street corners is the highest followed by places of attraction which are always high on any kind of rentals. Bus Stops are considered as least expensive when renting a bike from there. **Table 6** shows the Rent/bike for each location.

Location	Parking Cost/Bike	Total Cost/Bike
Street Corners	4	9
Shopping Complex	1	6
Railway Stations	1	6
Places of Attraction	3	8
Bus Stops	1	6

Table 5: Cost to Company

Duration (Minutes)	Street Corners	Places of Attraction	Shopping Complex	Railway Stations	Bus Stops
< 30	1.5	1.25	1	1	1
30 – 60	3	2.5	2	2	2
60 – 90	4.5	3.75	3	3	3
90 – 120	6	5	4	4	4
120 – 180	7.5	6.25	5	5	5
180 – 240	9	7.5	6	6	6
240 – 300	10.5	8.75	7	7	7
300 - 1440	15	12.5	10	10	10

Table 6: Rental Rate per Bike

3.2 Assumptions and Considerations

In the original system there are multiple locations under a single county. In Simio® this was a challenge to implement in that way, so all the individual locations data was rolled up to the county level for easier implementation. There was no financial data available, so this has been made up in the model. In the real world scenario there might be cases when the renter does not return the bike within the rental period the bike was rented for, or the bikes may be lost, damaged, crashed etc. These factors were not taken into consideration in the model. The arrival data in the model is an average data for the whole year, as the company data varies for different months in the year.

3.3 Method

Figure 5 below shows a screenshot of the simulation model with the Simio® software. Many different functions of the Simio® software have been used to implement the model. These functions have been described below.

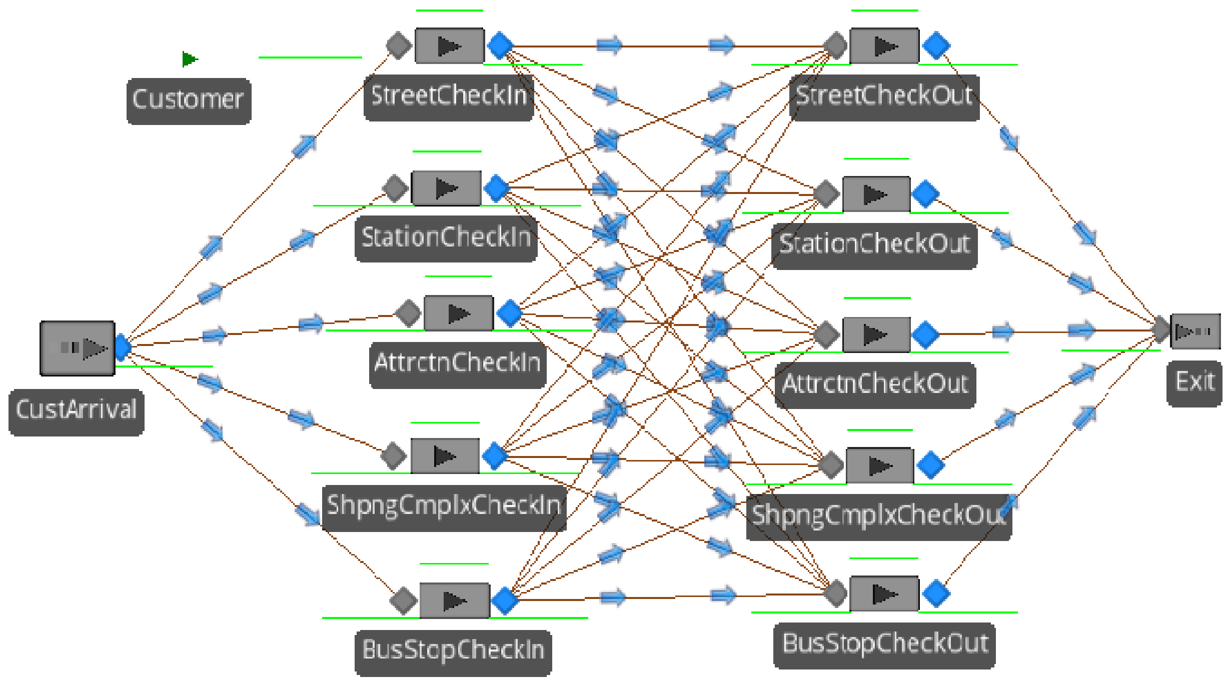

Figure 5: Simio® Model

Model Entity – Model Entity "Customer" represents the customers who will rent and return the bikes.

Source – "CustArrival" is the source from where the entities will originate at a customer arrival rate which is normally distributed depending upon the time of the day. Customer Arrival Rate is implemented using a Rate Table in Simio®.

Check-In Servers – There are 5 check-in servers which have been implemented each representing a different location – street corners, places of attraction, shopping complexes, railway stations, bus stops. The bikes are assigned to customers at check-in servers. When the bike is rented out at check-in servers, the bike-count is reduced by 1. The cost that the company has to bear in order to deploy the bikes at the server is also computed at each check-in server for each location category.

Paths – Customers originate from source and they go to different locations (represented by check-in servers) to rent bikes. In order to show how many customers go to each location, Selection Weight is assigned to each path originating from source to each check-in server.

Check-Out Servers – There are **5** check-out servers that have been implemented representing each type of location. Customers will return the bikes upon the completion of the rental duration either at the same location from where they picked up the bike or at any of the other 4 locations. When the bike is returned at the check-out server, bike count at that server is increased by 1**.**

Time Paths – Check-In Servers are connected to the corresponding Check-Out servers using the "Time Paths" provided in Simio®. As the customers can return the bikes at any of the 5 locations, Time Paths are implemented to originate from 5 check-in servers and terminate in any of the 5 check-out servers (one-many relationship). Customers can rent the bike from 0.5 hour to 24 hour period. The trip duration is specified as a discrete distribution on every timepath between check-in servers and check-out servers. Total trip duration is computed for each timepath implemented and cost of the trip is computed using the lookup tables containing rental rates/bike for each location for the trip duration computed.

Renege Process – Customers who do not get a bike at the check-in server after waiting for 15 min leave the system. The process is being triggered before renting a bike to the customer. The number of customers who left the system without renting a bike because of waiting over 15 min has been computed. At the same time, the loss incurred to the business due to customers leaving without renting the bike is also computed as part of this process.

Please refer **Appendix A** for more details on the implementation of Simio Model.

3.4 Verification and Validation

We performed verification and validation of the simulation model to ensure accuracy and credibility of the model. The development of the model has been done to replicate the same scenarios as the original data obtained from a real bike-sharing company "Capital Bike Share". The verification of the model input is done by comparing the number of customers in different location categories. The results of verification using the actual data from the bike-share company versus the results from Simio® simulation is given in **Table 7** below.

Locations	Actual Data	Simio Results
Street Corners	7249	7242
Railways Stations	90	89
Places of Attraction	72	84
Shopping Complexes	584	547
Bus Stops	17	18
Total	7975	8046

Table 7: Comparison of Number of Customers in the system

The results of the model for the Bike Rental System have been being validated analytically by performing mathematical calculations considering 500 bikes. It has been noted that the results produced by Simio® are comparable with the results computed analytically. Comparison of results is shown in **Table 8**.

Amounts	Analytical Results	Simio Results
Daily Cost to Company	4365.65	4420
Daily Revenue	13741.15	11600
Profit	9375.5	7077

Table 8: Analytical Computation vs Simio® Results

Since the original data from a real bike-sharing company does not have any loss incurred for the number of returning customers on account of waiting for more than 15 min, we can see there is a difference in Daily Revenue and Profit computed analytically versus the ones computed by Simio®.

4. Results

With our simulation, we saw that if our bike-rental company deploys 400 bikes, we are able to meet our goal to achieve minimum of 50% profit margins. Our company makes 55% profit when we deploy 400 bikes. Though we achieve our target of making desirable profit margins, however, the company has to compromise on the wait time. With 400 bikes deployed, the wait time is 392 seconds which is very high and results in about 2400 customers leaving the check-in booths without renting a bike.

On the other hand, if our company deploys 500 bikes, we achieve our target of realizing a minimum of 50% profit for the company. We see that our profit when deploying 500 bikes is 61%. At the same time, we achieved a very low waiting time of about 44 seconds in the queue for the customers to rent a bike which in turn resulted in a very small number of our customers leaving without renting a bike from our company. Only 154 customers leave without getting a bike if the wait exceeds longer than 15 min so this resulted in an overall reduction in loss-incurred for our business.

All the numbers provided above and in the table below are "daily" numbers.

Table 9 provides the results below when different number of bikes have been used to simulate the model.

Main Model				
Bike Count	Customers Returned	Revenue	Profit	Profit(%)
2661	0.56	11621.4	-11921.7	-102.58
1300	15.25	11631.9	118.663	1.02
1000	31.69	11632.1	2770.75	23.82
650	79.05	11649.9	5849.96	50.21
600	118.99	11604	6219.97	53.60
550	124.45	11621.6	6670.15	57.39
500	154.32	11599.7	7077.2	61.01
400	2399.95	11620.4	6493.06	55.88

Table 9: Main Model - Simulation Results with different no. of bikes deployed

Furthermore, below plot shows that as the number of bikes deployed goes on increasing, profit margins continue to decrease and number of customers returning without renting a bike also decrease.

However, we see that we achieve the most optimized number of bikes as 500 because that is where both the profit margins are high and number of returning customers is lowest. So our optimized number of bikes as explained above is 500.

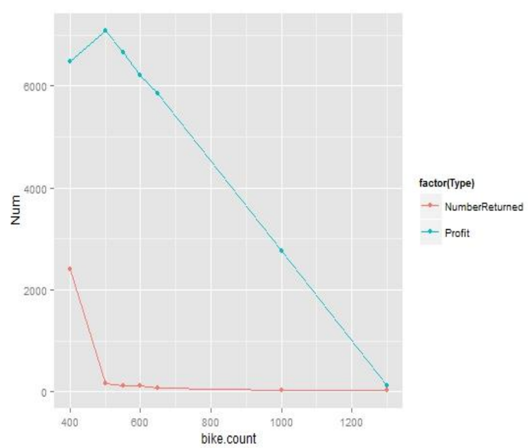

Figure 6: Profit Margins & Customer returned without renting vs the count of bikes

4.1 Comparison with an Alternate Simio Model

A different approach of simulating the model was taken as shown below which yields very similar results.

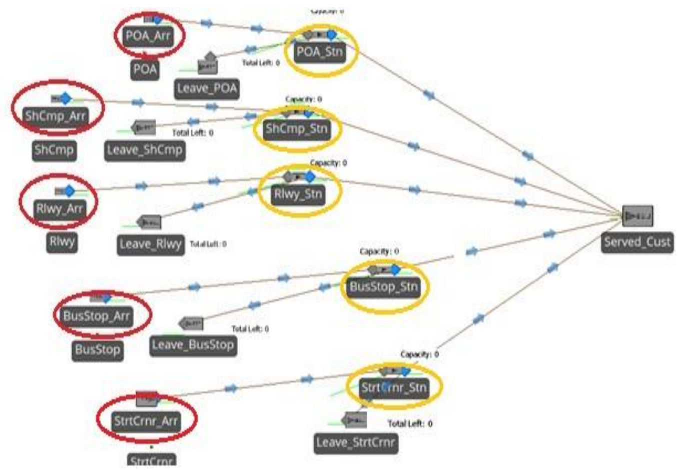

Figure 7: Alternate Design – Simio Model

- Customer arrivals happen from 5 different sources. Each source represents a different location (Street corners, Places of attraction, shopping complexes, railway stations, bus stops). Sources are shown in red.
- Entities from each of these sources go to the corresponding servers to get a bike. Servers shown in orange.
- If a bike is not available within 15 minutes at the server, then the entity leaves the queue and then checks out without the bike.
- At the 'Sink' there is an add-on process which re-distributes the bikes (server capacity) to any of the five servers based on a probability distribution. The input to the model remains same as the original model except instead of the normal distribution of the daily arrival pattern of bikes at different locations, an exponential distribution with (1440/average daily arrival) as mean is used.

  As a result of this model, the optimal number of bikes to be deployed is about 650 and the realized profit will be 61%.

Results of the model with different number of bikes deployed are shown in **Table 11** below.

	Alternate Model			
Bike Count	Customers Returned	Revenue	Profit	Profit(%)
2661	0	13229.34	-7741	-59
1300	0	13229.34	2988	23.00
1000	0	13229.34	5361	41
650	0	13231.61	8111	61.00
600	0.05	13218.93	8498	64.00
550	1.1	13232.3	8898	67.00
500	1.5	13224.62	9290	70.00
400	4.15	13146.94	9994.94	76.00
317	49.4	13097.2	10599.2	81.00

Table 11: Alternate Model -Simulation Results with different no. of bikes deployed

5. Concluding Remarks

In this paper, we have simulated a live bike-rental company in which the customers can rent bicycles from street corners, railway stations, shopping complexes, places of attraction and bus stops for rental duration up to 24 hours. We have used SIMIO® to perform the simulation and computed the total number of bikes required to be deployed at various locations to obtain a minimum of 50% profit for the company and at the same time have the lowest wait time for customers to get a bike which in turn will prevent the company from incurring losses on account of refunding 1.5 times the booking amount.

We have also concluded that we would need to increase number of bikes and the rental rate/bike for 2016 in order to achieve an exact 50% profit with minimum wait time and lowest number of returning customers.

Working with these models has given us an ability to plan the inventory of bikes required and decide the target profit margins for the following years.

Limitations and Future Extensions

Our model though has achieved our objectives, however, we felt that it can be extended to include the following functionalities which would provide a much better simulation of a live bike renting company and would help entrepreneurs with more accurate projection of number of bikes required and profit margins.

1) Bike Pick-Ups and Returns at multiple street corners, places of attraction, shopping complexes, bus stops, and railway stations

Our model above implements the renting of the bikes from various categories of locations. However, it does not consider an important aspect that each of these location categories can have multiple locations under them. For example – it's not just one street corner or bus stop or shopping complex where the bike can be picked-up and returned to. There are many street corners, shopping complexes, railway stations, bus stops, and places of attraction which need to be considered.

We plan to implement this functionality in our model by utilizing the sub-models feature offered in Simio®.

Category	Count
Street Corners	194.00
Shopping Complex	74.00
Railway Stations	30.00
Bus Stops	21.00
Places of Attraction	8.00

Table 12: Real-Data for Number of locations under a category

2) Account for stolen/damaged bicycles and charge fines for late returns

Our model computes the profit margins based on the rental rate/bike for a given location and the loss incurred due to the customers returning without renting a bike due to a wait time longer than 15 min, however it doesn't take into consideration the losses the company would incur due to bikes that have been lost or stolen and the bikes that have been damaged by customers. Also, our model doesn't consider charging fine to customers if they have not returned the bikes upon the expiration of the rental duration.
We plan to implement this functionality by having the customers pay a security deposit at the time of booking the bike and if the bike is lost/stolen/damaged or if the bike is not returned on time, we would deduct the equivalent amount of

money from their security deposit before returning the deposit to customers. This would ensure customers keep the bike safely and do not cause any damage to it.

3) Charge Membership based rental

Currently, our model charges every customer the same rent depending upon the location from where bike is rented. There is no incentive given to frequent customers. In order to reward our loyal customers, we would like to charge membership-based rentals. We would provide different membership options such as quarterly, semi-annual and annual memberships and based on the type of memberships we would offer the discounted rental rates for a given location for our members. Members would also get the first 15 min free for each trip that they rent the bicycle for

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References

[1] Paul DeMaio, MetroBike, LLC ; “Bike-sharing: History, Impacts, Models of Provision, and Future” . Journal of Public Transportation, Vol. 12, No. 4, 2009
http://bike.cofc.edu/bike-share-program/history%20of%20bike%20sharing.pdf

[2] Jia Shu , Mabel C. Chou, Qizhang Liu, Chung-Piaw Teo, I-Lin Wang ; “Models for Effective Deployment and Redistribution of Bicycles within Public Bicycle-Sharing Systems”
Operations Research; manuscript no. OPRE-2011-02-077.R2

http://bschool.nus.edu/Staff/bizteocp/SMRT2013R2edited2.pdf

[3] “Ridership” and “Fleet Performance and Safety” Data from
https://www.capitalbikeshare.com/system-data

Biographies

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Appendix A

Description of the implementation of main steps in Simio model is provided in this Appendix.

1) Source

The configuration of the arrival rate of the Source is done using Rate Table.

Figure A.1: Properties of Source

Rate Table is created assuming that the customer arrival is “Normally Distributed” considering 3 hour time intervals in the day. **Figure A.1** shows the properties of the source where the Rate Table “CustomerArrivalRate” is referenced and **Figure A.2** below shows the implementation of a Rate Table in Simio®.

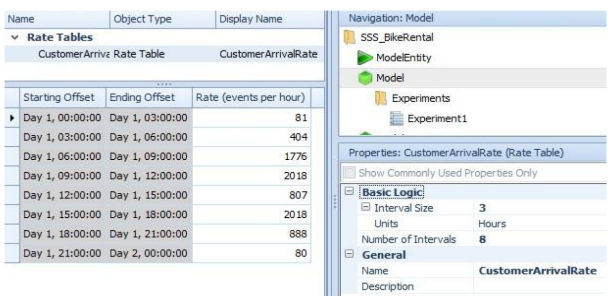

Figure A.2: Rate Table

2) Check-in Servers

Initial Number of bikes/ Initial Capacity at each check-in server/location is computed as times Total Bikes available with the company times the Percentage of Customers at that location shown in **Table 2** above. Formula shown below –

No. of bikes at each server = Total No. of Bikes available * (Percentage Allocation/100) *(for each location)*

Figure B.1 below shows the computation of the number of bikes at each check-in server. The figure explicitly shows the computation of initial number of bikes at street corners. 90.37% bikes out of the total number of bikes are located at street corners so as per formula above Initial Capacity = Total bikes * 0.9037. **Math.Round** Simio® function has been used to round the number of bikes to a whole number.

InitKiosk_Num has been defined as a State Variable which contains the total number of bikes.
Similar process has been followed to compute the initial capacity of bikes for other locations also.

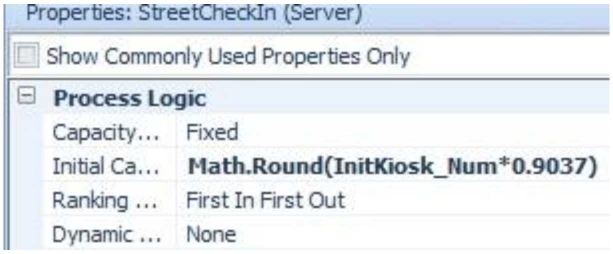

Figure B.1: Initial Capacity of bikes at Check-In Server (Street Corners)

Once the bike has been rented out at the check-in server, count of the bikes at that check-in server is reduced by 1 before exiting that check-in server. Example is shown below for street corners and same formula applies to all other locations as well.

Figure B.2 shows that the state variable is decremented by 1 when the bike is rented out.

Figure B.2: Decrement Bike Count at Check-In

Cost to Company of the bikes at each check-in server is computed in order to find what it costs to the company for 'n' number of bikes. This is computed as number of bikes at the check-in server times total cost/bike at each check-in server. The total cost/bike is mentioned in **Table 5** above. **Figure B.3** shows the cost to company at street corner check-in server. Total Cost to Company/bike at street corners is $9. Cost is computed same way for other check-in servers also considering the total cost/bike at each of the check-in servers.

Figure B.3: Cost to Company at check-in server

3) Paths

The demand of the bikes at each location category is different. The paths from source to the check-in servers are prioritized with selection weight. The selection weight is decided based on the arrival pattern of the customers as described in **Table 2**. **Figure C** below shows the selection weight assigned to a path from source to check-in server for street corners. 90.37% customers rent a bike from street corners so selection weight is nothing but the percentage of customers that go to each location for renting a bike.

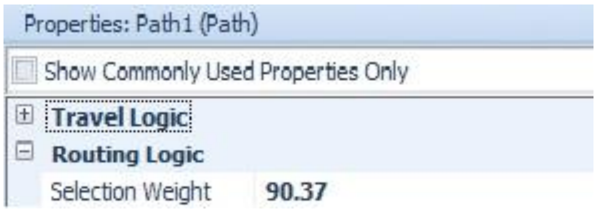

Figure C: Selection Weights to Paths

4) Check-Out Servers

Once the bike has been returned, the bike count will be incremented by 1 before exiting the check-out server. **Figure D** below shows the incrementing of bike count upon bike return. The CurrentCapacity property of the corresponding Check-in Server is increased by one when the customer returns the bike.

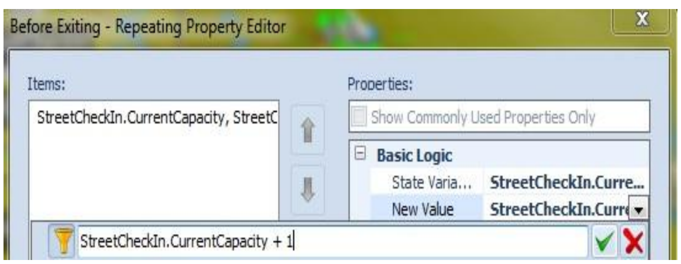

Figure D: Increment Bike Count at Check-Out

5) Time Paths

As the customers can rent the bike from each location for a duration from 0.5 hour to 24 hours, the trip durations based on the input data specified in **Table 3** are specified as Random.Discrete distribution for each timepath implemented. Figure E below shows the discrete distribution for 1 time path. The distributions of rental durations for other time paths from various check-in servers to check-out servers have been implemented in a similar way.

Figure E: Trip Duration Discrete Distribution

Travel Time for the customer from one location to another is computed for all combinations of pick-up and drop-off locations of bike. On Entering the Timepath, total trip duration is computed for each timepath implemented. **Figure F** below shows the computation of total trip duration for the timepath between checkin server of street corner and checkout server of street corner. Computations for all other timepaths have been done the same way.

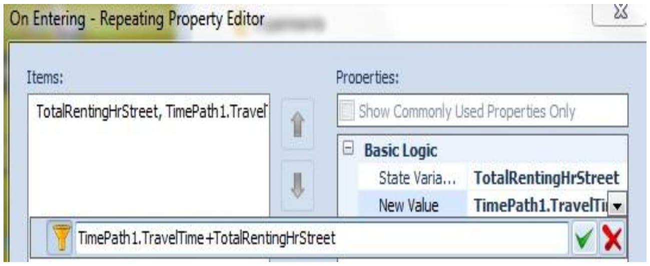

Figure F: Computation of trip duration for a timepath

Rent for the trip is computed for the computed trip duration on a timepath is also computed in order to find the revenue for the company. Before Exiting the Timepath, cost of the trip is computed using the lookup tables containing rental rates/bike for each location for the trip duration computed.

5 LookUp Tables similar to the one shown below have been created for 5 different locations. Rental Rate/bike(USD) for the trip duration (Minutes) has been entered in the table. **Figure G1** and **Figure G2** show the computation of cost of trip using the lookup tables.

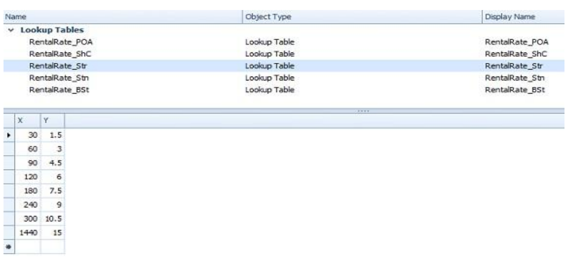

Figure G1 : Look Up Table with rental rates/bike for street corners

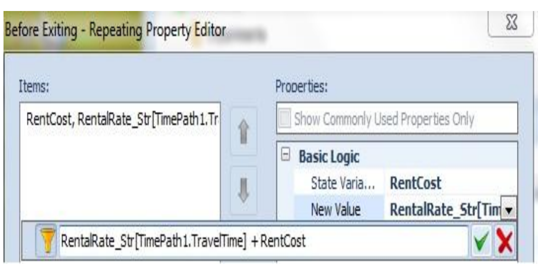

Figure G2: Computation of trip cost

6) Renege Process

The event of Renege process is triggered from the check-in server before the customer is serviced. Figure E.1 shows how the process is triggered.

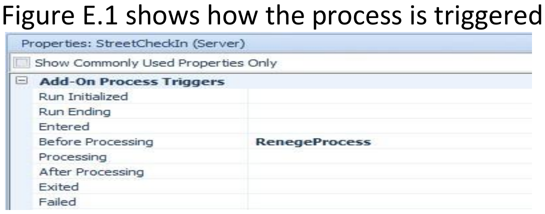

Figure E.1: Triggering of Renege Process from Check-in Server

Below are the steps implemented in the Renege process -

- Decide Step – If wait time > 15 minutes, follow process to exit the customer
- Assign Step – Number of customers who left after waiting are computed and loss incurred to the company is computed as a result of paying 1.5 times money-back to customer
- Tally Step - Save the number of customers who returned w/o service and loss incurred to business in tally registers for displaying in results
- Remove Step – Customer leaves the queue
-

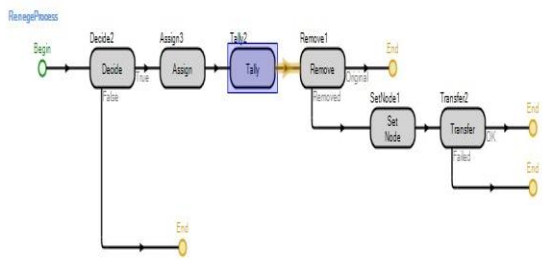

Figure E.2: Renege Process