MODELING OF REPOSITIONING ACTIVITIES IN BIKE-SHARING SYSTEMS

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ABSTRACT

Climate changes, declining inventories of fossil fuels, high space requirements, noise emission and congestion are only a few reasons why conventional cars are in discussion as individual means of transportation in cities. Bikes receive increasing attention in city transportation, mainly because they reach areas in cities that do not have direct access to public transport. Furthermore they do not contribute to congestion or pollution of the environment. The implementation of information systems in traditional bike renting leads to bike-sharing systems providing easy and quick city wide access. Thus, bike-sharing systems have rapidly emerged in major cities all over the world in recent years.
The planning and operations of such systems receive attention in academia as well as in practice. However, scientific literature in this field is still rather scarce. Recent articles focus on mainly practical advises. Some analyze bike-sharing data to get insights into customer behavior and for predicting the future number of rentals. A common issue observed in modern bike-sharing systems is imbalance in the spatial distribution of bikes over time caused by one-way use and short hiring times of bikes. The availability of bikes (= probability of successful bike rental) decreases nonlinearly with the number of requesting customers in the system. The active repositioning of bikes to stations of potential customer requests supports the objective of maximizing the availability of service.
Spatiotemporal modeling of repositioning activities for bike-sharing systems is a complex decision support task, which involves extensive data analysis or customer surveys to determine bike demand at stations and creating a suitable optimization model. In the first instance we refrain from building a spatial model. This contribution assesses the prospects of operational repositioning services by means of an aggregate feedback loop model. Therefore we adopt the approach of Karmarkar in the field of capacitated production planning. Karmarkar has developed a nonlinear “clearing function” in order to model the output of a production system as a function of the average work-in-process. We adopt this clearing function to model the probability of successful rentals under a certain number of requesting users in the system. The clearing function also contains a parameter modeling the benefit of the repositioning effort with respect to the probability of a successful bike rental. This function is engaged in a system dynamics model which allows insight in the dynamics resulting from

different levels of repositioning activities. First a causal diagram is built to depict the general interdependencies of the bike-sharing business model. Second an inventory and flow representation is used to simulate the impact on the corporate performance of bike-sharing systems under different effort spent on repositioning of bikes.
The findings from this model motivate repositioning activities in bike-sharing systems and can be used to determine a reasonable effort spent on repositioning. Results for different levels of repositioning effort are discussed.

Keywords: bike-sharing systems, repositioning activities, system dynamics

1 MOTIVATION

Climate changes, declining inventories of fossil fuels, high space requirements, noise emission and congestion are only a few reasons why conventional cars are in discussion as individual means of transportation in cities. Moreover cars are not considered as status symbols by younger generations and parts of urban population any more (Canzler 2009).
Bikes receive increasing attention in city transportation, mainly because they "provide the missing link between existing points of public transportation and desired destinations" (Midgley 2009). Furthermore they do not contribute to congestion or pollution of the environment. Comparing to other modes of transportation, bikes also have drawbacks. Using a bike as means of transportation depends on weather and topography of a city. Furthermore bikes are predominantly suitable for short trips (DeMaio 2004). The introduction of information systems supporting the provision of bike-services leads to modern bike-sharing systems (BSS) that stand out due to easy and quick city wide access (Bührmann 2008). Aims of cities implementing BSS are to encourage the use of bikes instead of cars for inner-city trips, increase mobility choices, improve air quality and reduce congestion (Midgley 2009). According to DeMaio (2009b), BSS increase "bike mode share between 1.0 - 1.5 percent in cities with pre-existing low cycling use". This underlines that BSS have a noticeable impact on the urban mobility. Thus, BSS have rapidly emerged in major cities all over the world in recent years. Examples for successfully implemented systems are given in the next section.
The planning and operations of such systems receive attention in academia as well as in practice. However, scientific literature in this field is still rather scarce. The majority of articles focus on mainly practical advises. Some analyze BSS data to get insights into customer behavior and for predicting future number of rentals. This article describes the history of BSS and their operation (Section 2). A common issue observed in BSS is imbalances in the spatial distribution of bikes over time due to one-way use and short hiring times of bikes. Therefore we describe causes of imbalances and measures to overcome these imbalances, e.g. active repositioning of bikes. Further insights into BBS are given by modeling repositioning activities with the help of a system dynamics approach (Section 3). Interdependencies in the BSS business model are presented and a non spatial stock and flow model is derived. We verify the interdependencies with simulating the outcome of different effort spent on repositioning with self-generated data. The findings from this model motivate repositioning activities in BSS. Finally, the paper is concluded (Section 4).

2 OPERATING BIKE-SHARING SYSTEMS

Monitoring and maintaining the service quality in BSS is important for the acceptance of bike-sharing programs. One-way use and short hiring times lead to imbalances in bike distribution. A brief history of BSS is given in this section to explain the general functionality of BSS. This is followed by a description of problems arising from this modern type of bike-sharing. Finally, measures to overcome imbalances are described.

History of bike-sharing systems

Over the past years traditional day rentals in tourism have evolved into modern BSS. In recent years the implementation of information systems in bike-sharing led to easy and quick city wide access with one-way use. For a better understanding of BSS, a brief summary of bike-sharing history is given according to DeMaio (2009a). This is followed by examples for the two main bike-sharing business models.

Three generations of BSS can be identified: The idea to provide the general public with bikes for intra-city trips was put into practice in Amsterdam in 1965. This first generation of bike-sharing programs started with ordinary, white painted bikes. Anyone could ride these bikes to a destination of their choice and leave it there. Burglary and vandalism caused the system to collapse within days. It almost took thirty years until a second generation of BSS was invented in the 1990s. The Copenhagen “Bycyklen” introduced special designed robust bikes with advertising plates on the spokes. A coin deposit is necessary for picking up a bike at one of the special locations distributed all over the inner city. Therefore customers were still anonymous and the program had an issue with theft. The next generation of BSS was smartened with electronically locked racks or bikes. Users had to identify themselves with a smartcard to rent bikes. Furthermore information and telecommunication systems for a better customer and bike tracking were established.

The Bike-Sharing World Map (Metro Bike 2009) currently records about 160 BSS worldwide compared to 90 at the end of 2008. Midgley (2009) talks about 80 systems with almost 27.000 bikes and more than 4.600 stations in May 2009.

A distinction between commercial and non-commercial models of provision can be made (DeMaio 2009a). Providers are advertising companies, quasi-governmental transport agencies, non-profit and for-profit organizations, governments and universities. In addition, BSS differ in how bikes are provided to the customer. There are rack-bound systems and mobile phone based services. In both types users have to register their name and credit card information, which is typically done on the provider’s website. In rack-bound systems, bikes are made available at certain locations throughout the city. Picking up a bike is done by user authentication at the bike with a smart card or at a self-service kiosk where users have to type in their login information. The biggest rack-bound system worldwide is the “Vèlib” in Paris, operated by the advertising company JCDecaux. This BSS was implemented in 2007 and offers more than 20.000 bikes at almost 1.450 stations with different rack sizes (Midgley2009). There is no charge for the first 30 minutes of a ride. According to DeMaio (2009b) about 50 million bike trips were reported in the first two years. Also 28 percent of asked users in 2008 were less likely to use their personal vehicle, which increased to 46 percent in 2009. An example for a mobile phone based system is “Call a bike”, which is operated by the German railways agency “Deutsche Bahn” in many German cities. More than 1.600 bikes are provided in Berlin. Bikes can be dropped off at any intersection and the location is transmitted via phone call to the provider. When picking up a bike users request the bike’s unlocking code via phone call. Users pay according their travelling time per minute (Call a bike 2009).

Causes of imbalances in bike-sharing systems

A common issue observed in BSS is imbalance in the spatial distribution of bikes. Users pickup bikes and return them at stations at their own discretion. In most major rack-bound BSS the first half hour of usage is free of charge. In Paris’ BSS 92 percent of the trips last less than half an hour (Midgley 2009). After the free minutes, charges increase exponentially forcing people to keep trip length short. These factors lead to one-way use and short hiring times that cause imbalances in bike distribution. Therefore bikes have to be efficiently distributed within the system to assure a good quality of service for the customers. In this section we classify causes of imbalances and then recapitulate an analysis of Barcelona’s BSS.

Bikes are not uniformly distributed among stations, because certain stations are more popular than others regarding pickups and/or returns. Two causes of imbalances can be identified: continuous and discrete. Continuous imbalances arise due to unilateral input or output bike flows as well as a change in the direction of flows. At high elevation stations more pickups than returns occur, because people avoid riding uphill. In addition to this unilateral imbalance, there are temporal patterns in incoming and outgoing bike flows at stations. For example stations with a high amount of returns in the morning and a high number of pickups in the late afternoon. Imbalances are also caused by discrete events such as a sudden change of weather like starting rain.

An example of user behavior in BSS is given by Froehlich et al. (2009). They analyze the user behavior of Barcelona’s BSS “Bicing” to detect temporal and spatiotemporal patterns in bike usage. Bicing comprises of 390 stations and 6.000 bikes with over 150.000 subscribers. The analyzed data covers 13 weeks and contains the bike stock at each station every five minutes leading to 288 snapshots of the bike stock per day. This data includes repositioning activities. Individual bike flows are not considered. One result of the analysis is that the system-wide number of used bikes during workdays follows a three-pronged spike. This spike corresponds to a high bike usage in the morning, during lunch time and in the evening. Furthermore a cluster algorithm is applied to identify stations with similar behavior in terms of available bikes in accordance with the day-time. Stations that tend to be empty are located between 80-110 meters above sea level in contrast to stations at the coast that tend to be full during the whole day. The bike availability of midtown and downtown stations drops in the morning when people ride to work and increases in the late afternoon, whereas stations in business areas show the opposite behavior and are full during working hours.

Monitoring and maintaining the distribution of bikes is important to ensure a good quality of services to the user. Therefore the allocation of bikes is discussed in the following section.

Resource allocation in bike-sharing systems

The allocation of resources in BSS means providing customers with free bikes and free racks respectively. This task is split into long-term and mid-/short-term measures to improve the availability of bikes. Both planning types require a prediction of bike demand. For that reason we describe two models of future rentals prediction.

Expanding the infrastructure is afflicted with high costs and therefore has to be planned in the long run. Costs for bikes range from 250 to 1.200 Euro added by costs for racks and service terminals (Midgley 2009). When planning and implementing or expending a rack-bound BSS, a sufficient number of stations have to be placed at suitable locations. The distance to popular locations should be between 300 and 500 meters (Bührmann 2007). In the Vèlib system, stations are located at about every 300 meters in central Paris (Nadal 2007). The same high density of stations is found in Barcelona's Bicing (Midgley 2009). This raises the probability of finding a free bike and returning it near the rider's destination.

Two short- and mid-term measures of overcoming imbalances can be identified: direct provider based distribution through repositioning activities and indirect customer based distribution through pricing or incentives.

By offering incentives customers are encouraged to use certain stations. Reaching a good acceptance means keeping the usage of BSS simple and clearly communicating terms of rentals to the user (Bührmann 2007). Incentives should not change frequently to avoid customer confusion. Therefore determining incentives can be considered as a mid-term planning task. In Paris' BSS, users have 15 extra minutes to return a bike at special labelled high elevation stations, because there is high effort spent to reach such stations. Another concept is to accumulate extra time for picking up or dropping off bikes at certain stations. Besides that extra time can be used for other trips, it would be possible to exchange extra time for money paid by the operator (DeMaio 2009a). This could reduce active repositioning of bikes and save money respectively when choosing adequate payouts. A special form of incentives observed in BSS can be called compensation. If a bike cannot be returned at a certain station because it is already full of bikes, users get frustrated. Therefore the Citybike in Vienna (CBW 2010) and many other BSS provide extra free 15 minutes to return the bike at another station. The station's terminal shows stations with available boxes that are nearby. This measure keeps the dissatisfaction of customers low.

Repositioning overcomes spatial imbalances with the help of service staff reallocating bikes from low demand/high supply to high demand/low supply areas based on a daily basis. Therefore special service vehicles are used that carry several bikes. Estimated 3 US Dollar are spent per repositioned bike in the Vélib system (DeMaio 2009a). Annual operating costs per bike, including maintenance, repositioning, service, staff, electricity et cetera, vary from 250 to 1.600 US Dollar depending on the used technology (DeMaio 2009b, Midgley 2009). The analysis of usage data as well as critical user feedback is the basis for improving the distribution of bikes (Bührmann 2007). Therefore we recapitulate two approaches of predicting future bike demand in the remainder of this section.

In order to improve the availability of bikes and boxes respectively a prediction of future demand is needed. Borgnat et al. (2009) develop a linear regression model to predict the system-wide number of bikes hired per day and fluctuation per hour from historical data for Lyon's bike-sharing program Vélo'V. The underlying data contains rental operations with starting and ending stations and time. The model holds parameters for the number of subscribed users, weather (temperature, volume of rain), day of week, hour of day and the occurrence of holidays and strikes. Froehlich et al. (2009) use a Bayesian network to predict the number of available bikes at a station up to 120 minutes in the future for the Barcelona BSS. Individual bike flows are not considered. They use snapshot data with the bike stock at each station.

3 MODELING REPOSITIONING ACTIVITIES IN BIKE-SHARING SYSTEMS

The conventional approach of modeling repositioning is spatial and temporal. Spatiotemporal modeling of repositioning activities for bike-sharing systems is a complex decision support task. Although extensive analysis of bike data or customer surveys can be applied to predict future bike demand at stations, the demand still has to be considered stochastic and not deterministic. Moreover various points in time have to be incorporated in a suitable mathematical optimization models that yield decisions on the adequate level of repositioning activities. Such a stochastic and dynamic model can be computational intractable. In addition, customer behavior cannot be modeled in these mathematical optimization models. Therefore we refrain from building a spatial model at first. This contribution assesses the prospects of operational repositioning services by means of a system dynamics aggregate feedback loop model. According to Forrester (1991) system dynamics combines theory and methods for analyzing the behavior of systems in management and many other fields. Wherever we want to understand and influence how things change over time, system dynamics provides a common foundation that can be applied. Concepts from the field of feedback control are used to organize available information and generate computer simulation models. The findings from these models can be used to improve decision making.

Modeling repositioning activities in BSS requires understanding the structure and behavior of such systems. Therefore we apply a system dynamics approach to discover and represent the interdependencies and feedbacks in the bike-sharing business model. This is a proper analyzing instrument because BSS fulfill the following properties according to Strohecker (2007): The availability of bikes evolves over time according to the number of users. Furthermore feedback loops can be identified that have a balancing or self-reinforcing structure.

We follow the modeling process according to Sterman (2006). This process starts with an articulation of the problem, namely imbalances in bike distribution, for which reasons and solutions have to be found. After that we develop a causal loop diagram that explains the bike-sharing business model and includes measures to overcome bike imbalances. On that basis a nonlinear function is developed that models the probability of successful rentals under a certain number of requesting users on an aggregate, system-wide view. This function also holds a parameter for effort spent on repositioning activities and is engaged in a stock and flow model to simulate impacts on the corporate performance under different levels of repositioning.

The bike-sharing business model

That the factors quality and satisfaction contribute to the company's success is a common acknowledged statement. The transaction specific satisfaction of a service is based on the experienced quality of this service (Kaiser 2004). The satisfaction in turn enhances the company's success. Thus ensuring a certain quality of service in BSS is crucial for a high customer satisfaction and the accompanying business success.

These factors are modeled in a causal loop diagram. For the sake of comprehensibility, rentals but no returns are considered. Figure 1 gains insights in the operational dependencies and feedback loops of a BSS operated by an advertisement company. There is a certain amount of requesting bike-sharing customers that use the provided bikes for their trips around the city. Revenue generating advertisement is displayed on bikes and stations throughout the city. The bigger the amount of bike-sharing users the better advertisement contracts can be acquired by the provider, which leads to higher income. But customers also generate costs due to maintenance of bikes and stations as well as complaints, stolen bikes et cetera. Income and costs determine the company’s profit. If more customers request a bike the availability of bikes drops and so does the number of successful rentals. The more customers find a free bike the higher is the experienced quality of service leading to more satisfied customers. Positive word-of-mouth increases the number of users. If the availability of free bikes decreases the number of unsuccessful rentals increases. This leads to a higher number of dissatisfied customers. Due to frustration the number of bike-sharing users decreases.

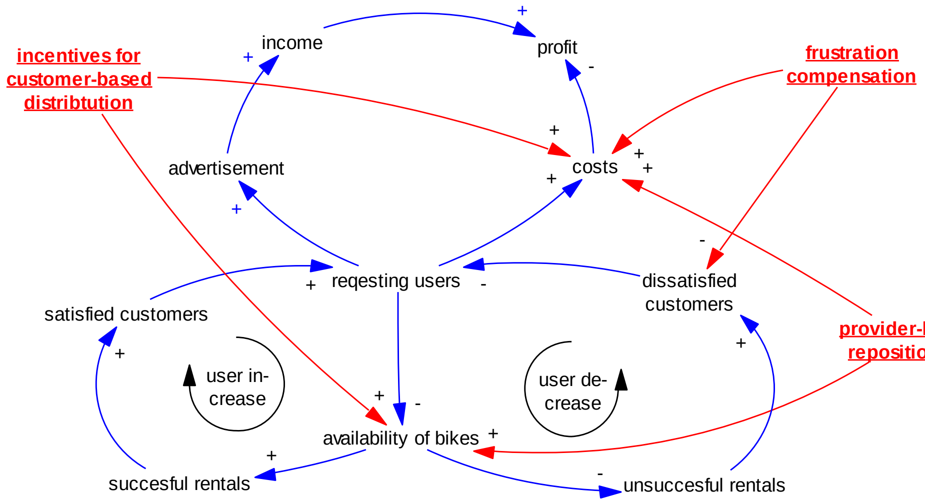

Figure 1 - Bike-sharing business model with measures to overcome imbalances

We assume that the increase of users in the system has an s-shaped growth: The growth of bike-sharing users is exponential at first, because enough bikes are provided and satisfied customers generate more customers. Then it gradually slows down as the number of successful rentals decreases and unsuccessful rentals increase because not every costumer finds an available bike. These frustrated customers leave the BSS which leads to an equilibrium level of bike-sharing users.

As we have stated above incentives for customer based distribution and provider based repositioning improve the availability of bikes. The impact of incentives on bike distribution has to be considered lower than active repositioning because actions of customers cannot be controlled to the full extend. Frustration compensation lowers the number of dissatisfied customers. All three measures increase operation costs. Determining adequate incentives is not in the focus of this paper and we refer to literature on Revenue Management and Dynamic Pricing. In the next section we model the availability of bikes and quality of service used in the system dynamics model.

Modeling bike availability and service quality

Modeling the behavior of BSS on an aggregate level requires a definition of the key factors availability and quality of service. Extensive numerical studies would be necessary building a spatial model. We refrain from building a spatial model; instead we adopt findings in the well studied field of capacitated production planning to make assumptions for the user behavior in BSS under a certain workload.

Availability of bikes

Due to one-way use and short rental times imbalances in the spatial distribution of BSS arise. User behavior can be described with probabilities for picking up and retuning bikes at each station. As stated above the popularity of stations varies. If the number of bikes and bike boxes at stations is not limited, buffer sizes according to a certain storage policy (Günther 2002) can be determined that unsuccessful rentals and returns are unlikely. But in short term planning changing the infrastructure is not possible. The system's behavior with fixed station sizes, number of bikes and stations can be described as follows:
If the number of requesting customers is low compared to the system's capacity, the probability of successfully renting a bike is rather good. When more users request bikes, stations still provide bikes until certain stations start running out of bikes, whereas other stations have enough bikes on stock. Therefore we assume that the probability of successful rentals decreases nonlinearly with the number of requesting customers in the system. This relation is derived from the field of capacitated production planning. A nonlinear relation between workload and lead-time in aggregate planning is observed here due to queues at the capacitated resources.
Karmarkar (1989) developed a nonlinear clearing function in order to model the output of a production system as a function of the average work-in-process. We adopt this clearing function to model the probability of successful bike rentals under a certain number of requesting customers in the system. This function yields the approximated impact of different repositioning activities without an extensive spatial modeling.
The Karmarkar clearing function yields the output X of a production system under the work-in-process W. The maximum output and capacity respectively is given by C and batch sizes by K.

$$X = \frac{CW}{K + W}$$

In the context of BSS we interpret K as the used repositioning capability $K = C - R$ with R being the number of repositioned bikes. Repositioning increases the system's capacity:

$$X = \frac{(C + K)W}{K + W}$$

Furthermore the work-in-process of the system is determined by the available capacity minus requesting users N. With $W = C - N$ this leads to:

$$X = \frac{(C+K)(C-N)}{K+C-N}$$

Normalizing this function yields the probability of a successful rental under a certain number of requesting users:

$$P(X) = \frac{(C+K)(C-N)}{C(K+\ C-N)}$$

Figure 2 (left) depicts the probability of successful bike rentals for a given capacity of 100 bikes. The number of requesting users is plotted on the x-axis. The curves shapes show that the probability of a successful rental decreases nonlinearly for every new user at each level of repositioning activities. Imbalances are reduced due to repositioning of bikes. The more bikes are repositioned the higher is the probability to get a free bike under certain capacity utilization. A high repositioning effort yields a higher probability under increasing user utilization than lower repositioning effort. As the system reaches its capacity the probability for a high number of repositioned bikes drops significantly. The absolute number of available bikes (Figure 2 right) under a given utilization is the cumulative probabilities of successful rentals. Under a system utilization of 30% almost every user gets a free bike for different repositioning effort. Under a higher workload the number of successful rentals disperses increasingly.

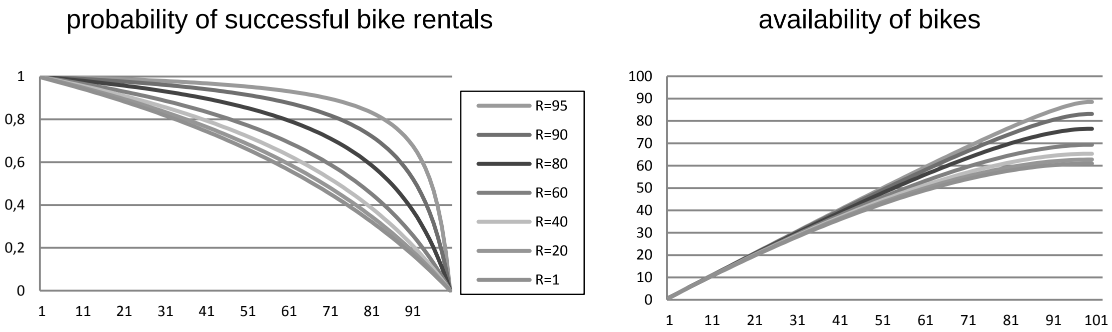

Figure 2 - probability of successful rentals and availability of bikes for different repositioning activities

Quality of service and population growth

Quality of service is a crucial factor for the acceptance and growth of the system regarding the users. Quality is defined as the number of successful rentals divided by all rental attempts, which is the proportion of users that can successfully rent a bike.

In 1838 Verhulst (Sterman 2006) discovered that the net growth rate of a system is determined by the population size P and the carrying capacity C:

$$net\ growth\ rate = g^*\left(1 - \frac{P}{C}\right)P$$

Factor g^* is the maximum growth rate when the population is very small. This function is also known as logistic growth and models an s-shaped curve, because the net growth rate is positive if $P < C$, null if $P = C$ and negative if $P > C$. We transfer these findings to BSS by assuming that users who do not get a free bike evoke a negative growth rate and users leave the system. In contrast, users who successful rent a bike generate positive growth and attract more customers. The impact of successful and unsuccessful rentals in BSS is not studied and general conclusions do not exist. Therefore we assume that only a small fraction of successful rentals generate new customers, since users expect finding a free bike. That is why we introduce a customer attraction factor with values up to 0.5. We claim that the disaffection effect is much bigger and holds values bigger than 0.5. The higher the disaffection factor the less tolerant users are regarding unsuccessful rentals.

Formulation of a stock and flow model

Simulating the behavior of BSS requires the formulation of a stock and flow model (Figure 3) that is derived from the bike-sharing business model diagram. We refrain from building a spatial model. Instead we observe the interdependency on an aggregated level to show changes in the number of requesting customers regarding the availability of bikes. Therefore the nonlinear clearing function is engaged in the model. For the sake of comprehensibility, rentals but no returns are considered.

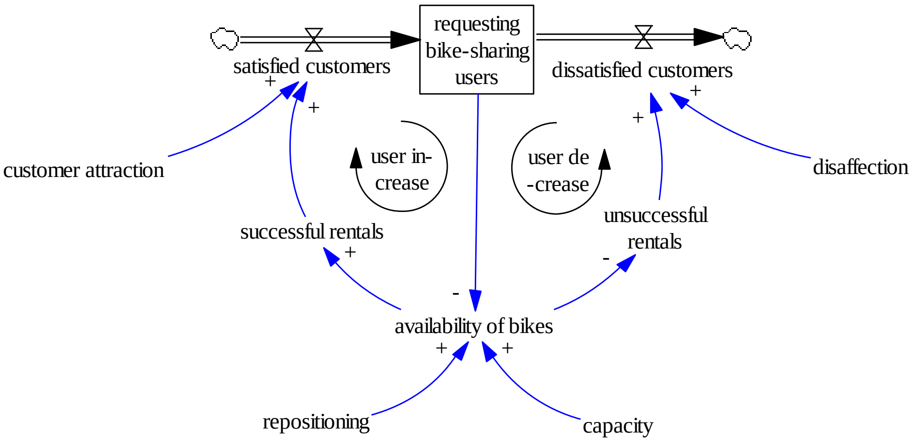

Figure 3 - Stock and flow model of a BSS

A certain number of bike-sharing users request a bike. Whether users get a free bike or not depends on the availability of free bikes. The outcome of successful und unsuccessful rentals is determined by the number of requesting customers, the BSS capacity and number of repositioned bikes. According to the customer attraction factor, a certain fraction of satisfied users generate new customers. The dissatisfaction factor determines the fraction of frustrated users who leave the system. If the capacity and repositioning activities are rather high compared to the number of requesting costumers, users will likely get a free bike and new costumers are attracted. Unsuccessful rentals will barely occur. Therefore the number of bike-sharing users grows and the availability of bikes drops. This is followed by a decrease in the number of successful rentals and attracted costumers respectively on the one hand and an increase in the number of unsuccessful rentals and dissatisfied costumers respectively on the other hand.

Simulation

After building the stock and flow model, experiments with different levels of repositioned bikes, attraction and disaffection factors are made to observe the impact on satisfied customers. We use the simulation tool VENSIM PLE from Ventana Systems. Basis of all experiments is a carrying capacity C of 100 bikes and the simulation horizon is 20 periods. The initial number of requesting users is 20. All users request a bike in every period and a certain number of bikes R are repositioned within every period. We assume that the clearing function does not change over time, because customer growth is in the focus of the simulation.

Table 1: Number of requesting users and satisfied customer

			# requesting users			# satisfied customers		
α	β	Ø quality of service	$R = 10$	$R = 40$	$R = 80$	$R = 10$	$R = 40$	$R = 80$
0,1	0,9	0,91	32	36	56	29	33	52
0,2	0,8	0,80	62	70	94	50	56	75
0,3	0,7	0,70	85	93	108	60	65	76
0,4	0,6	0,60	103	108	126	62	65	76

Results for different combinations of customer attraction α and disaffection β for varying repositioning activities are shown in table 1. The quality of service in the BSS depends on the combination of α and β. Users are more tolerant regarding unsuccessful rentals if the disaffection factor declines and the attraction factor increases. This leads to higher number of requesting users, but also increases the gap between requesting users and satisfied customers. Therefore the quality of service drops. The higher the number of repositioned bikes, the more requesting users and satisfied customers are the system. This holds for every combination of α and β. Therefore the assumption that a higher amount of repositioning activities leads to a higher number of requesting users in the BSS is verified by the simulation model.

The BSS behavior regarding user growth for one combination of the attraction and disaffection factor and different effort spent on repositioning is depicted in Figure 4. Time steps are displayed on the x-axis and the number of users on the y-axis. All curves show the described s-shaped growth. Depending on the level of repositioned bikes, the number of requesting users increases. The more effort is spent on repositioning the higher is the growth at first until the user increase gradually slows down. The system's equilibrium is also reached earlier. This leads to the conclusion that applying a higher level of repositioning leads to a higher number of satisfied customer and a more intense growth in the BSS customer number.

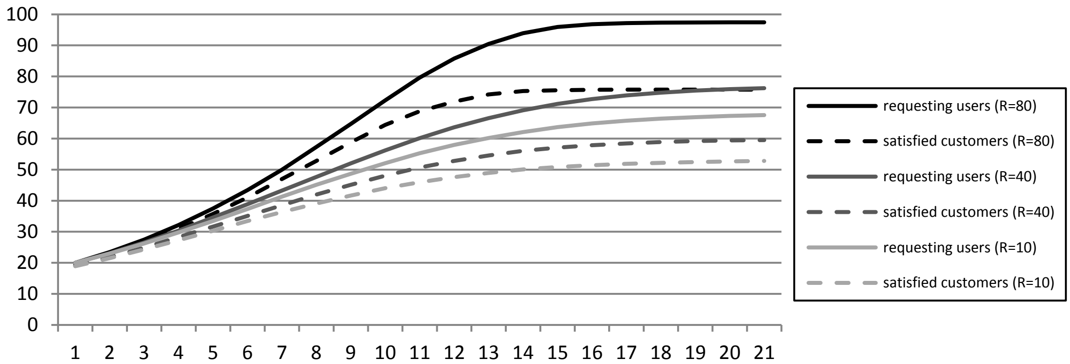

Figure 4 – User growth for different levels of repositioning and $\alpha = 0,2$, $\beta = 0,7$

4 CONCLUSION

This paper deals with modeling repositioning activities in BSS. One-way use and short hiring times cause imbalances in the spatial distribution of bikes over time. In order to alleviate these imbalances, two possibilities are presented and modeled in a system dynamics causal diagram. One the hand side direct provider based distribution through repositioning activities and on the other indirect customer based distribution through pricing or incentives. A nonlinear clearing function is introduced to model repositioning activities on an aggregate level. On the basis of simulation experiments, we present the outcome of different effort spent on repositioning activities. We conclude that more effort spent on repositioning leads to a better corporate performance in terms of satisfied customers.

In further research the systems dynamics model should be validated by means of real BSS data. Therefore, data analysis is necessary in order to derive system's behavior regarding pickups and returns at stations and the number of customers. A comparison of the corporate performance with and without repositioning activities should be made. For that reason a spatial simulation model should be build to replicate the customer behavior and corporate performance of BSS without repositioning. Furthermore a spatiotemporal transportation model can be applied to determine repositioning flows. Repositioning flows engaged in the spatial model lead to the BSS corporate performance with repositioning. The presented clearing function can also be validated by the findings from the transportation model.

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