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## Data-Adaptive Simulation: Cooperativeness of Users in Bike-Sharing Systems

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# Data-Adaptive Simulation: Cooperativeness of Users in Bike- Sharing Systems



# Data-Adaptive Simulation: Cooperativeness of Users in Bike-Sharing Systems

*Thomas Preisler, Tim Dethlefs and Wolfgang Renz*

Bike-sharing systems undergo a rapid expansion due to technical improvements in the operation combined with an increased environmental and health awareness of people. The acceptance of such system depends heavily on the availability of bikes at stations. In spite of truck-based redistribution efforts by the operators, stations still tend to become empty/full, especially in rush-hour situations. In this paper, we explore an incentive scheme that encourages users to approach nearby stations for renting or returning bikes, thereby redistributing them in a self-organized fashion. A cooperativeness parameter is determined by the fraction of users that responds to an incentive by choosing the proposed stations. The microscopic simulations of the actual bike-sharing system is based on data taken from Washington, D.C. (2014). From these data, stochastic parameters can be determined such as the rush of users for a station given as a function over time. Here, we propose a data-adaptive simulation approach to measure the impact of different cooperativeness parameters. The proposed approach realizes a data-adaptive simulation where the knowledge/data space of the application is filled on demand. If knowledge/data already exist, no further simulations are required. If not, the required microscopic simulations are executed and the data set is enriched with their results.

**Keywords:** Bike-Sharing System, Data-Adaptive, Simulation, Self-Organization

## 1 Introduction

Due to climate changes, declining inventories of fossil fuel, noise emission and congestion cars are in discussion as individual means of transportation in cities. Therefore, bikes are receiving an increased attention in city transportation, as they offer a healthy and environment-friendly way of transportation, while also allowing to reach areas in cities that do not have direct access to public transportation. This and technical improvements led to a rapid expansion of bike-sharing systems worldwide (Vogel & Mattfeld, 2010). In addition, younger generations and parts of urban population do not consider cars as status symbols anymore. Of course, bikes have drawbacks in comparison to other modes of transportation, as the usage of bikes strongly depends on the weather and topography of the city, making bikes more suitable for short trips (DeMaio, 2009). As consequence, modern bike-sharing systems are mainly used for short-term rentals. The increasing success of bike-sharing systems depends not only on the previous mentioned reasons but also on the introduction of information systems supporting the renting process (Bührmann, 2008). In order to improve respectively reduce inner-city air quality and congestion many cities aim at implementing bike-sharing systems (Midgley, 2009).

The operation of modern bike-sharing systems in big cities mainly depends on the availability of bikes at the stations, but the systems often exhibit the problem of reliability. According to rush-hour situations, stations may run out of bikes while others become full. Therefore, the planning and operating of redistribution attempts is essential to ensure proper reliability and user satisfaction. Several attempts have been ventured to overcome these problems in scientific research as well as in practice (Vogel & Mattfeld,

2010). For example, the availability of bikes at the stations in Barcelona's Bicing bike-sharing system has been analyzed by (Kaltenbrunner, et al., 2010) in order to detect temporal and geographic mobility patterns within the city, to predict the number of available bikes for stations ahead. Similar work, again for Barcelona's Bicing system, was done by (Froehlich, et al., 2009) where clustering techniques were used to identify shared behavior across stations in order to predict short-term station usage.

In this paper, an incentive scheme that encourages users to approach nearby stations for renting and returning bikes, thus redistributing them in a self-organized fashion is investigated. In order to do so, a microscopic simulation of an idealized Monday based on data from Washington, D.C. (2014) is realized. This simulation system will be used to measure the impact of a cooperativeness parameter determined by the fraction of users that responds to an incentive by allowing their trip to be detoured to proposed alternative stations. The approach picks up ideas from previous work, where first studies regarding the self-organizing redistribution of bikes based on an incentive scheme for the users were performed (Preisler, et al., 2013). This work is extended by a more sophisticated simulation system and approach.

The implemented simulation system is based on a data-adaptive simulation approach to measure different cooperativeness parameters. The approach realizes a data-adaptive simulation, where the knowledge of the application is filled on demand. If simulation results already exist for specific simulation parameters, no further simulations are required. If not, the required simulations are executed and the knowledge/data space is enriched with the results.

The remainder of this paper is structured as follows: Section 2 gives an overview about the historic development of bike-sharing systems in general and takes a closer look at Washington, D.C.'s bike-sharing system in particular. Section 3 describes the data-adaptive simulation as a service approach. The implemented bike-sharing simulation system and the results of the self-organizing redistribution strategy are described and discussed in Section 4. Finally, Section 5 concludes the paper.

## 2 Bike-Sharing Systems

This Section will give a short overview about the history of bike-sharing systems before the bike-sharing system of Washington, D.C. will be described and analyzed in detail. Data about the trips in Washington, D.C. in 2014 will be used as a foundation for the constructed simulation system used as a test-bed for the proposed incentive scheme.

### 2.1 History of Bike-Sharing

The history of bike-sharing systems is characterized by three different generations (DeMaio & Gifford, 2004). The first bike-sharing system was introduced in Amsterdam (the Netherlands) in 1965. The so called Witte Fietsen (white bikes) were ordinary bikes, painted white and provided for public uses. The bikes could be used to ride to the designated destination and be left there for the next user. Unfortunately, the program collapsed within days, as bikes were thrown into the canals or appropriated for private use (DeMaio, 2009).

The second generation started in the early 1990s in Denmark with small programs, like the 26 bikes at four stations in city of Nakskov (Nielsen, 1993). In 1995 the first large-scale 2nd generation bike-sharing system was launched in Copenhagen. The bikes were specially designed for intense utilitarian use equipped with solid tires and wheels as well as advertising plates. They could be picked up and returned at specific locations throughout the central city with a coin deposit. Even more formalized as the previous generation with dedicated stations and operated by a non-profit organization, the bikes were still stolen in many cases due to the anonymity of the users (DeMaio, 2009).

This led to a new generation of bike-sharing systems with improved user tracking. It started in 1996 at the Portsmouth University of England, where students could rent bikes with magnetic stripe cards. The 3rd generation of bike-sharing systems is based on a variety of technical improvements, including electronic locks, telecommunication systems, mobile phones and on-board computers. A noticeably impact on 3rd generation bike-sharing system in general had the introduction of the Velo'v system in Lyon, France with 1500 bikes. Until then the largest system at all. Over the next years, bike-sharing systems generated enormous interest and around the world and different programs were started worldwide. By the end of 2009 there were up to 120 3rd generation bike-sharing systems globally (DeMaio, 2009).

## **2.2 Bike-Sharing in Washington, D.C.**

The Capital Bikeshare bike-sharing system in Washington, D.C. was started in September 2010. Until May 2013, when Citi Bike began operation in New

York City, it was the largest bike-sharing service offered in the United States (Martinez, 2010). Currently, the system has 345 stations and about between 2400 and 2900 bikes were available for usage in 2014. All data concerning the system is freely accessible using the Capital Bikeshare Dashboard (<http://cabidashboard.ddot.dc.gov>, retrieved June 25, 2015). Like in many other bike-sharing systems the pricing is based on the principle that the first 30 minutes of a rental are for free (except a fixed membership fee). Each additional 30 minutes require an additional fee. Figure 1 shows the system-wide number of trips by month for Washington, D.C. It illustrates a constant growth in the number of trips since its start in September 2010. Starting from about 4.000 trips to about 220.000 trips in September 2012 and 330.000 trips in September 2014. The Figure also shows how the number of trips peaks during spring and summer and decreases in fall and winter, as the usage of bikes strongly related to weather conditions.

To ensure the reliability of the system and therefore, both the availability of bikes and free docks at the stations, Capital Bike Share uses trucks to redistribute bikes (Maus, 2013). This redistribution and the anticipation, which stations will require more bikes or free slots in order to handle rush-hour situations is one of the main challenges when operating bike-sharing systems. Figure 2 shows the balancing efforts ventured by Capital Bikeshare in 2014. It becomes apparent that there is a correlation between the number of trips in this period (as shown in Figure 1) and the number of balancing efforts. If more trips are ventured, more rebalancing efforts are required to ensure the availability of bikes and free docks at the stations. Furthermore, the Figure shows that the operation of such a bike-sharing systems requires a significant amount of redistribution efforts.

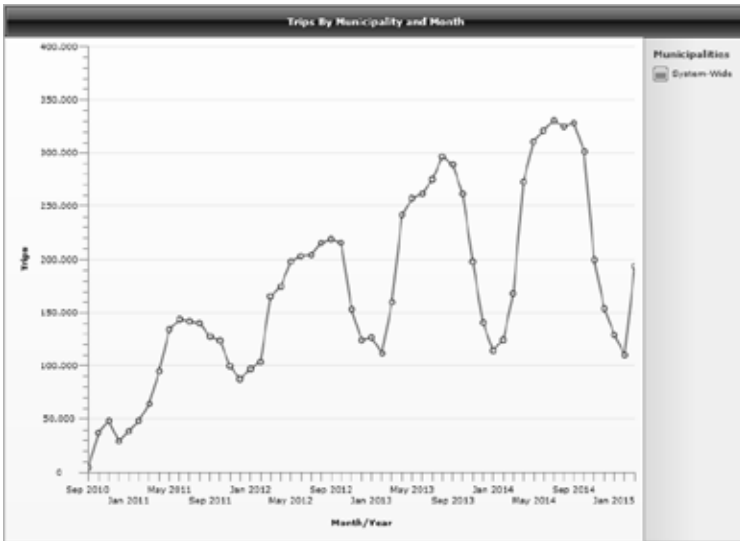


Figure 1 Capital Bikeshare system-wide number of trips by month from September 2010 until March 2015 (taken from Capital Bikeshare Dashboard)

However, stations still tend to become full or empty, as shown in Figure 3. With regard to Figure 1, the amount of full or empty stations correlates to the number of trips. When the number of trips rises, the number of full respectively empty stations also arises. The data in Figure 3 also shows that the amount of empty stations is higher than the amount of full stations, indicating that the stations may be designed to have spare capacities to increase the chance that a bike can be returned at a station. In conclusion, the Figure shows that despite the redistribution efforts that are already carried out, there is room for improvement. Either by increasing the number of truck-based attempts or through the introduction of new approaches,

especially to overcome the problem of empty stations. The incentive scheme proposed in this paper, that encourages users to approach nearby stations for renting or returning bikes, aims at solving this open problem by redistributing bikes in a self-organized fashion.

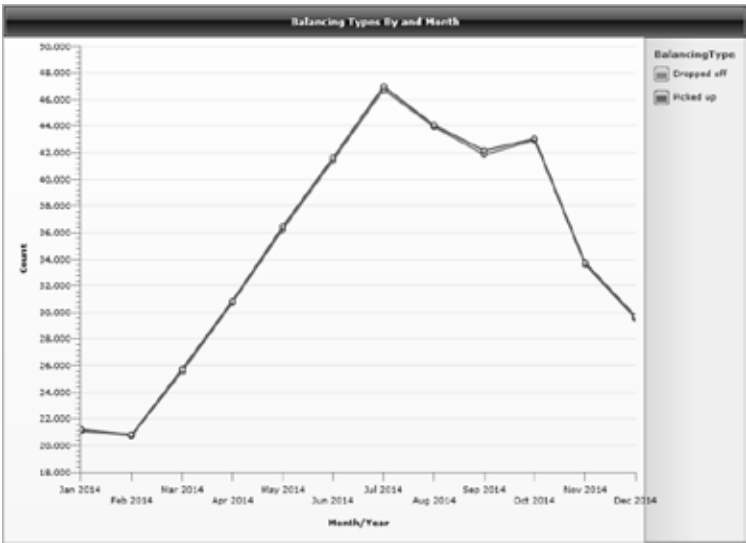


Figure 2 Capital Bikeshare balancing efforts in 2014 (taken from Capital Bikeshare Dashboard)

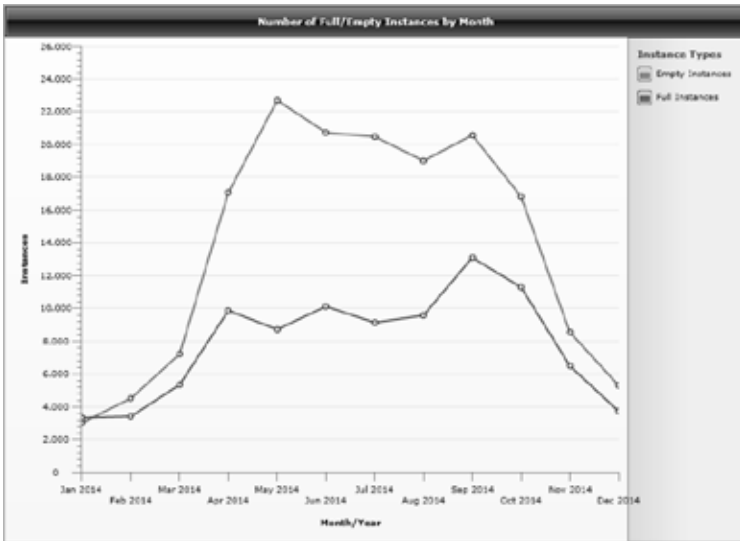


Figure 3 Number of full/empty stations in 2014 (taken from Capital Bikeshare Dashboard)

### 3 Data-Adaptive Simulation as a Service Approach

The simulation concept presented in this paper is based on two approaches. The first one regards the data-adaptivity of the simulation system. This means that the system is adaptive with regards to its data, resulting in a data/knowledge space that is filled on demand. If the required data for a simulation request already exists it is returned directly, if not the required simulation is performed and the data/knowledge space is enriched with this information. This approach is depicted in Figure 4. It is based on the concept, that a simulation system handles simulation requests for specific

simulation component. These requests contain a variable tuple of criteria that parametrize the execution of the simulation component. The simulation systems forwards these requests to an active data/knowledge space, where the simulation results for different parameter tuples are stored. The space is active with regards to its ability to start the execution of the simulation component, in case the space does not already contain data for the given parameter tuple. In this case, the simulation component will be executed and the results are stored in the data/knowledge space and returned to the simulation system. Further simulation requests for this tuple of parameters do not require the anew execution of the simulation component instead the associated results can be read directly from the data/knowledge space.

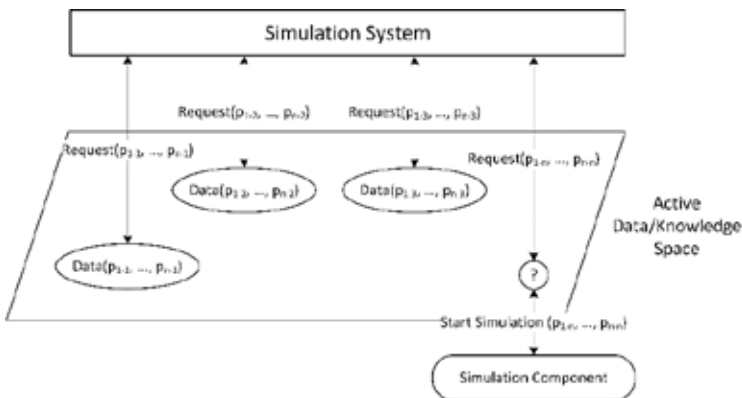


Figure 4 Data-Adaptive Simulation Approach

The second aspect of the approach focuses on service-orientation. Service-orientation is a design paradigm for software systems in the form of services. Its design principles strengthen the separation of concerns and a loose coupling in the resulting software system. Applying this approach results in entities of software partitioned into operational capabilities, each designed to solve individual interests. These units are qualified as services (Allen, 2006). Service-orientation has received a lot of attention since 2005 (Liebhart, 2007). The Simulation as a Service approach combines concepts from service-orientation with cloud computing technologies and aspects. Cloud computing (Sosinsky, 2011) is seen as a new approach to IT infrastructure management that facilitates a pay-as-to-go usage model. Computational resources are made available on a demand-driven basis; instead, of statically dedicated physical systems. Therefore, the approach minimizes idle times and optimizes the utilization of resources, leading to a minimization of resource dissipation. Cloud computing applications are typically built on the Infrastructure as a Service (IaaS) or Platform as a Service (PaaS) layer. On the IaaS layer, access to the cloud is granted by virtual machines that allow fine-grained control of the software stack and provide low-level aspects like operating systems. On the PaaS layer, a cloud operator establishes a new software layer with a dedicated middleware programming interface, and thus lower level details are abstracted. The Software as a Service (SaaS) layer are user-ready applications running in the cloud, which are typically built upon the IaaS or PaaS layer. The Simulation as a Service approach adopts this concept to the domain of simulations and provides simulations as a user-ready service in a cloud-computing infrastructure. Figure 5 shows the architecture of the data-adaptive simulation

service approach designed to realize a simulation of Washington, D.C.'s bike-sharing system. The service encapsulates the actual implementation of the bike-sharing simulation component and the data-adaptive behavior. Following the data-adaptive approach, the simulation service checks whether its data/knowledge space contains results for the requested parameters (1). If so, the results are directly returned to the client. If not, the service executes the bike-sharing simulation component (2), stores the results in data/knowledge space for further requests (3) and returns the results to the client. In this case, the active behavior of the data/knowledge space is realized as part of the simulation service and the database just provides storing capabilities. Another possible realization is to implement this behavior as part of the database, e.g. as stored procedures.

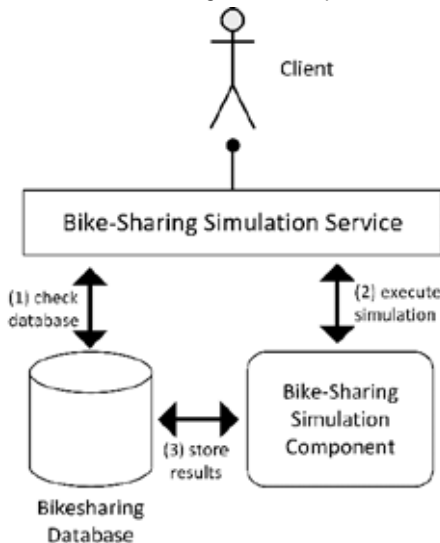


Figure 5 Bike-Sharing Data-Adaptive Simulation Service Architecture

## 4 Simulation of Washington, D.C.'s Bike-Sharing System

This Section describes the implementation details of the realized simulation system, as well as the analyzed simulation scenario, the self-organized redistribution strategy and the simulation results.

### 4.1 Implementation Details

Essentially, the implementation of the bike-sharing systems consists of three main components. The first component is the actual simulation system simulating the rental and movement of bikes in Washington, D.C. The second component is a relational database management system used to store the simulation results. The third and final component is the simulation service that encapsulates the two previous components and realizes the data-adaptive simulation approach.

The actual simulation system was realized using RinSim (van Lon & Holvoet, 2012), a logistics simulator written in Java. It supports (de)centralized algorithms for dynamic pickup-and-delivery problems (PDP). From a conceptual point of view, the simulation system bases on the paradigm of Multi-Agent Systems (Wooldridge, 2009). The usage of agent technology for simulation has a long tradition in computer science and has successively replaced other approaches (Davidsson, 2001). The main advantage of agent-based simulation is the ability to model the characteristics of each entity individually. This allows building very close mappings between the considered systems and the generated model since there is no need to

compress features of the modeled entities. The cyclists renting bikes at stations were realized as agents. They are created at a specific station, where they try to rent a bike and if a bike is available at the station, they drive it to their designated destination stations, where they return it. In order to map the road model of Washington, D.C., the corresponding area was extracted from OpenStreepMap (OSM) (Haklay & Weber, 2008) and transformed into the graph-based road model supported by RinSim. Thus, the movement of the cyclists along the roads can be simulated by moving them on the edges of the resulting graph. Following the PDP-modeling approach, the bikes were modeled as parcels and the bike stations as depots. Time in the simulation system is simulated in a discrete manner, divided into ticks of 60 seconds length. Therefore, the simulation of a whole day consists out of 1440 simulation ticks.

In order to store the results of a simulation run the open-source relational database management system MySQL (DuBois, 2013) was used. Each simulation run is identified by its simulation parameters. The most important parameter in the context of the ventured study is the cooperativeness of cyclists to rent or return a bike at an alternative station. Other parameters are the cyclists' speed, the initial number of bikes at the stations, the number of docks at the stations and the communication range of the bike-stations used for the self-organized redistribution of bikes. Therefore, the database stores a mapping of these parameters to the corresponding simulation results.

The final component was the bike-sharing simulation service to realize the data-adaptive simulation service approach. This component was realized using the Jadex Active Components Platform (Braubach, et al., 2014). This

platform offers a middleware to implement service-oriented applications with focus on distribution transparency and supports the realization of cloud computing applications by providing a PaaS-layer infrastructure. Thus, the implemented simulation service can be executed on a cloud-infrastructure. It encapsulates the functionality offered by the simulation component and extends it with a data-adaptive behavior by interconnecting it with the database system to provide a data/knowledge space as described in Section 3.

## 4.2 Simulation Scenario

A typical Monday was examined in order to simulate Washington D.C.'s bike-sharing system and to evaluate the impact of the cooperativeness of users for the self-organized redistribution of bikes. Therefore, the trip history data for all Mondays (except holidays) from 2014 provided by Capital Bikeshare, was analyzed. To do so, the day was divided into 24 time slices, one for each hour of the day. For each of these 24 time slices the departure and dependent destination probabilities for the bike-stations were calculated based on the ventured trips. By counting all trips started at a specific station A in the considered time window and by dividing them by the total amount of trips in this time window, departure probabilities were calculated for all bike stations in the systems. To calculate the destination probabilities, as a dependent probability that if a user departs from station A it drives to station B, all departures of station A in the observed time window were counted. This value was then used to determine the specific destination probability for a station B, by counting all departures to B and dividing them by the total value. This resulted in a scenario configuration for the

simulation that described an idealized Monday based on all trip data from 2014, divided into 24 time slices, where each time slice consists out of specific departure and dependent destination probabilities for each station. The number of docks and the initial occupancy of the bike stations were modeled as variable parameters of the simulation, because the trip history data does not contain information about the number of docks at the bike stations and their occupancy. The simulated idealized Monday scenario started at 12 a.m. In order to simulate the different rush at different times of the day, the median total number of trips for each of the 24 hours of the day was determined based on the trip history data. During the execution the simulation component generates the number of cyclist agents specified by the rush equally distributed for the currently simulated time slice. The according departure and destination probabilities for the stations are used to determine from which departure station the agent will rent a bike and drive it to which destination station. Besides their cooperativeness, the cyclists are simple agents that rent a bike from the departure station where they are created and drive it to their desired destination station where they return it. As a simplification, they all move with a constant speed along the graph-based road model. In order to find a route from the departure to the destination stations, they use a shortest path approach and traverse the edges of the graph road model, considering the edge weight as the distance to the next node. The simulation was configured to allow an overcrowding of bike stations, if no free docks are available. If a cyclist agent tries to rent a bike at an empty station, this incident is reported and the total number of rides that did not take place is returned as part of the simulation results for evaluation purposes.

### 4.3 Self-Organizing Behavior

In order to rebalance the availability of bike at the stations, as a possible addition to the truck-based redistribution efforts ventured by Capital Bikeshare, an incentive scheme for the users to stimulate them to redistribute bikes in a self-organizing fashion is proposed. The approach is based on the concept that whenever a user tries to rent a bike at an empty station, an alternative rental station with a sufficient amount of bikes is suggested to the user. Equivalent, whenever a user tries to return a bike at a full or critical occupied station, an alternative return station with a sufficient amount of free docks is suggested to the user. Thus, the distribution of bikes among the stations will be balanced in a self-organizing way, as users renting a bike are detoured from empty stations to, preferably full or critical occupied ones or at least non-empty ones. The same goes for the returning of bikes, where users are detoured from full or critical occupied stations to, preferably empty or at least non-full ones.

The approach strongly depends on the cooperativeness of the users to be detoured to an alternative rent or return station. Therefore, some sort of incentive scheme, that motivates the users to do so would raise their cooperativeness. The operator of a bike-sharing system realizing such a self-organized redistribution of bikes could, e.g. offer additional free minutes of usage. For the evaluation of the impact of the proposed self-organized redistribution strategy and the cooperativeness level of users, different cooperativeness values are used as simulation parameters and their results compared. Hereby, it is differentiated between the cooperativeness of a user to rent a bike at an alternative station and the cooperativeness to re-

turn it to an alternative suggested station. These are two independent values each ranging from 0%, meaning a user never follows such a suggestion to 100%, meaning the user always follows a suggestion.

A decentralized coordination approach is used in order to calculate the alternative rent and return stations that are suggested to the users. Therefore, each bike stations send its current occupancy rates to all other bike stations within a certain circular communication range every minute. The communication range determining which other bike stations are within reach is also a variable parameter of the simulation. Figure 6 shows an extract of the simulated map and displays how the communication ranges of different bike stations overlap. Bike stations receiving such status updates from other stations collect them and use them to calculate alternative rent and return stations in a decentralized way. Whenever such status updates are received, the receiving bike station determines the station with the lowest and the highest occupancy rate from the list of stations. The station with the lowest occupancy rate is selected as the alternative return station and the station with the highest occupancy rate is selected as the alternative rent station. These alternative stations are suggested to a user whenever it tries to rent a bike at the station when the station is currently empty, respectively when the user tries to return a bike at the station when it is currently full or critical occupied. So, the maximum detour distance equals the communication range of the stations, as only stations that are within a station's communication range are considered. The critical occupancy rate of stations is also a parameter of the simulation. For the simulated scenarios a critical occupancy rate of 75% is used.

## 4.4 Simulation Results

In order to evaluate the impact of the self-organizing redistribution strategy in correlation to the user cooperativeness a reference scenario without any self-organizing behavior was simulated. In this scenario and all of the following the cyclists moved with a fixed speed of 18km/h and all bike stations had a maximum number of 20 docks, whereof 10 were initially occupied.

The results of this reference scenario are shown in Figure 7. It shows the number of "normal" stations (neither empty nor full), the number of empty ones, the number of overflow stations (stations that are overcrowded) and the so-called "no bike" occurrences. These are the incidents when a cyclist could not rent a bike at an empty station and therefore, the trip could not be simulated. It is observable how the number of normal stations declines, while the number of empty and overflow ones rises with the morning rush-hour beginning at around 7 a.m. (minute 420). Over the day, these numbers fluctuate only a little with reoccurring no bike incidents (701 in total). In the late afternoon (around minute 1000) the number of normal stations recovers a bit, while both the number of empty and overflow stations also declines. This behavior can be explained by the rush-hour movements of commuters in the morning they drive from the suburbs to the city center and return in the afternoon. Stations in the suburbs tend to become empty during the morning rush-hour, while stations in the city center tend to become full or overcrowded. The returning commuters in the afternoon take bikes from the overcrowded stations in the city center and refill the empty ones in the suburbs when they return.

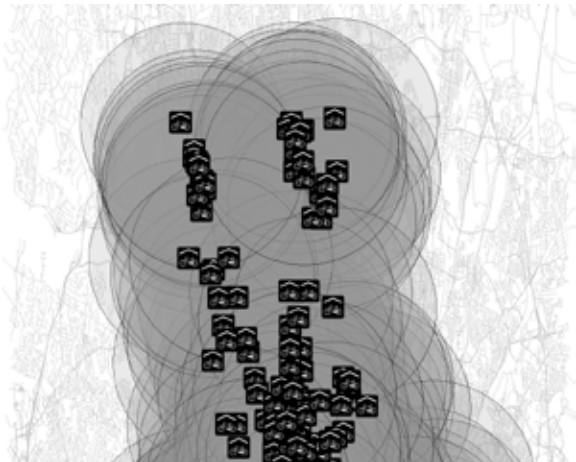


Figure 6 Extract of the simulated map showing the road model and some of the bike stations and their communication range

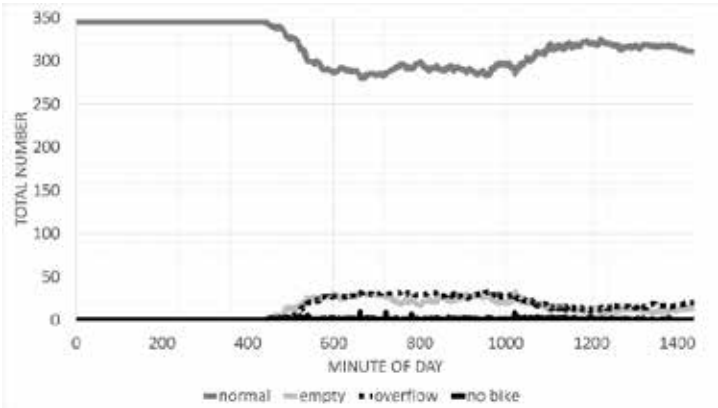


Figure 7 Results of the reference simulation scenario with no self-organizing behavior

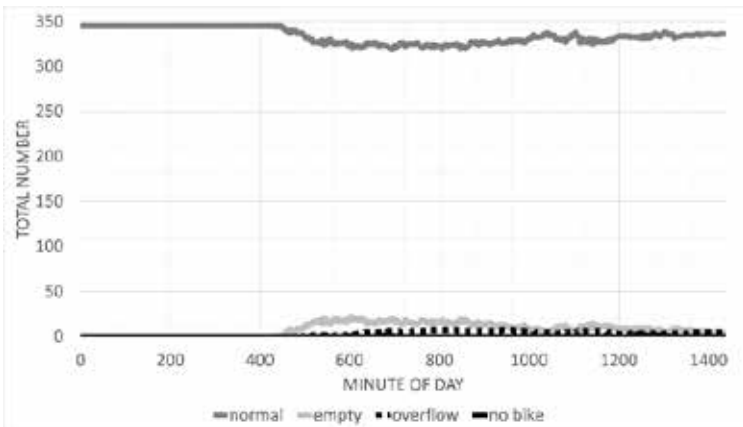


Figure 8 Results of the simulation scenario with 100% user cooperativeness (rental and return)

In order to measure the impact of the self-organizing redistribution strategy, a scenario with 100% user cooperativeness was simulated. In this case the users always follow a suggested detour to an alternative rental or return station. To simulate the reduced movement speed of the cyclist when they are detoured to an alternative rental station before they have picked-up a bike, their by-foot speed was reduced to 6 km/h. The communication range of the bike stations was limited to 1km, to narrow the possible detour distance for the cyclists. The results of this simulation scenario are shown in Figure 8. As in the simulation scenario with no self-organized redistribution of bikes, the number of normal stations declines with the beginning of the morning rush-hour, while the number of empty and overflow stations rises. However, due to the suggestion of alternative rental and return stations to the users and their cooperativeness to be detoured, noticeable

more stations stay in the normal state. In addition, the number of overcrowded stations is obviously reduced. The number of empty stations is also less in comparison to the reference scenario with no redistribution. Most significant is the reduction of the "no-bike" occurrences by 90.16% to 69 in total. The fact that these events still occur even with a 100% user cooperativeness to be detoured to an alternative rental station is based on the modeling decision that users only accept a suggested detour once. If they have already been detoured to an alternative rental or return station, they will not accept another detour. Thus, resulting in a no bike incident in case of a previous rental detour or the return of the bike at an already overcrowded station in case of a previous returned detour.

In order to evaluate the impact of the user cooperativeness in the proposed self-organizing redistribution strategy, a series of simulations with different cooperativeness parameters were performed. To measure and compare the impact of the users' cooperativeness to rent or return bikes at alternative stations two different cooperativeness parameters were introduced.

The rental cooperativeness describes the cooperativeness of a user to be detoured while trying to rent a bike and the return cooperativeness describes the user's cooperativeness to be detoured while trying to return it. The probed knowledge space contains independent cooperativeness value pairs ranging from 0% to 100% in 10% steps. The results of the first evaluation are shown in Figure 9. It contains the mean relative deviation of the number of normal stations in comparison to the previous described reference scenario with no self-organizing behavior. This value states how many more stations in average over the simulated day are in the normal state in comparison to the reference scenario (percentaged value). The results

show that the self-organizing redistribution strategy increases the number of normal stations about 9% at maximum. They also show that the return cooperatives has a higher influence on the overall improvement than the rental cooperativeness. This is because the cooperativeness of users to return bikes at an alternative station arranges an equal distribution of bikes at the stations, as the number of stations that are either full or tend to become full is reduced while empty stations are replenished at the same time. The reason is that the stations prefer empty stations while calculating alternative return stations.

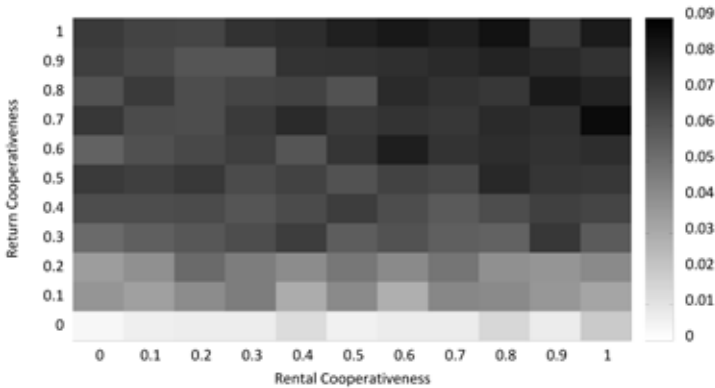


Figure 9 Mean relative deviation of the number of normal stations in comparison to the reference scenario with no self-organizing behavior

Besides the number of normal stations another important quality criteria is number of trips that could not be ventured, because of cyclists not being able to rent a bike at an empty stations. The so-called no bike occurrences. Figure 10 shows how the self-organizing redistribution strategy decreases the number of these incidents depending on the rental and return cooperativeness of the users. Again, the relative deviation to the reference scenario with no redistribution is taken as the quality characteristic. The results show that the number of no bike occurrences is reduced by slightly above 90% with total rental cooperativeness. Obviously the impact of the rental cooperativeness is much higher than the impact of the return cooperativeness, it directly influences the reduction of no-bike occurrences by detouring users in such an event.

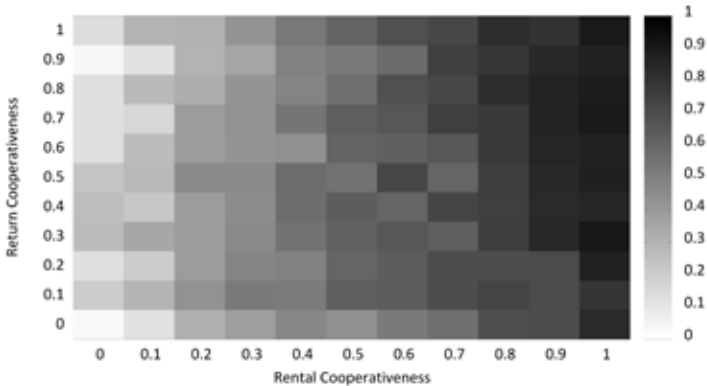


Figure 10 Relative decrease in the number of "no-bike" occurrences in comparison to the reference scenario with no self-organizing behavior.

## 5 Conclusion

The acceptance of bike-sharing systems depends heavily on the availability of bikes at the stations. In spite of truck-based redistribution efforts by the operators, stations still tend to become empty or full, especially in rush-hour situations. In this paper, we explored an incentive scheme that encourages users to approach nearby stations for renting or returning bikes to redistribute them in a self-organized fashion. Based on a microscopic simulation of a bike-sharing system based on data taken from Washington, D.C. (2014), we measured the impact of two independent cooperativeness parameters that determine the fraction of users that respond to an incentive to rent or return a bike at a suggested alternative station. Both results showed that in order to have a significant impact on the evaluated quality criteria a user cooperativeness, to rent or return bikes at suggested alternative stations, of above 50% is needed. This means, that operators of bike-sharing systems need to create significant incentives for the users to participate in the self-organizing redistribution of bikes, if they want to adopt this approach in order to extend their already established redistribution approaches. In this case, a cost analysis needs to be conducted in order to analyze if the increased costs caused by the incentives is worth the increased user satisfaction because of the increased reliability of the system. Such an analysis exceeds the scope of this paper, as it requires detailed information about the costs and gains of a bike-sharing system, which are not published openly by a bike-sharing system operators.

Based on a data-adaptive simulation approach, we showed how the proposed self-organized redistribution strategy increased the number of stations that are neither empty nor full and how the proposed strategy is able

to reduce the number of incidents where a user is not able to rent a bike at an empty station in dependence of the users' cooperativeness. The facilitated data-adaptive simulation approach is based on the concept, that the simulation results stored in a database represent the knowledge about the system behavior that is enriched on demand by the execution of further simulation scenarios, if no results are available for the requested set of simulation parameters.

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