Bicycle sharing system repositioning techniques simulated using agent-based modelling

Citation for published version:
Malan, PC & Searle, C 2022, Bicycle sharing system repositioning techniques simulated using agent-based modelling. in *Supply Chain Innovation: People, Process, Technology.* The Chartered Institute of Logistics and Transport, pp. 274-279, 27th Annual Logistics Research Network Conference 2022, Birmingham, United Kingdom, 7/09/22.

Published In:
Supply Chain Innovation: People, Process, Technology

BICYCLE SHARING SYSTEM REPOSITIONING TECHNIQUES SIMULATED USING AGENT-BASED MODELLING

***Philip Christian Malan*[1], *Christa Searle*[2,1*]**

[1] Stellenbosch Unit for Operations Research in Engineering, Department of Industrial Engineering, Stellenbosch University, Private Bag X1, Matieland 7602, South Africa, phillip.christian.malan@gmail.com, [2]Centre for Logistics and Sustainability, Edinburgh Business School, Heriot-Watt University, Edinburgh, EH14 4AS, UK, c.searle@hw.ac.uk*

** Corresponding author*

Introduction

Bicycle sharing systems (BSSs) are one of the most effective solutions for transport in urban areas. A modern BSS consists of three main components: Bicycles, docking stations and an accompanying information system (Shaheen, Guzman and Zhang 2010). Commuters are registered on the system which allows them to pick up a bicycle from any one of the docking stations throughout the city. The user may then return the bicycle to a station that is closest to their destination. Trips are typically short and one-way, and the system is operational at any time of the day. Customer satisfaction largely depends on the availability of bicycles at the origin station and an open slot at the destination station.

This level of availability is restricted by the imbalance of bicycles throughout the BSS, which is brought about by frequent and short one-way trips, a highly dynamic demand, and the tendency of commuters to travel to specific stations more frequently than others. During peak times in the morning, for example, people tend to travel from the outskirts of town to the city centre. As a result, bicycles tend to heap up in the city centre throughout the morning, while they are depleted at docking stations near residential areas (Labadi, et al. 2015). This may be combated by means of bicycle repositioning amongst the various docking stations.

The repositioning problem is a critical aspect for ensuring that BSSs remain efficient and financially viable. In this paper a BSS and different repositioning techniques are modelled in evaluating the effect of these techniques on the success of the system. An agent-based simulation model utilising input from a mathematical modelling technique is developed. Purely operator-based repositioning techniques are compared to the additional implementation of user-based repositioning techniques with the focus on minimising the cost of repositioning operations, as well as the number of dissatisfied users throughout the system.

In addition to this introductory section, the remainder of this paper encompasses a literature review on BSS repositioning techniques and existing repositioning models for BSSs. This is followed by a description of the development and validation of the proposed generic agent-based simulation model of a BSS. Furthermore, the model is applied to a case study, and the results of the case study are discussed. In conclusion, a discussion on the developed agent-based simulation model and its utility is provided.

Repositioning techniques in bicycle sharing systems

In the literature, different repositioning techniques have been studied in an attempt to find the most economic approach. These techniques can be divided into two main categories, namely operator-based and user-based (Caggiani and Ottomanelli 2013). Operator-based repositioning is an operational task, assigned to staff who use trucks or vans to move bicycles between stations. This could either be done at night when the system's use is negligible (known as static repositioning), or during the day if the system is prone to a highly dynamic demand (known as dynamic repositioning) (Raviv, Tzur and Forma 2013). User-based repositioning, on the other hand, is a strategy that incentivises users to reposition the bicycles themselves. Users are offered some form of incentive, such as a reduced price or a free trip, to return a bicycle to specific alternative stations, which are more favourable to the system (Singla, et al. 2015).

The literature on repositioning in BSS generally indicate two main objectives: Minimising the measure of dissatisfied users and minimising the operating costs. In a deterministic model for static repositioning, Raviv, Tzur and Forma (2013) aim to minimise the total cost of the system. This comprises the operating cost, as well as a penalty cost which is a measure of user dissatisfaction as a function of the expected number of shortages during the next working day. Similarly, a model by Caggiani and Ottomanelli (2013) aims to minimise the sum of repositioning cost and lost users cost, where the repositioning cost is assumed to be €0.30 per kilometre, while the cost per lost user is fixed to €0.70 per user.

For the static repositioning problem, Raviv, Tzur and Forma (2013) proposed a mixed integer linear programming model to schedule routing for multiple vehicles, assuming all vehicles start and finish at a depot. Ho and Szeto (2014), on the other hand, consider the case where only one vehicle is used for repositioning, and where that vehicle may only visit a station once. Each station is defined as either a pickup or a drop-off station, based on its optimal and actual fill level at the end of the day. Furthermore, a fixed amount of time is allotted to each repositioning action, and the aggregate of all actions may not exceed a given time limit.

In the case of the dynamic repositioning problem, Contardo, Morency and Rousseau (2019) developed a model that minimises customer loss during peak hours of a BSS. The model, however, does not consider the future demand of the system, and decisions are based solely on the requirements of the current time step. Shu, et al. (2013) additionally considered future expected demand in a dynamic repositioning model. This formulation, however, does not include vehicle routing, but only repositioning decisions (i.e., where to pick up and drop off bicycles). Ghosh (2017) proposed a model that dynamically generates both vehicle routing and repositioning decisions, based on the expected demand at each station at each time step. The model aims to minimise both the lost demand, and cost incurred by vehicles performing dynamic repositioning actions. In each repositioning action, the future expected demand is considered.

Finally, with respect to user-based repositioning, Fricker and Gast (2014) proposed two models: A one-choice and a two-choice model. In the one-choice model, a destination station is selected at random for a commuter. In the two-choice model, however, two stations are selected at random, and the user selects the station that is least full. Although this may be a simple form of user-based repositioning that considers only the fill level of two stations, the study shows that the performance of the system improved dramatically, even if as few as 20% of users obeyed the two-choice rule. Singla, et al. (2015) developed a pricing mechanism, with dynamic budgeted procurement using upper confidence bounds, to be used on a smartphone application to incentivise user-based redistribution. The implementation of this system resulted in a 60% acceptance of incentive offers and the best overall results were achieved when used in combination with operator-based repositioning. Pfrommer, et al. (2014) proposed an incentive scheme where a payment is periodically calculated and offered to a commuter to change their destination. The probability of accepting the incentive is based on the value a commuter places on the additional time spent travelling to the alternative station, as well as the payment offered.

Model development

An agent-based modelling approach is followed in developing a generic BSS simulation model. The bottom-up approach inherent to the agent-based modelling paradigm considers agents with a certain degree of autonomy, that are placed in an environment where they follow certain individual rules and maintain relationships (Macal and North 2014, O'Sullivan and Haklay 2000). An agent has the ability to process information as input and take action based on these inputs (Duggan 2007). This allows for the behavioural aspects within a system to be modelled. The key performance indicators captured in the model output include the repositioning cost and number of dissatisfied customers.

Modelling of a bicycle sharing system

The simulation model defines two primary agent classes, namely stations and commuters. The station agent class represents the multiple docking stations throughout the city with attributes pertaining to each station including the location and bicycle capacity of the station. During initialisation of a simulation run, the number of bicycles available per station are set according to a user-defined global fill level. Throughout the simulation, the station agents keep track of the number of bicycles and open slots available at any given time.

The commuter agent class models users within the BSS. The behaviour of a commuter agent is illustrated by the flowchart presented in Figure 1. Upon entering the system, a commuter arrives at their origin station of choice and checks if a bicycle is available. If there are no bicycles available, the commuter will, according to a user-specified probability, either walk to the nearest neighbouring station in search of a bicycle, or exit the system. In the case where a bicycle is available, the commuter will pick up a bicycle and commence their trip. Upon arrival at their destination station of choice, the commuter will search for an open slot. If an open slot is available, the commuter will dock the bicycle and exit the system. If this is not the case, the commuter will travel to the nearest neighbouring station in search of an open slot. Every instance where a commuter does not find an available bicycle or an open slot, the number of dissatisfied customers in the system increments by one.

The arrival rate of commuter agents, as well as the origin and destination stations associated with each trip are stochastically determined, based on empirical distributions. As the demand varies significantly throughout the day, each day is divided into 24 time segments and each of these segments has unique empirical distributions pertaining to the arrival rate and the selection of origin and destination stations. The arrival rate of commuter agents is determined for each time segment based on the average number of arrivals per time segment according to historical data. For each commuter agent, the selection of an origin station is stochastically determined based on the historical number of trips taken from each station in a given time segment. Finally, a Markov chain is constructed for each time segment based on historical data to describe the probability of travelling to any station, given a particular origin station. A destination station is therefore selected from the appropriate Markov chain once a commuter agent arrives at its origin station.

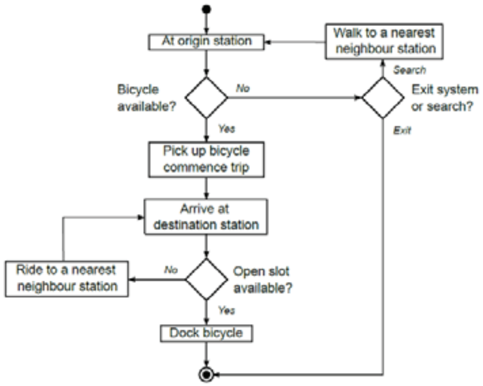

Figure 1: The commuter agent flowchart.

Modelling of repositioning techniques

The proposed BSS simulation model considers both operator-based and user-based repositioning. The model user is given the option to select between implementing static or dynamic operator-based repositioning. User-based repositioning may additionally be applied to the selected operator-based repositioning implemented. Repositioning strategies may vary significantly among different BSSs, and the implementation within the simulation is therefore a simplified algorithm that aims to represent the general performance of these repositioning techniques. It is important to note that the modelled algorithm may be adjusted based on the governing rules within a specific BSS. Another assumption made for the sake of simplicity is that the repositioning actions occur instantaneously.

There are two primary costs assigned to repositioning actions performed in the model, namely the cost of physically moving the bicycles (operator-based repositioning), as well as the cost of paying an incentive (user-based repositioning). A fixed cost is assigned per bicycle moved, regardless of the distance travelled by the operator. For modelling purposes, the repositioning of a bicycle is therefore equal to one unit cost. Furthermore, the cost of an accepted incentive is assumed to be a fixed cost of 0.5 unit cost, based on the research by Haider, et al. (2017) which suggested that the cost of an incentive is significantly lower than the cost of an operator-based repositioning action.

Static repositioning is scheduled to occur daily at a time when demand becomes negligible. For the modelling thereof, the fill levels of all stations are reset to the initial user-defined global fill level upon the initialisation of static repositioning during a simulation run. This ensures that the total number of bicycles in the system remains constant.

For the modelling dynamic repositioning, critical upper and lower fill levels are defined by the model user. Station agents may therefore change to a state of full or empty when its fill level is greater than the critical upper level or less than the critical lower level, respectively. Dynamic repositioning is achieved by repositioning bicycles from full to empty stations. The repositioning occurs periodically throughout the peak hours of the BSS's operations. The model user may determine the frequency of and time intervals between the repositioning actions based on the peak hours of the BSS.

The modelling of user-based repositioning is embedded in the behaviour of a commuter agent. Once a commuter agent selects a destination station, the system compares the fill levels of the destination station to that of its nearest neighbouring station. If the neighbouring station has a lower fill level, an incentive is offered to the commuter agent to select that station as their destination station. The commuter agent will, according to a set probability, accept or reject this incentive.

Calibration of parameters

Parameter variation was performed for the calibration of user-specified input parameters, such as the initial fill level of station agents, as well as the critical upper and lower levels at which dynamic repositioning occurs. As the fill level tends to 1, the model becomes invalid as there are no slots available for commuter agents to drop off bicycles and the agents are caught in an endless loop in search of an available slot. Furthermore, if the initial fill level is greater than the upper critical level, the model is invalid, as all stations will constantly be classified as full. Based on the parameter variation performed, it is recommended to fix the initial fill level to approximately 0.5, while setting the critical upper and lower levels to approximately 0.75 and 0.25, respectively.

A sensitivity analysis was performed on the relative cost of an incentive. It was found that the total cost of repositioning increases linearly as the relative cost of an incentive is increased. This increase may be exacerbated by a high incentive acceptance probability. Thus, if the relative cost of an incentive is overestimated, the model validity will not remain intact. As mentioned previously, the relative cost of an incentive is per default set to 0.5 unit cost. Finally, the probability that a commuter agent will exit the system if a bicycle isn't available is calibrated and set to a default value of 0.5.

Case study: Seattle bicycle sharing system

The proposed model is applied to a case study based on historical data of the Pronto Cycle Share BSS in Seattle, Washington (City of Seattle Open Data 2019). The data available contain the location and capacity of the 59 docking stations situated in the city, as well as information on the trips taken within the span of a year. The trip data include the origin and destination stations, as well as the start and end time of each trip. In evaluating different strategies for implementing repositioning techniques, the model output is analysed with respect to the cost and the number of dissatisfied customers.

For this analysis, simulation runs are executed to consider the implementation of each operator-based repositioning technique for the cases where no user-based repositioning are implemented, as well as where it is implemented. For the latter cases, a variation of the incentive acceptance probability is considered. An analysis of variance is performed to determine if there are statistically significant differences when comparing the output of various repositioning strategies. The model output for the different repositioning strategies is depicted in Figure 2.

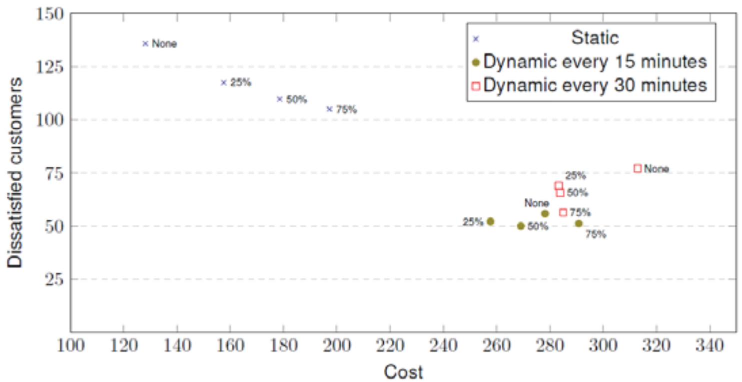

Figure 2: The resultant cost and dissatisfied customers of different repositioning strategies.

The implementation of static repositioning (with or without the addition of user-based repositioning) results in the lowest cost, although it results in the highest number of dissatisfied customers. This is true regardless of whether or not user-based repositioning is implemented. The additional implementation of user-based repositioning does, however, decrease the number of dissatisfied customers, although it results in a greater cost as more incentives are being paid. This increase in cost is statistically significant when comparing acceptance probabilities of 0.25, 0.5 and 0.75. The decrease in the number of dissatisfied customers, however, is only statistically significant when enabling an acceptance probability of 50% or higher. Thus, it should be carefully considered whether or not to implement user-based repositioning in conjunction with static repositioning at the Pronto Cycle Share BSS. This strategy may have an adverse effect (causing an increase in cost), without having a significant positive impact on the number of dissatisfied customers.

The implementation of dynamic repositioning every 15 minutes during peak hours results in a significantly larger daily cost when compared to the static operator-based repositioning, although it reduces the number of dissatisfied customers significantly. The additional implementation of user-based repositioning affects neither the cost, nor the number of dissatisfied customers statistically significantly.

When the frequency of dynamic repositioning is reduced to every 30 minutes during peak hours, both the cost and the number of dissatisfied customers increase, in comparison to dynamic repositioning every 15 minutes. The number of dissatisfied customers is, however, still less than when implementing static repositioning. The implementation of user-based repositioning in conjunction with dynamic repositioning every 30 minutes does not have a significant impact on the cost and the number of dissatisfied customers is only statistically influenced once the incentive acceptance probability is greater than 75%.

Thus, for the case where dynamic repositioning is implemented at the Pronto Cycle Share BSS, the use of user-based repositioning is not recommended. This course of action will most likely increase the complexity of operations, without having a positive influence on the primary goals, namely decreasing cost and number of dissatisfied customers.

The overall effect of the various repositioning strategies should be analysed with reference to constraints specific to the BSS under investigation. In this case, if the primary aim is to reduce cost, with a lesser focus on customer satisfaction, static repositioning is recommended as the operator-based repositioning technique. To additionally improve commuter flexibility, user-based repositioning may be introduced depending on the cost of an incentive.

If the primary focus of the Pronto Cycle Share BSS is to improve commuter flexibility, and therefore reducing the number of dissatisfied customers, the dynamic repositioning approach may be more effective. The implementation of repositioning every 15 minutes during peak hours is recommended. The additional implementation of user-based repositioning may have a further positive effect on commuter flexibility.

Conclusion

BSSs exist all over the world and the manner in which repositioning is executed varies from system to system. A generic agent-based simulation model of a BSS was developed for the modelling of repositioning techniques in evaluating the effect of various repositioning strategies on the performance of a BSS. The model was applied to the Pronto Cycle Share BSS in Seattle as a case study. Various operator-based repositioning techniques were implemented, including static repositioning, dynamic repositioning every 15 minutes and dynamic repositioning every 30 minutes. The effect of additionally implementing user-based repositioning in conjunction with each of these operator-based technique was assessed.

The model may be applied to different BSSs in which case the input parameters may be adjusted according to the real-world system under investigation. The model in its current form allows for a basic comparison between a set of simplified repositioning techniques which is limited by the set of assumptions. Future recommendations may involve the refinement of assumptions and the incorporation of weekly or seasonal trends, along with a more detailed investigation into the human behavioural aspect when considering incentives.

LOGISTICS RESEARCH NETWORK CONFERENCE 2022 I 7 – 9 SEPTEMBER I ASTON UNIVERSITY

References

- Caggiani, L, and M Ottomanelli. 2013. “A dynamic simulation based model for optimal fleet repositioning in bike-sharing systems.” Procedia: Social and behavioral sciences (87): pp. 203-210.
- City of Seattle Open Data. 2019. Seattle Pronto Cycle Share data. Available from https://www.kaggle.com/city-of-seattle/seattle-pronto-cycle-share-data.
- Contardo, C, C Morency, and LM Rousseau. 2019. Balancing a dynamic public bike-sharing system. Technical report CIRRELT, Montreal, Canada: University of Montreal.
- Duggan, J. 2007. “A simulator for continuous agent-based modelling.” Proceedings of the 25th International Conference of the Systems Dynamics Society. Boston (MA). pp. 1-16.
- Fricker, C, and N Gast. 2014. “Incentives and redistribution in homogeneous bike-sharing systems with stations of finite capacity.” EURO Journal on Transportation and Logistics 5 (3): pp. 261-291.
- Ghosh, S. 2017. “Dynamic repositioning to reduce lost demand in bike sharing systems.” Journal of Artificial Intelligence Research 58: pp. 387-430.
- Haider, Z, A Nikolaev, JE Kang, and C Kwon. 2017. “Inventory rebalancing through pricing in public bike sharing systems.” European Journal of Operational Research 270 (1): pp. 103-117.
- Ho, SC, and WY Szeto. 2014. “Solving a static repositioning problem in bike-sharing systems using iterated tabu search.” Transportation Research Part E 69: pp. 180-198.
- Labadi, K, T Benarbia, JP Barbot, S Hamaci, and A Omari. 2015. “Stochastic petri net modeling, simulation and analysis of public bicycle sharing systems.” IEEE Transactions on Automation Science and Engineering 12: pp. 1380-1395.
- Macal, C, and M North. 2014. “Introductory tutorial: Agent-based modeling and simulation.” Proceedings of the Winter Simulation Conference. Argonne (IL). pp. 6-20.
- O’Sullivan, D, and M Haklay. 2000. “Agent-based models and individualism: Is the world agent-based?” Environment and Planning 32 (8): pp. 1409-1425.
- Pfrommer, J, J Warrington, G Schildbach, and M Morari. 2014. “Dynamic vehicle redistribution and online price incentives in shared mobility systems.” IEEE Transactions on Intelligent Transportation Systems 15 (4): pp. 1567-1578.
- Raviv, T, M Tzur, and IA Forma. 2013. “Static repositioning in a bike-sharing system: Models and solution approaches.” EURO Journal on Transportation and Logistics 2 (3): pp. 159-167.
- Shaheen, S, S Guzman, and H Zhang. 2010. “Bikesharing in Europe, the Americas, and Asia.” Transportation Research Record: Journal of the Transportation Research Board 2143: pp. 159-167.
- Shu, J, MC Chou, Q Liu, CP Teo, and IL Wang. 2013. “Models for effective deployment and redistribution of bicycles within public bicycle-sharing systems.” Operations Research 61 (6): pp. 1346-1359.
- Singla, A, M Santoni, G Bartok, P Mukerji, M Meenen, and A Krause. 2015. “Incentivizing users for balancing bike sharing systems.” Proceedings of the 29th AAAI Conference on Artificial Intelligence. Austin (TX): Association for the Advancement of Artificial Intelligence. pp. 723-729.