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A simulation model for public bike-sharing systems

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Abstract

Urban areas are in need of efficient and sustainable mobility services. Public bicycle sharing systems stand out as a promising alternative and many cities have invested in their deployment. This has led to a continuous and fast implementation of these systems around the world, while at the same time, research works devoted to understand the system dynamics and deriving optimal designs are being developed. In spite of this, many promoting agencies have faced the impossibility of evaluating a system design in advance, increasing the uncertainty on its performance and the risks of failure. This paper describes the development of an agent-based simulation model to emulate a bike-sharing system. The goal is to obtain a tool to evaluate and compare different alternatives for the system design before their implementation. This tool will support the decision-making process in all the stages of implementation, from the strategical planning to the daily operation. The main behavioral patterns and schemes for all agents involved are designed and implemented into a Matlab programming code. The model is validated against real data compiled from the Barcelona's Bicing system showing good accuracy.

Keywords: bike-sharing; simulation; agent-based; object-oriented programming

1. Introduction to bike-sharing systems

Since the appearance of the first bike-sharing system in the sixties, the concept has evolved through three distinct generations. The first generation, known as White Bikes, was created in Amsterdam in 1965, and consisted of 50 bikes (painted white) spread around the city permanently unlocked, for the public to use them freely. However, due to the high number of thefts and damage to the bicycles, the system quickly failed after its launch (DeMaio, 2009). The idea

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was set aside, and it was not until the early 1990's that a second generation of public-bikes system was raised. The improvements included the design of docking stations where bikes could be locked (DeMaio, 2009; Shaheen and Guzman, 2011), and the request of small deposits to unlock bikes. This made this generation to be known as coin-deposit systems. In this context, the city of Copenhagen, under the name of Bycyklen, opened the first large-scale bike-sharing initiative in 1995, which is considered the pioneer of most current systems. Nonetheless and despite the improvements, users continue to remain under anonymity, so that thefts were still the main problem. It was not until the implementation of electronic membership cards, clearly identifying the user of the bike, that exposure to vandalism and theft was minimized. Thereby, the third generation of bike sharing systems (based on specially designed bikes, docking stations, and membership cards) finally succeeded and spread to many cities. By April 2013 there were around 535 operating schemes around the world, with an estimated fleet of 517,000 bicycles (Larsen, 2013). This number increased to 712 cities and 806,000 bikes by June 2014, and to 1,286 cities and approximately 3.5 millions of bikes in use by December 2017. Today, the introduction of electrical bikes and the development of free-floating systems (i.e. eliminating the need for stations) are the challenges towards a fourth generation of bike-sharing. Meanwhile, operational problems still represent main worries in the already implemented systems.

The system unbalance, caused by the randomness and asymmetry of demand (i.e. variable requests vs returns at different zones) is the main problem currently faced by operating agencies. Unbalance gives rise to undesired situations in which there are not available bicycles in a particular station while others are jam packed. This situation causes disturbances to users, who in some cases cannot use the system due to the lack of available bikes at the origin station, and in others have to return the bike far away from their intended destination station. In order to mitigate these situations, the need for repositioning operations is widely accepted, and most systems include a fleet of light trucks that artificially redistribute bicycles among stations.

The optimal solution of the unbalance problem does not only depend on the rebalancing strategy used (e.g. definition of tasks, routes and number of rebalancing trucks), but also on the strategical design of the bike-sharing system (i.e. fleet size, station density). Note that while the unbalance problem will tend to grow with the number of stations, it can be alleviated by over-dimensioning the bicycle fleet. Different interrelated trade-offs could be defined [Soriguera and Jiménez, 2018], meaning that an integrated approach including the strategical and operational levels is needed. Specific solutions could vary, depending on the demand patterns and shape of the service region. Nevertheless, many preliminary studies tend only to give general recommendations based on previous experiences and trial and error. This can lead to unexpected systems' performance which could eventually imply the failure of the system.

The ability of simulating bike-sharing systems' design and operation in advance would warn and prevent against such failures. To this end, the present paper proposes the development of an agent-based simulator in order replicate the performance of bike-sharing systems. This involves stablishing a series of assumptions and methodologies which can successfully emulate the real behavior.

The structure of the remainder of the paper is as follows. Next, Section 2 presents all the inputs, assumptions and behavioral rules that are considered in order to replicate the real performance of bike-sharing systems. In Section 3 the Barcelona case study is analyzed and a summary of the obtained results is presented. Finally, the paper ends with some conclusions, acknowledgements and a reference list.

2. Simulating a bike-sharing system

The first step in the construction of an agent-based simulator is the definition of the involved agents and their interactions. Four types or agents are considered here: stations, bikes, users, and repositioning trucks. Docking stations and bikes are passive agents, and their amount and location are inputs to the simulation. This means that the simulation should rely on a higher-level model in order to establish the optimality in these inputs. Users and repositioning trucks are the active agents who take decisions, which result in a flow of bikes between stations.

Behavioral rules must be stablished for the active agents. On the one hand, users will pick-up available bikes as near as possible to their origin, and they will leave them as near as possible to their desired destination. On the other hand, the repositioning teams will basically pick-up bikes in stations where they accumulate and will move them to stations where they are missing. The objective of repositioning operations is to maximize the availability of both, bicycles and free docking spots, at all times and with minimum costs. Next subsections present the assumptions made to model as realistically as possible these agents' behavioral rules and their interactions.

2.1. Stochastic demand generation and user dynamics

Mobility is a derived demand in order to satisfy the need for travelling between an origin and a destination. Demand for the bike-sharing system is considered as an external input to the simulator. In this context, demand is specified by generating users at a given rate (i.e. the demand level) with their pre-defined O-D relationships. Users are randomly generated in the different zones of the service region according to a Poisson distribution [(Vogel, 2014)] with mean equal to the average trip generation rate in the zone for the current time step. Service zones are defined as the influence area of stations, whose location is an input to the simulator. Their influence area is determined through the construction of Voronoi polygons (also known as Thiessen polygons or Dirichlet tessellation; this is a partitioning of the service region into influence zones based on the minimum distance to a particular station). Origins' locations are uniformly distributed across the zone. Users are generated with two additional attributes. First, their trip destination zone according to the O/D inputs. The final destination location is uniformly distributed inside the influence area of the destination station. Second, the availability of a mobile app letting the user know the stations' occupancy in real time. This is drawn from a Bernoulli trial, where the probability of success is a given input. The app availability allows the user walking not to the closest station but to the closest station with available bikes.

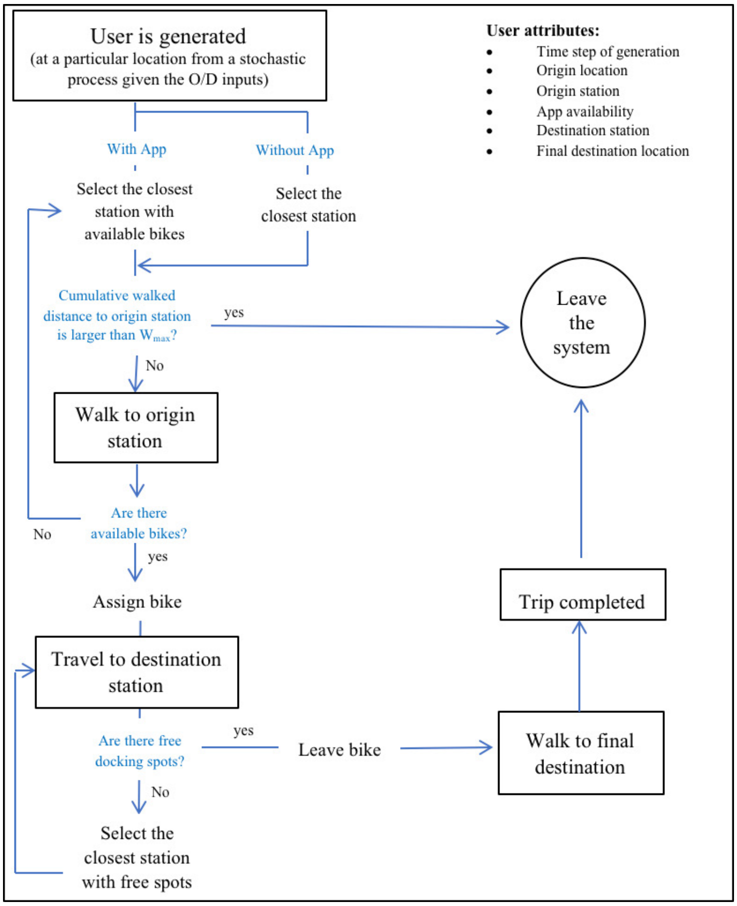

Fig. 1. Users' behavioral rules flow chart.

According to the previous stochastic demand generation procedure, the user's behavior will be as follows (see Fig. 1). From the origin location the user walks to the origin station and looks for available bikes. If there is at least one, he will pick it up. If the station is empty, he will need to walk to another station and repeat the operation until finding one available bike. It is assumed that at empty stations there is a display panel with real time information about the closest station with available bikes. A total maximum walking distance, W_{max}, is considered, so that if the walking distance is larger than this value, the user gives up and leaves the system without completing the trip. The user will ride to the closest station to his destination, and the process for returning the bike is similar to the picking-up. If there is an available slot, the user returns the bike and completes the trip by walking to the final destination. If there are no free slots, the user must ride to the next station with available slots and repeat the process until finding a station where to return the bike. In this case, users cannot leave the system without returning the bike.

2.2. Rebalancing dynamics

The distribution of trips over the service region is rarely uniform. Actually, asymmetric demands (i.e. requests vs returns) are the main problem regarding the availability of bike-sharing systems, as it turns into excess of accumulation or lack of bicycles at some stations, leading to the collapse of the system. The unbalance phenomenon is mainly due to two reasons: the users' aversion to uphill trips, which will depend on the topography of the city, – and the existence of centrality areas with unbalanced trip generation/attraction rates (i.e. downtown, office areas, central business district, etc.).

As a response to asymmetric demands and in order to alleviate its harming effects by improving system availability, repositioning strategies are widely established. Rebalancing systems consist on truck fleets and operators aiming to relocate bikes from full to empty stations. The objective of the rebalancing algorithms is to rebalance the system with the available repositioning teams and with minimum time. Periodic and continuous rebalancing strategies are implemented in the simulator. On the one hand, periodic rebalancing implies returning the bicycles to their initial balanced distribution after some period of time, typically every 24 hours. This balanced distribution is a tactical decision variable subject to optimization and should be defined so that it minimizes the no-service probability in the system. Typically, periodic rebalancing takes place when the system has a low demand or it is closed. On the other hand, continuous rebalancing takes involves the relocation of bicycles while the system is in operation. This aims to solve particular no-service situations that may arise during peak demand periods.

2.3. Battery constraints for e-bikes

The simulator includes the possibility of considering an electric bike fleet. In this operating mode, the battery level will be included as an additional attribute of bikes. This battery level will be consumed when the bike is in use and will be recharged when it is idle in a station. The battery level represents an additional requirement to users and modifies their dynamics. Users will always pick-up the available bike with the highest battery level. In addition, bicycles with very low battery levels will be considered as unavailable. All the other previous assumptions and dynamics will remain unchanged. Note however that the inclusion of electrical bikes in a bike-sharing system would probably imply a change on demand patterns. Electric bikes would allow users making longer trips with a lower aversion for travelling uphill, on average. These could be included in the simulator as demand is treated as an external input. So, in order to make relevant comparisons between traditional and electric systems, it would be advisable to perform a demand analysis beforehand.

3. Case study: Barcelona´s Bicing

A 24-hour simulation is run with the inputs of a real case study. Bicing, the Barcelona's bike-sharing system, is selected as a benchmark. The open data policy of the Barcelona council, including Bicing's data, was decisive in such selection. The Bicing open data portal includes the real time occupancy of every station with a one minute update frequency. These data allow assessing some aspects of the performance of the simulator. For others, comparable data is not available and results will be qualitatively discussed.

Demand was generated according to the proposed stochastic process (see Section 2.1), using the requests and returns rates of all Bicing stations every minute. This dataset was collected on May 7th, 2014. The rest of inputs, obtained from different sources (see Soriguera and Jiménez, 2018), are summarized in Table 1.

Table 1. Summary of simulation inputs

Parameter description	Units	Value
Simulation Parameters		
Total simulation time	[min]	1440
Simulation time step	[min]	1
Demand updating period	[min]	1
Bike Parameters		
Total fleet of bikes	[bikes]	4479
Average riding speed	[km/h]	15
E-bike mode	-	0 - Traditional bikes 1 - Electric bikes
E-bike complete battery charging time	[min]	120
E-bike battery autonomy under regular use	[min]	200
Service Region Parameters		
Service region boundary (UTM coordinates)	[m]	
Stations' location coordinates (UTM)	[m]	
Stations' capacity	[slots]	Total of 10246
System balanced configuration	[bikes/station]	
Repositioning trucks depot location coordinates (UTM)	[m]	
Users/Demand Parameters		
Origin-Destination matrix	[trips/min]	
Stations' demand generation rate	[trips/min]	
Stations' demand attraction rate	[trips/min]	
Walking speed	[km/h]	3.6
Maximum distance that users are willing to walk (*Wmax*)	[m]	750
Time to pick-up/return a bike in a station	[min]	1
App availability:	-	0 -No app 1 - Available app
Percentage of users with app	-	100%
Repositioning Parameters		
Repositioning truck speed	[km/h]	21
Repositioning truck capacity	[bikes]	32
Time to load/unload bikes from the truck	[min/bike]	0.625
Number of trucks on periodic rebalancing	[vehicles]	13
Periodic rebalancing period	[hours]	24
Number of trucks on periodic rebalancing	[vehicles]	13

Note: Parameters without a specific value in Table 1 imply that multiple values are required (e.g. one per station). Fig. 2 provides some additional information about the values of these parameters.

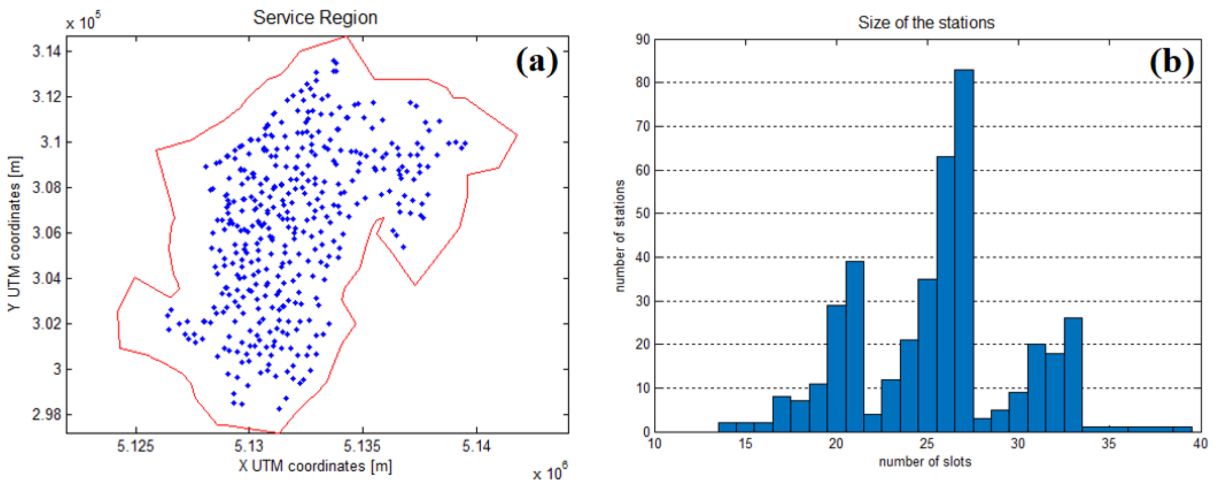

Fig. 2. Bicing system simulated layout. (a) Service region and stations' location; (b) histogram of stations' size.

3.1. System's accessibility in the simulation

One relevant aspect to evaluate on every transportation system is the level of service offered. It describes how well the system addresses users' needs, and it could be an imposed policy goal to be met by the operating agency. In particular, on bike-sharing systems the level of service offered depends on their accessibility. This is measured by two different variables: the access time (or distance), and the percentage of users that cannot access the system because of empty / full stations. Both variables are directly related to the user and partly happen outside the system, meaning that they cannot be assessed from the system's operative data. It is in these situations when the simulator appears as a useful assessment tool.

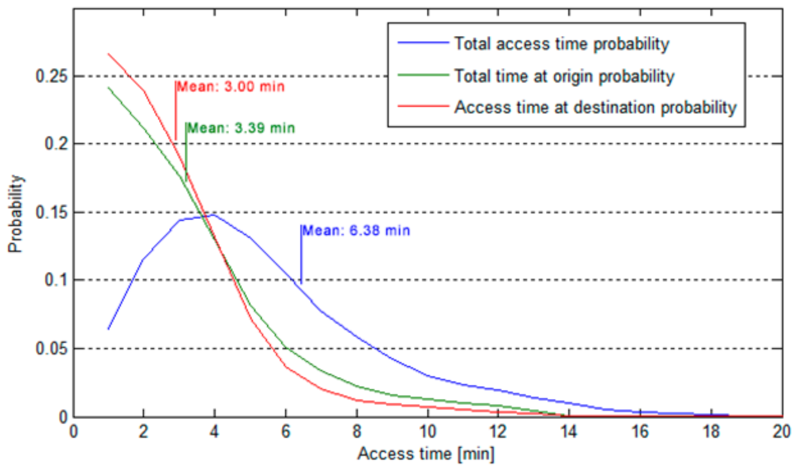

Fig. 3. Normalized access time histogram resulting from the simulation.

The access time is defined as the time users spend walking to the nearest station (at origin), and from the return station to their final destination. The access time is determined by the station density, and it increases when users have problems to find an available bicycle at the origin, or conversely, when the destination station is full. Figure 3 presents the histogram of access times resulting from the simulation. It shows a mean of 3.39 min. for the access time at the origin and 3 min. at the destination. This small difference is due to the fact that on average users find more frequently empty stations than full ones (Figure 4), because rebalancing algorithms give priority in serving full stations, as they are more penalizing for the user (i.e. not knowing where to return the bike). Because the access distance is limited by W_{max} = 750 m, the difference will remain small. Users will leave the system before walking excessively. In the present simulation an average of 2406 users left the system due to lack of bikes at origin, which represent 4.3% of the total demand.

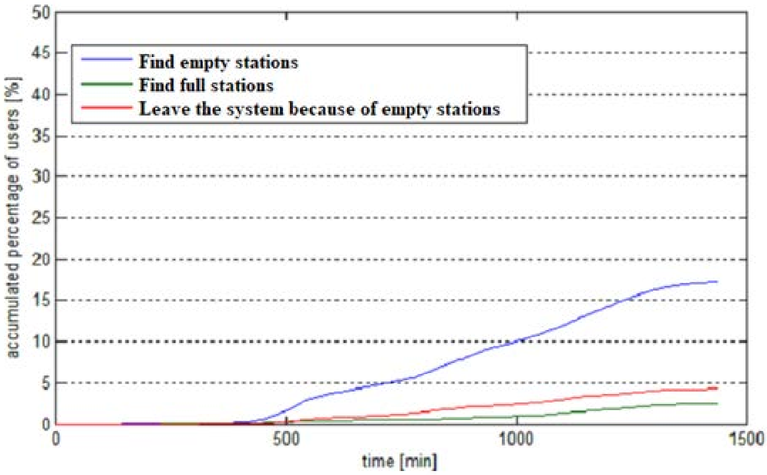

Fig. 4. Accumulated percentage of users that find an empty or full station.

At the destination there is no option to abandon the system, and users must always find a station for returning the bike. This situation is most penalizing as it can imply users riding far away from their destination (or even backtracking) in order to find a station with free slots. This problem could be solved if users had the possibility of reserving in advance a docking position at the desired destination. In such case, the access distance at destination would be reduced but the number of users leaving the system at the origin would increase. Thus, when optimizing the system, both, the access distance and the no-service probabilities should be considered in the accessibility definition.

3.2. Repositioning operations in the simulation

First, it is interesting to simulate the system performance without any kind of artificial rebalancing. Results show how the system rapidly collapses. In less than 12 hours of operation, more than 60% of stations are completely full or empty. This gives an idea of the importance of repositioning operations in bike-sharing systems.

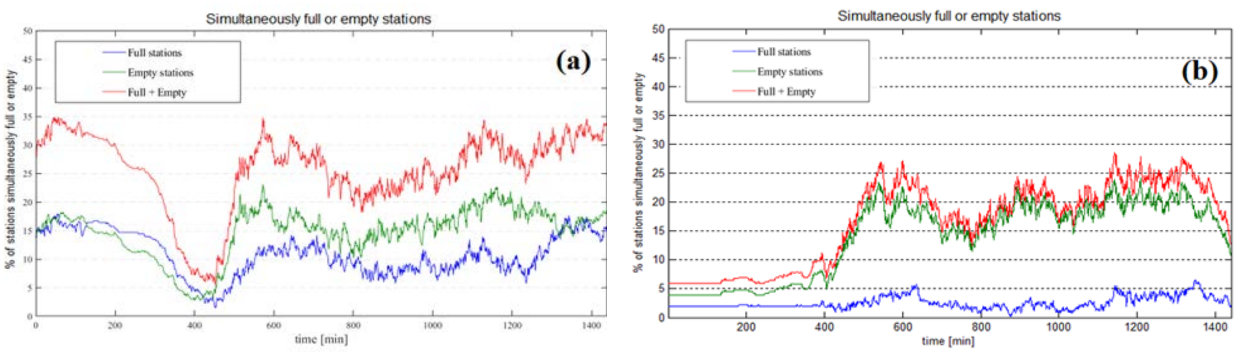

Fig. 5. Comparison of simultaneously full and empty stations on the real system (a) and the simulator (b).

Figure 5 shows the percentage of full and empty stations at a given instant, both, from real data and resulting from the simulation. According to Bicing data, the simultaneous percentage of full and empty stations reaches peaks of 30-35%. In the simulation this percentage is 27% at most. The main difference resides in the percentage of full stations. In the current performance of the Bicing system full stations represent between 5-15% of all the stations during the operation period, while in simulation they are less than 5%. This means that the repositioning algorithm implemented in the simulation outperforms the real system, as it is able to keep the system better balanced with the same resources. Note that the actual Bicing's repositioning algorithm is unknown to the authors. In this context, the objective of the simulation is not to replicate Bicing results but to implement an efficient rebalancing system.

The simulation results regarding system's accessibility and repositioning have been presented as an example of the usefulness of the simulator to assess the performance of bike-sharing systems before implementation or, for those in operation, to analyze some aspects which are especially difficult to measure. Other results could be analyzed from the simulation, like the performance of different repositioning algorithms or the additional restrictions if using e-bikes. Furthermore, the simulator could also be used as an optimization tool in the planning stage of bike-sharing systems.

4. Conclusions and further research

One of the main problems on the current bike-sharing systems is the difficulty to assess designs in advance, especially when there is an interest in innovation, optimization or the system includes some particularity that makes it difficult to compare to any other system in operation. This paper develops a fully functional open-source simulator for bike-sharing systems, which is able to reproduce current systems given a series of basic, easy obtainable inputs. The simulator is programmed in Matlab and built in blocks, allowing the introduction of new subroutines or the modification of the existing ones, only by performing "external" changes. This is an important feature, as it offers the possibility to easily apply further improvements in the simulator. For example, to test different repositioning dynamics, which probably are the most fundamental operational tasks in vehicle-sharing systems, or to modify user behavioral rules (e.g. wait for a bike/slot at an empty/full station before deciding to move to another station). Another modification could include the definition of a free-floating system (i.e. station-less). The simulator is in continuous development and many improvements are foreseen, such as the building of a user interface or the definition of a user-friendly data and graphical output. Also, the efficiency of the code can also be addressed. In conclusion, the simulator is intended to be an attractive tool for any researcher or practitioner in this field.

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