Improving Sustainable Mobility with a Variable Incentive Model for Bike-Sharing Systems Based on Agent-Based Social Simulation

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Abstract. Bike-sharing systems (BSS) have been implemented in numerous cities around the world to reduce the traffic generated by motorized vehicles, due to the benefits they bring to the city, such as reducing congestion or decreasing pollution generation. Caused by their impact on urban mobility, the research community has increased their interest in their study, trying to understand user behavior and improving the user experience. This paper has the goal of analyzing the impact of different policies of incentives on the user experience and their impact on the BSS service. An agent-based simulation model has been developed using data collected from the BSS service of Madrid, so-called BiciMad. Route generation has been calculated based o n OpenStreetMaps. The system has been evaluated, analyzing the results generated on different incentive policies. The main conclusion is that variable incentives outperform the current incentive policy of the service. Finally, a sensitivity analysis is presented to validate the proper variability of results for the model parameters.

Keywords: Bike sharing systems · Incentives · Agent based social simulation

1 Introduction

According to a recent study of the United Nations [20], 55% of the world's population was concentrated in urban areas in 2018. This proportion is expected to increase to 68% by 2050. One of the consequences is increasing congestion in the urban areas that brings other problems such as the increase in air pollution. Since today 64% of all travels are made within urban environments [27], urban mobility demand has exploded, and its improvement has become a global challenge.

The future of urban mobility is foreseen as a transition to integrated mobility [2] that integrates efficiently different types of transport, including new forms

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of mobility. Specific attention should be paid to sustainable mobility projects whose objective is to reduce pollution in urban areas [21]. Many fast-moving trends are shaping the future of urban mobility, such as autonomous driving, vehicle electrification, shared mobility, decentralization of energy systems, and smart public transit systems [2].

New shared mobility options (i.e., bike-sharing, car-sharing, and ride-sourcing) complement public transport and are growing in significance [9].

In this article, we pay attention to bike-sharing systems. Numerous companies are supporting their use through the creation of Bike-sharing systems (BSS) [17,29]. Bike-sharing technology has evolved for decades exponentially. As a matter of fact, according to the Bike-sharing World Map [16], in February 2018, there were more than 1500 active BSS all over the globe. However, according to data provided in the European bicycle market research by Confederation of the European Bicycle Industry [5], the adoption of the bicycle is different depending on the country. European countries such as Germany, France, and Great Britain account for more than half of total sales in Europe being the three countries with the highest numbers.

On the other hand, other countries such as Spain, Poland, and Italy barely manage aggregate 20% as a whole. Comparing the first set of countries with the second one, the big difference in the level of sales (+150%) contrasts with the population differences (+50%). One of the main challenges that BSS must face is the demand management, to avoid situations where there is a lack of bicycles for rent or docks to park them and thus causing a deficit of service availability. For this reason, the existence of policies to reduce inequality in the occupation of stations provides benefits to both users and BSS providers [6].

This paper aims at analyzing the bike-sharing service of the city of Madrid, Spain, so-called BiciMad, managed by the Municipal Transport Company of Madrid, *Empresa Municipal de Transportes* (EMT). In particular, we are interested in analyzing alternative incentive models to the models already in use in the city. For this, we have used the data available of this service to develop a realistic simulation model based on multiagent simulation. Then, the variable incentive policy is included in the model. The remainder of this article is structured as follows. Section 2 presents the related works. Section 3 describes the BSS of Madrid, which is used for evaluating our proposal. Section 4 introduces the proposed model, the policies implemented, and the external modules used. Section 5 studies the evaluation of the results obtained. Finally, Sect. 6 closes with a conclusion and outlook.

2 State of the Art

Following systematic review methods [19,23], several questions have been formulated to review the state of the art. Particular emphasis has been put to analyze research papers where the bike-sharing systems have a similar context to our case study.

These questions are the following: (Q1) Does the work deal with bicycle traffic?; (Q2) Does it study a bicycle renting service case?; (Q3) Does it involve

Table 1. State of the art papers. Check mark: yes, empty space: No

Ref			[13]	[14]	[4]	[24]	[15]	[11]	[12]	[28]	[10]	[25]	[22]	[26]	[8]	[7]
	Target	Q1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
		Q2	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓
		Q3					✓	✓			✓	✓	✓	✓	✓	✓
		Q4	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓
	Method	Q5					✓	✓	✓	✓	✓					
		Q6							✓	✓	✓			✓	✓	
		Q7	✓						✓		✓					
		Q8										✓	✓			

a Spanish city?; (Q4) Is real data employed in the study?; (Q5) Does it include a visualization of the traffic simulated?; (Q6) Is there an agent-based social simulation?; (Q7) Does it contrast different policy results?; and (Q8) Does it implement a system of variable incentives? They can be classified into two types: type of target (Q1–Q4) and method used (Q5–Q8). The summary of the selected papers is shown in Table 1.

Several studies use machine learning techniques for predicting bike demand for rebalancing purposes in New York [4,13,14,24], Washington DC stations [24] and Barcelona [11]. The principal used variables are time, speed, traffic as well as meteorological data (e.g., temperature, humidity, and visibility). One of the most used techniques is the applications of clustering methods for stations [4,13] for predicting the over-demand of each cluster.

Agent-based modeling is another popular technique for studying BSSs [3]. These techniques propose bottom-up modeling of the individual behaviour of bikes and stations as well as their interactions. Model realism is frequently validated with real data, as discussed for many cities such as Sydney [12], Salamanca [15], Madrid [10], or Barcelona [26], to name a few. The analysis of traffic flows can help to understand the bike-riders' preferences (e.g., shorter routes [12]) or the impact of factors such as peripheral areas on city traffic [28]. Besides, multiagent models provide the capability to experiment with different policies, such as passive occupation balance [10] and analyze their effects.

Other modeling factors are user satisfaction with the service [22] or their willingness to accept incentives if they contribute to rebalancing the system [25].

Also, machine learning techniques and agent-based mode ling are frequently combined by integrating the predicting capabilities of a machine learning module into a multiagent simulation model. Some examples are the integration of a probabilistic prediction module of station loads [8] using synthetic data or a neural network forecasting model the number of empty parking slots based on a dataset of the city of Valencia [7].

In summary, social behavior around BSSs has been widely studied. However, there are gaps in the possibilities of modifying it. In particular, with variable incentive policies, there are still a large number of variables to be studied in order to optimize results.

3 Case Study

As previously introduced, this work is focused on the study of the BSS of the city of Madrid, Spain, so-called BiciMAD, which is operated by EMT. This service was inaugurated in the summer of 2014 with the novelty of the utilization of electric bicycles. In 2015, the number of stations and bicycles was expanded, reaching the current number of 171 stations and 2028 bicycles. These stations are distributed throughout the city of Madrid in an area of approximately 5×5 km^2.

Table 2. Description of the variables selected from BiciMAD Open Data plaftorm.

Variable	Description
idplug_station	Destination station identifier
idunplug_station	Origin station identifier
travel_time	Trip duration
unplug_hourTime	Time when the bike was rented
user_type	Type of user (subscriber, casual, EMT employee)

(a) Routes Dataset

Variable	Description
id	Station integer identifier
date	Date of recording
name	Station name including address
total_bases	Number of docks at the station
free_bases	Available docks without bikes
dock_bikes	Available docks with bikes
latitude	latitude
longitude	longitude

(b) Stations Dataset

Open data are provided by EMT[1] information about usage by users and hourly records of the state of the stations. This open data service provides two main kinds of data: the trips made during every month, and the situation (i.e., load/occupancy) of the stations with a one-hour time gap. For modeling purposes, data from August to November 2018 have been used. The selected variables for our work are shown in Table 2 and properly subdivided per dataset.

Regarding the trip routes, the variables selected are shown in Table 2a. The most relevant fields for the study we have carried out are the *ids* of origin and destination stations, which show us the route followed by users on every trip. It is also important to track information about the time at which the bicycle was rented. However, due to user privacy terms, only hours are tracked, without providing the minute details. Thus, we will assume an even distribution of trips during that hour. Besides, the duration of the trip is preserved to enable its comparison with the simulation results. Lastly, we keep the variable *user_type*, which indicates the type of user who has made the trip (subscriber, casual, or EMT employee), since these records contain the balancing measures carried out by EMT employees. The trips not belonging to public users are discarded.

[1] BiciMAD Open Data: http://opendata.emtmadrid.es/Datos-estaticos/Datos-generales-(1).

Regarding the station status, selected variables are shown in Table 2b. Most relevant variables have been identified, and the rest have been filtered. In particular, we use *ids* and *station names* to identify stations and be able to link them with the routes dataset. Also, the *date* variable provides the temporal context. The most relevant variables are *the total bases*, which, along with the information of the bases that are occupied (*dock_bikes*) and the empty ones (*free_bases*), indicate the *base occupation*. Moreover, lastly, the *station position* represented by its *longitude* and *latitude* variables.

A preliminary analysis of the BSS use has been carried out for understanding better the behavior of the system and its users. For this purpose, we have considered the hourly and weekly distribution of trips according to the type of user. The data collected for this study contain information about more than 1.5 million trips made during these four months (August-November 2018), which are distributed according to the user type. The distribution of trips throughout the week can be characterized as follows. For subscribed users, we found a high usage on Monday and Tuesday, which decreases the following two days. The days corresponding to the weekend (Friday, Saturday, and Sunday) show a higher amount of use. As for the EMT employees, we observe a practically homogeneous use throughout the week.

The purpose of the simulation model is to study the effect of implementing a policy of variable incentives for BiciMad, the BSS of Madrid. To do this, we have followed the following methodology based on the methodology described in [23]. The first task has been a *data analysis* of BSS data. Apart from the exploratory analysis previously presented, decision matrices have been created to calculate the points of origin and destination of users. Then, the next phase has been *model construction*. Different agent types have been identified (bike, station, and truck), and their behavior has been specified and implemented, as detailed in Sect. 4.1. The next phase has been *model validation*, where the realism of the model is validated with the real data, as detailed in Sect. 5, which is described in an independent section for the sake of clarity. Once the model is validated, the next phase has been *policy experimentation*. Taking as a baseline the policy used in BiciMad, we have implemented other strategies to see their effects as detailed below.

The data offered by EMT during August and November 2018 have been analyzed to estimate the real behavior of the users. Two logs are provided: trip records and the logs of the station status every hour After filtering the data as described in this section, the resulting dataset includes information about the origin station, destination, time spent in the trip, type of user, and date. Besides, the study has filtered weekends and ha s been focused on the workweek.

4 Model Description

Two probability matrices have been created. These matrices will be used by the agents when deciding their origin and destination stations. In order to achieve a more realistic behavior of the actions of the users, the probabilities will be

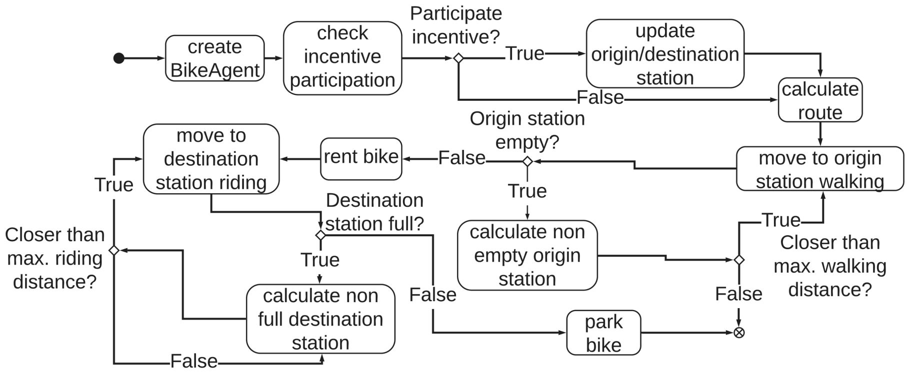


Fig. 1. UML activity diagram for BikeAgent.

calculated based on the time of the system. In this way, it is possible to simulate the use changes according to the time of day.

The first matrix O is the origin station probability matrix. The matrix element $\boldsymbol{O_{hi}}$ represents the probability that a user takes a bicycle from the station i at hour h. This probability has been calculated, as shown in Eq. 1, where $\boldsymbol{N_{hi}}$ is the number of routes whose origin is the station i at hour h, and $\boldsymbol{N_h}$ is the total number of routes at hour h.

$$O_{hi} = N_{hi}/N_{ht} \tag{1}$$

The second matrix is the destination station probability matrix, which has three dimensions. The matrix element $\boldsymbol{D_{hij}}$ represents the probability that a user takes a bicycle from the origin station i to the destination station j at hour h. This probability has been calculated as shown in Eq. 2, where $\boldsymbol{N_{hi}}$ is the number of routes whose origin is the station i and the destination is the station j at hour h and $\boldsymbol{N_h}$ is the total number of routes whose origin is the station i at hour h.

$$D_{hij} = N_{hij}/N_{hi} \tag{2}$$

The number of available bicycles and bases is calculated as the average of the actual records. This value is set at the beginning of the simulation. As the simulation starts at 0 o'clock, this will be the hour used to calculate the average.

4.1 Agents Description

Three types of agents have been identified: BikeAgent, StationAgent, and TruckAgent, which are described below.

The **BikeAgent** is the principal agent of the system. It represents each user of the system that makes use of the BSS service. Its variables contain information about its status, whether the agent is currently on the move, has rented or parked the bike, position, and the route to be carried out. Given that we know the position and speed of the agents, we have implemented a simple short-term prediction of the station's load: the station registers Bike Agents that are less than 10 min away from their destination station, including if their intention. (i.e., renting or parking a bike).

The behavior of the agent is described in the diagram shown in Fig. 1. When a BikeAgent starts, the system assigns the values of origin and destination stations based on the decision matrices. The incentives are calculated at the moment the agent is created, so that the BikeAgent's routes should not be changed during the trip. Then, the agent decides whether to participate in the incentive program, depending on the extra distance to be covered and the incentive offered. We have used the data obtained in the survey carried out by Singla et al. [25] are used. In this survey, an approximation of the participation probability evolution is made, based on the incentive offered and the extra distance. The economic reward offered depends on the scenario. If the agent participates, origin, and destination stations are updated accordingly.

The next step is calculating the route based on a GIS system. Once the route has been calculated, the agent walks to the initial station. When it has arrived, a bike is rented if available. Otherwise, a new origin station is calculated, and the agent walks towards it. This is repeated until the BikeAgent can rent a bike. Once it rents a bike, it rides to the destination station. Finally, it parks the bike at the destination station if it has available bases. If not, it looks for a station with an available base within the area covered by its maximum riding distance and heads for it. If not found, the agent simply waits until the next step. As in the real case, the agent gets the discount associated with the incentive if it rents/parks the bicycle at a station with a lack of bicycles/bases, respectively.

The **StationAgent** acts like a bicycle container. It is also responsible for updating its status. In particular, it should keep updated the load of the station. This load variable will enable the identification of stations needing a balancing action. Based on Ban et al. [1], their value is low if the capacity is less than 30% of the maximum station capacity; high if it exceeds 70% of the maximum capacity; and normal between 30% and 70%. The model has made a simplification, not taking into account the charging time of electric bikes. Therefore the parked bikes are available for rental by another user instantly.

TruckAgent. They are the agents that represent the rental company workers who travel throughout the city, relocating the bicycles between stations. Their primary mission is balancing the station load so that fewer stations are out of service because of a lack of bikes or docks. As far as the truck policy is concerned, there is no precise information on actual usage. It is therefore assumed that the deployed fleet is similar to the hourly distribution of journeys made by company employees. The choice of the station is based on both the distance and the number of bikes or free bases. Due to the nature of the study, the trucks' behavior remains unchanged in every scenario.

4.2 Scenarios Description

Different scenarios have been designed, taking as a reference the actual behavior, to evaluate the effects of the policies.

Base Model (BM): This model simulates the real behavior of BiciMAD, that is, a system that implements an incentive policy with an amount of 0.10€ and the policy of repositioning bicycles with trucks.

Base Model with 0.50€ Incentive Reward (BM50): In this policy, an incentive reward of 0.5€ will be used instead of the existing 0.10€. With this incentive amount, according to Singla et al. [25], a participation of half of the users is achieved. Similarly, according to the study carried out by Ban et al. [1] with an incentive of between 0.5 and 0.6 USD, an average walking distance of about 500 and 600 meters is obtained.

Variable Incentives with Logarithmic Urgency (VI-LOG): A variable incentive policy is now introduced according to the urgency of balancing the station's load. The objective of this type of incentive is to increase user interest during periods of high system load. Two variables are taken into account to calculate the amount of the incentive: the distance to the new station and the short term estimation of that station. This estimation has been calculated as described in the behavior of the BikeAgent in Sect. 4.1. The first step is to determine the price at which agents have a 100% chance of accepting the incentive. We have used the results from the survey carried out by Ban et al. [1]. From this, we obtain data about the influence of the extra distance to be covered and the economic reward. Once this amount is obtained, a level of urgency is stated to apply the policy, based on the current status and short term changes of the concerned station. An approximation is then made, according to a logarithmic distribution, of the level of urgency. The threshold value for action is set at 30% of the station capacity.

$$P_i = B_i - CI_i + CO_i \tag{3}$$

$$U_i = max(min((T + P_i) * log(e), 0.0), 1.0), \quad U_i \in [0, 1] \tag{4}$$

$\boldsymbol{B_i}$ being the number of bicycles or available decks at the station i; $\boldsymbol{CI_i}$ the number of agents intending to rent in a range of fewer than 10 min of the station i; $\boldsymbol{CO_i}$ the number of agents in a range of fewer than 10 min intending to park at the station i; $\boldsymbol{U_i}$ the urgency for the station i; **T** is the threshold value for action; and $\boldsymbol{P_i}$ the short term estimation for the station i.

According to the urgency calculated for station i and the price for guaranteed participation at a distance m ($\boldsymbol{Pg_m}$), the price offered to the BikeAgent is adjusted as follows, and the probability of acceptance by the agent is calculated.

$$P_{im} = U_i * Pg_m, \quad P_{im} \in [0, 2] \tag{5}$$

Variable Incentives with Lineal Urgency (VI-LIN): This scenario includes the same policies as the previous case, 0.10€ incentives, variable incentives, and trucks. However, there is a difference in the way the level of urgency is calculated. A linear distribution is now followed according to the number of bikes or docks available in the forecast. The rest of the process for applying the incentive remains unchanged.

$$P_i = B_i - CI_i + CO_i \tag{6}$$

$$U_i = max(min((T - P_i)/(2 * T), 0.0), 1.0), \quad U_i \in [0, 1] \tag{7}$$

This research work has used the agent-based simulation framework MESA[2], an Apache2 licensed Agent-based model (ABM) framework in Python. Its usefulness is to facilitate the creation of agent-based models using built-in core components. It also displays results in a browser-based interface, allowing its subsequent analysis of the resulting data. Regarding route calculation, we have used **OpenRouteService (ORS)**, a library developed by GIScience Research Group[3] in Java, which offers a route calculation service, customizable depending on the vehicle type (bicycle or truck). Finally, a **Tornado Web Server**[4] deployment has been used for providing a visual interface.

5 Evaluation

In order to obtain results, seven simulations of a 4-day use situation have been performed, since the ABM represents 1 min per step. This gives us a total of 5760 steps per simulation. Certain variables are set according to real values to compare the results between behaviors. In particular, the following setting has been used: bike speed (18 km/h), truck speed (40 km/h), number of trips (74.000), the maximum number of trucks (6), truck capacity (20), the maximum walking distance (1 km) and the maximum riding distance (1 km). We have studied the distribution of the trip, the evolution of the station load, the unavailability rate (ratio between failed trips and total trips), and the total profit (the difference between travel income and incentive costs).

Model realism has been evaluated by correlating the distance of both BiciMAD trips and BM simulated ones Fig. 2b shows the distribution of the trip duration of both BM and BiciMAD datasets. Both define a skew normal distribution, being BM durations average slightly higher. This may indicate a higher real speed than that used in the simulations. Higher dispersion of values in the BM is also observed. Despite the differences, both cases show apparent similarities, so we assume a correct functioning of the BM, and it will be taken as a reference from now on.

The distribution of the **duration** for each model is shown in Table 3a. There are no significant differences between the results of the different scenarios. However, the best results are obtained for BM50, obtaining an average duration of half a minute less than BM. Regarding the **occupancy of the stations** in Table 3b, the data about the number of stations in an unbalanced situation can be found. The best results are obtained for the BM50 scenario with an

[2] https://github.com/projectmesa.
[3] https://github.com/GIScience.
[4] https://github.com/tornadoweb/tornado.

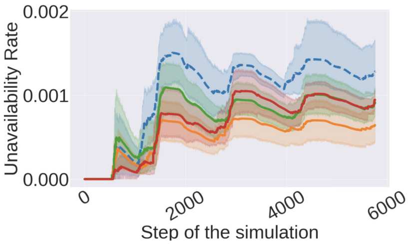
Table 3. Unavailability rates and load of stations.

	Trips duration		Unavailability rate	
	μ (sec.)	σ (sec.)	μ (%)	σ (%)
BM	972.53	535.96	0.1024	0.061
BM50	**941.42**	587.67	**0.0507**	**0.034**
VI-LOG	962.29	592.79	0.072	0.044
VI-LIN	951.48	**535.39**	0.0659	0.044

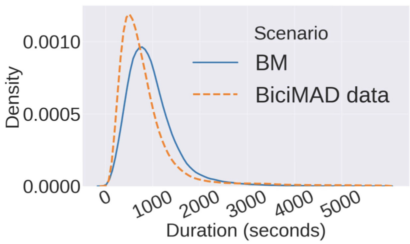
(a) Mean (μ) and standard deviation (σ) of trips duration and unavailability rate.

Scenario	LL μ	LL σ	HL μ	HL σ
BM	34.853	20.37	16.27	9.94
BM50	**25.894**	**17.30**	**10.544**	**8.154**
VI-LOG	33.09	24.92	15.158	9.14
VI-LIN	32.826	19.4	15.26	9.18

(b) Mean (μ) and standard deviation (σ) of the number of low and high load stations. Low Load (LL) and High Load (HL).



(a) Unavailability rate evolution. Dotted blue BM, orange BM50, green VI-LOG, red VI-LIN.



(b) Behavior comparison according to trips duration.

Fig. 2. Failure evolution and trip duration distribution.

Table 4. Morris analysis: values ranges and indices for unavailability rate.

Variable	Value
Bike speed	[10,30] (km/h)
Max. distance walking	[250,1000] (m)
Max. distance riding	[250,1000] (m)
Incentive amount	[0.1,0.5] (€)

(a) Value ranges for Morris analysis.

Parameter	μ	μ*	σ
bike_speed	-0.00621	0.0086	0.0088
walking_max	**-0.6649**	**0.0664**	**0.0119**
riding_max	-0.01362	0.0136	0.0139
base_incentive	-0.0121	0.0133	0.0112

(b) Morris indices for the unavailability rate.

improvement of 25.7% and 35.2% in the number of low and high load stations, respectively. This stands out against the small improvements achieved by the policy of variable incentives. Peaks can be observed corresponding to the rush hours (17:00 to 20:00). The study of the **unavailability rate**, which can be seen in Fig. 2a and Table 3a, allows us to indicate what percentage of users have not been able to make their journey and therefore have had to leave the system. This ratio has been calculated according to the failed trips with relation to the totals. Where F is the number of failed trips, and S is the number of completed trips.

$$UR = F/(F + S) \tag{8}$$

An agent leaves the system when it is unable to find an available bicycle at its station or elsewhere in its area of action. This area is bounded by the maximum walking distance. When the agent fails to find an available base to park, it decides to wait. The dataset provided by BiciMAD has only the trips completed satisfactorily, so it is not possible to make a comparison. An improvement in the unavailability rate can be observed, especially in the case of BM50, with a 50% reduction. In the case of VI-LOG and VI-LIN models, no assumptions can be made as their levels do not vary significantly from each other.

As for the **total income**, since the trips made in the different models follow the same distribution, the income received is practically identical, 37,000€. As for the expenses associated with the incentives we observe a very similar distribution for the VI-LOG and VI-LIN scenarios with BM, reaching a total of approximately 5,000€ spent. With this, the profit associated with these three scenarios is approximately 32,000€. On the other hand, in the BM50 scenario, the incentive costs are increased to 22,000€, resulting in a profit of 15,000€.

The model has been evaluated using the sensitivity analysis Morris [18] method with the support of the SALib[5] library. Those have been set as output variables: the number of full stations (without available bases) and empty stations (without bicycles), the duration of the journeys, the unavailability rate, and the total income. The study of the variation of these outputs has been focused on the following input variables: the speed of the bike, the maximum walking distance, the maximum riding distance, and the basic incentive offered. There have been generated five trajectories that give us a total of 25 samples of variables that will simulate 4-day of usage of the system. In Table 4a, the value ranges for these parameters are shown.

The maximum walking distance (*walking_max*) is one of the most influential parameters in several outputs, such as the number of empty and full stations or the unavailable rate, Table 4b. This is due to the increase in the number of possible check-in stations. Another variable that stands out is the base amount of the incentive (*base_incentive*), which has a great impact on the number of stations in an unbalanced load and on the system's income. The maximum riding distance mainly influences the duration of the trips, indicating that the waiting time to find a free base is one of its main factors.

6 Conclusions

A multiagent social model has been designed to analyze the influences of passive repositioning policies on a BSS. In this model, four scenarios with different policies have been implemented. We have also tested the influence of increasing the incentive amount in a separate way, even though this reduces the reported income.

[5] https://salib.readthedocs.io/en/latest/.

The main contribution is the proposal of a variable incentive policy using the validated simulation model. These incentives are offered during hours of high levels of system use. Simulations show a reduction in the amount of money invested in incentive payments in these scenarios. It also shows better results in balancing the load between the stations and reducing the unavailability rate in making the trips. This policy yields positive results over the reference scenario in every variable studied.

The main future work in this research line is the integration of a machine learning system to forecast user demand on the stations. With this, we will be able to predict inequality in the stations and act before it happens.

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Preface

Research on agents and multi-agent systems has matured during the last decade and many effective applications of this technology are now deployed. An international forum to present and discuss the latest scientific developments and their effective applications, to assess the impact of the approach, and to facilitate technology transfer, became a necessity and was created almost two decades ago.

PAAMS, the International Conference on Practical Applications of Agents and Multi-Agent Systems, is the international yearly tribune to present, discuss, and disseminate the latest developments and the most important outcomes related to real-world applications. It provides a unique opportunity to bring multi-disciplinary experts, academics, and practitioners together to exchange their experience in the development and deployment of agents and multi-agent systems.

This volume presents the papers that were accepted for the 2020 edition of PAAMS. These articles report on the application and validation of agent-based models, methods, and technologies in a number of key application areas, including: advanced models and learning, agent-based programming, decision-making, education and social interactions, formal and theoretic models, health and safety, mobility and the city, swarms, and task allocation. Each paper submitted to PAAMS went through a stringent peer-review process by three members of the Program Committee composed of 136 internationally renowned researchers from 27 countries. From the 64 submissions received, 12 were selected for full presentation at the conference; another 17 papers were accepted as short presentations. In addition, a demonstration track featuring innovative and emergent applications of agent and multi-agent systems and technologies in real-world domains was organized. In all, 17 demonstrations were shown, and this volume contains a description of each of them.

We would like to thank all the contributing authors, the members of the Program Committee, the sponsors (IBM, Armundia Group, EurAI, AEPIA, AFIA, APPIA, FBKI, CINI, CNRS, KUL, AIR Institute, and UNIVAQ), and the Organizing Committee for their hard and highly valuable work. We are thankful for the funding/support from the project "Intelligent and sustainable mobility supported by multi-agent systems and edge computing" (Id. RTI2018-095390-B-C32). Their work contributed to the success of the PAAMS 2020 event.

Thanks for your help – PAAMS 2020 would not exist without your contribution.

April 2020

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