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Author(s):
Dubernet, Thibaut Jean Pierre Axhausen, Kay W.

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A Multiagent Simulation Framework for Evaluating Bike Redistribution Systems in Bike Sharing Schemes

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Thibaut Dubernet
Institute for Transport Planning and Systems (IVT), ETH Zurich, CH-8093 Zurich
phone: +41-44-633 68 65
fax: +41-44-633 10 57
thibaut.dubernet@ivt.baug.ethz.ch

Kay W. Axhausen
Institute for Transport Planning and Systems (IVT), ETH Zurich, CH-8093 Zurich
phone: +41-44-633 39 43
fax: +41-44-633 10 57
axhausen@ivt.baug.ethz.ch

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ABSTRACT

In the recent years, more and more cities implement bike sharing schemes, where a set of bike is available for short-term rental between an origin and a destination station.

Those systems are seen as an effective way to improve the image of biking in a city, but come with operational challenges. One particularly difficult problem is bike redistribution. Indeed, asymmetry in the travel demand and aversion for uphill riding often leads to shortage of bikes in stations with lots of departures and shortage of available slots in stations with lots of arrivals. This leads to the necessity to design redistribution strategies, usually by having light trucks take bikes from some stations and put bikes in others.

The design of redistribution strategies to allow the provision of a reasonable Level of Service has mainly been studied under the angle of optimization, using historical data to create a model of demand. However, none of those approaches contains a model of the reaction of the demand to a change in the quality of the redistribution process. This paper thus takes the problem from a different angle: rather than designing optimal relocation strategies given a demand, it proposes a method to estimate the reactions of demand to a change in the relocation strategy.

It demonstrates the usage of multi-agent activity-based simulation to estimate the reactions of demand to changes in the relocation strategies, taking into account explicitly the fact that a more efficient redistribution strategy will lead to a higher level of service, generating a new demand that might change the quality of the redistribution. This simulation system is tested on a scenario for the Zurich area, Switzerland, analysing the reaction of demand to two ideal redistribution strategies, i.e. no redistribution and optimal redistribution.

Simulations show a big difference in demand depending on the quality of the redistribution, and even though no specific behavioral parameters for bike sharing were included, they seem to be able to reproduce the most salient characteristics of bike sharing travel from structural constraints only.
INTRODUCTION

In the recent years, more and more cities implement bike sharing schemes, where a set of bike is available for short-term rental between an origin and a destination station. In 2010, Shaheen et al. estimated the number of cities implementing such a system to be 125 worldwide, for a total of around 140,000 bicycles (1). Though it is sometimes marketed as “ecologically-friendly”, based on the simple assumption that trips performed by bike-sharing would have been performed by car, the impact of bike sharing schemes on the mode shares are limited: not only is the capacity of the system rather small, but it was also observed that users of bike sharing systems use it mainly to perform trips that they would have performed with “sustainable” modes (2). What was observed however is a strong impact of those systems on the image of biking in the city, pushing more individuals to use their private bikes regularly: after introduction of the two big French bike sharing systems, a significant increase of bike use was observed: 44% in Lyon, and 70% in Paris (1). Such an effect is usually seen as positive, for environmental, public health and “livability” reasons. Another strong point in favor of such systems is that they might help to solve the “first/last mile problem”, that is, the loss of attractiveness of public transport due to the difficulty to get to the initial station or go from the end stop to the destination of the trip. Indeed, a study in Dublin showed that 55% of the bike sharing trips were actually performed as part of a more complex multimodal chain (2).

Those systems come however with operational challenges. One particularly difficult problem is bike redistribution. Indeed, asymmetry in the travel demand and aversion for uphill riding often leads to shortage of bikes in stations with lots of departures and shortage of available slots in stations with lots of arrivals. To address this problems, several approaches can be used. The most common is the usage of relocating trucks, that redistribute bikes during the day. This kind of strategy however comes with a high monetary cost, and might threaten the environmental credibility of bike sharing (2). Another approach is the usage of incentives to push the system to regulate itself better. Those incentives can typically take the form of station-dependent fares, coupled with an information system. In the case of Paris, for instance, while trips are normally free up to 30 minutes, some stations situated uphill or in the outskirts of the city, labeled “Velib’+”, give right to an additional 45 minutes of free travel time (3).

The design of redistribution strategies to allow the provision of a reasonable Level of Service while keeping the costs as low as possible has of course received attention from the research community. Raviv et al. for instance consider the static redistribution problem, when bikes are only redistributed once during the night (4). Other Operations Research approaches have included some model of demand, based on historical data, to design dynamic redistribution strategies, where trucks relocate bicycles throughout the whole day (5–7) to satisfy most of the demand. Similar work is also done in the car-sharing field (8, 9). (7) also consider the possibility of “incentives”, which take the form of directives from the operator, such as proposition of an alternative drop-off station, that the user is assumed to follow. (10) considers dynamic price incentives, and estimates their effect by considering customers with a linear value of time. However, none of those approaches contains a model of the reaction of the demand to a change in the quality of the redistribution process. This paper thus takes the problem from a different angle: rather than designing optimal relocation strategies given a demand, it proposes a method to estimate the reactions of demand to a change in the relocation strategy.

While those studies of redistribution strategies are not based on explicit behavioral models, such models are widely used in transportation. A kind of model particularly well suited to the study of bike sharing systems are multi-agent activity-based models (see e.g. (11)) for an
introduction). Those models represent travel behavior as the result of the need, or willingness, to perform different activities in different locations. By representing individuals by software agents, they allow to represent individual heterogeneity. More importantly, some of those models adopt a game theoretic view of the transportation system, popular since Wardrop (12), wherein individuals are seen as competing for limited joint resources. Though the usual resource considered is road capacity, this framework naturally extends to the bike sharing case: individuals consider bike sharing not only based on its intrinsic value, but also on the availability of bikes, which depends on the behavior of others.

This paper demonstrates the usage of multi-agent activity-based simulation to estimate the reactions of demand to changes in the relocation strategies, taking into account explicitly the fact that a more efficient redistribution strategy will lead to a higher level of service, generating a new demand that might change the quality of the redistribution. This simulation system is tested on a scenario for the Zurich area, Switzerland, analysing the reaction of demand to two ideal redistribution strategies, i.e. no redistribution and optimal redistribution.

MODEL

For the purpose of this study, a prototypical simulation framework was designed. It was designed to allow emulating travelers behavior as accurately as possible, with a high level of detail, and to be extensible with any kind of relocating agents. This framework allows to represent the interdependency of traveler behavior and redistribution strategies — both vehicle and incentive based.

Though in those first experiments, only best and worst case redistribution strategies are implemented, the software architecture allows to experiment with truck-based systems, considering congestion or reactive relocation strategies, that generate redistribution routes by reacting to events in the system. Its usage of behavioral travelers also allows to experiment with incentive-based strategies, such as the aforementioned “Velib+” stations.

The proposed simulation tool is built using the MATSim simulation framework. MATSim is an open-source project, usable as a basic standalone simulation software, as an extensible simulation framework, or as a library to build highly specific simulation software. It relies on a game-theoretic view of the traffic system, as is frequently done since the seminal work of Wardrop (12), extending it to the activity-based demand description framework, in which individuals satisfaction depends of contradictory objectives, namely performing activities at different locations while avoiding too much travel. The unification of those two views recognizes that the daily plans performed by individuals lead to usage of joint resources, such as space (on roads, in buses, at facilities such as shops or restaurants) or, in our case, bike sharing bicycles, influencing the satisfaction of other individuals via congestion, crowding or unavailability of bikes or free slots at bike sharing stations (13, 14).

This basic formulation leads to an equilibrium problem, which is solved using a co-evolutionary algorithm, embedding this equilibrium solution concept. In short, co-evolutionary algorithms extend the evolutionary algorithm concept by having the solution of the problem split into several components, which fitness is evaluated via interactions with other components. Most of the strength (and challenges) of such algorithms is their essentially game theoretic nature (15). In the case of daily mobility behavior, the decomposition is natural: individuals in the population are represented by agents, each agent performing an evolutionary algorithm to optimize its daily plan, starting with an initial plan generated externally. The scores of daily plans are estimated by letting the agents interact in a mobility simulation. This score, by
default, takes the form proposed by Charypar and Nagel (16), with a linear disutility of travel
time and a logarithmic utility of time passed performing activities. The implementation takes
the form of a feedback loop, as illustrated on Figure 1: agents iterate between replanning and
evaluation, keeping only the plans with the highest score in their memory. A large proportion
of the agents simply select an existing plan based on the score, allowing to update the score
given the new plans of other agents, as well as reducing the randomness of the simulation to
ensure convergence. This process is iterated until the system reaches a steady state, used as an
approximation for the equilibrium.

FIGURE 1 The MATSim co-evolutionary process

One of the important features of bike sharing compared to using one’s own bike is the
ability to ride only for downhill trips, and use an alternative mode, such as public transport,
for the uphill counterpart. Thus, the simulation framework needs to be as precise as possible
in its representation of the influence of the slope on the biking experience. A first important
factor, reasonably easy to represent, is the influence of the slope on travel speed. To compute
person-dependent walk and bike travel times, the approach from Dobler and Lämmel (17)
used. It takes into account steepness, age, gender and inter-personal differences (represented by
a random person-specific term) to compute walk and biking speeds in a network shortest-path
computation.

Another important factor is the highest required effort for uphill progression, which has
probably an influence on the marginal utility of travel time or distance. This factor is however
much more difficult to include consistently in the simulation, and was left aside for the time
being.

One of the most critical parts of the simulation framework is the co-evaluation step, where
the influence of agents decisions on each other is evaluated. This is particularly important in
case studies focusing on joint use of joint resources, and even more for resources as scarce
as bikes in a bike sharing system. Hence the system was designed to be highly extensible, to
allow iterative complexification, while being able to represent the most salient features of a bike
sharing system from the very beginning. The basic design is based on the separation between
three entities:

1. Agents, which navigate in the system, taking and disposing bikes. They include the agents
   whose daily plan is part of the relaxation process, and are potential users of the bike
sharing system. Capabilities of within-day replanning, such as heuristic rules to follow
in case no bike or no free slot is available, are easily implemented. Those agents can
also be redistribution agents, which can be as sophisticated as truck drivers reacting to
modifications of the state of the system on the fly.

2. Bike sharing stations, which are containers with a capacity.
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3. **A Bike Sharing Manager**, which acts as intermediary between agents and stations, checks that capacity constraints are fulfilled, and notifies listeners (e.g., redistribution agents) of changes in the state of the system.

For the simulation system to be complete, one needs to extend the capabilities of the agents, roughly speaking extending their choice set of daily plans with bike sharing opportunities. To do so, routing procedures have to be implemented, both for single bike-sharing trips and for bike-sharing *stages* part of a bigger multi-modal trip. This last part is particularly important when one considers bike sharing as a potential way to solve the “first/last mile” problem. A particularity of routing bike sharing trips is the unpredictability of the availability of bikes at any given station at the time of the trips. Hence, rather than trying to find an “optimal” route, which might contain a station chronically empty, bike sharing routes are produced by choosing a random station close to the origin and destination points, which are then aggregated into access walk, bike, and egress walk. This randomization helps the agents to try out different possibilities during the co-evaluation phase, allowing the demand to spread over the stations according to their capacity, very much the same way traffic spreads over road paths according to capacity for the case of car traffic.

An important feature of activity-based models is the level of granularity at which they handle mode choice, which goes from day-level mode choice (a person is assumed to use the same mode for all trips) to trip-level mode choice. An intermediate granularity is often used: the “subtour” level, which is finer than the rough day-level choice, while keeping it easy to handle chaining *constraints*, that is, the fact that a personal vehicle has to be picked up where it was last parked, and returned home at the end of the day. An important feature of one-way vehicle sharing systems is that they allow to break those constraints. The simulation framework thus uses trip-level granularity, but considers chaining *constraints* by constraining what Miller et al. call a “chain-based mode” (*18*) to subtours “anchored” at home, or at an activity part of a subtour of this same mode.

**CASE STUDY**

The following text describes the application of the prototypical simulation framework presented in the previous section to the simulation of a real-world bike-sharing system. In a first time, the hypothetical system is presented. In a second time, the results of its simulation are detailed.

**Description of the Simulated Supply**

The supply used in this simulation experiment is based on a base scenario being developed for the Zurich Urban Area, extended with information on the bike sharing system planned by the city of Zurich, Switzerland.

As stated above, we see agent-based simulations as a useful approach to the problem of redistribution, complementary to optimization techniques, in that they are able to represent the interaction between the effectiveness of the relocation strategy and the demand. Thus, the current study focuses on comparing two ideal cases: the *worst case* redistribution (where the system is left to itself, without any active redistribution of bikes during the day), and the *best case* redistribution (where bikes are assumed to be redistributed where the demand is — the only possible case when it may be impossible to find a bike is when all the bikes are rented).

The base scenario is a work in progress, which should become the standard baseline scenario for MATSim simulations in Switzerland, using data collected around the year 2010. It aims at
The scenario is composed of the following elements:

1. **Population**: Synthetic agents are generated using data from the national census, as well as the national travel diary survey. For the restriction to the Zurich Area, only agents performing a trip passing less than 15km from the Bellevue Place, in the center of Zurich, are kept. A sample of 10% of those persons is used for the simulation.

2. **Freight Traffic**: Synthetic agents reproducing the number of freight trips specified by the OD matrices of the Cantonal Transport Model are used.

3. **Cross-border Traffic**: Synthetic agents reproducing the number of crossborder trips specified by the OD matrices of the National Transport Model are used. Those agents, as well as the freight agents, are only allowed to modify their routes.

4. **Network**: A detailed navigation network is used, representing the Swiss street pattern with a high level of detail — which is necessary, particularly to get reasonable walk and bike travel time estimates. The major arterials in the neighboring countries are represented as well, to allow the inclusion of cross-border traffic. Slope information is attached to the network for bike and walk travel time estimation.

5. **Public Transport**: the public transport schedule from the Cantonal Transport Model is used to obtain realistic travel time estimates.

6. **Facilities**: the “facilities” contain the information about opening times for different activity types, and roughly correspond to buildings. Data comes from the federal enterprise census 2008 for the location of firms, as well as the register survey (containing basic information that any person living in Switzerland has to communicate to the municipality) of 2010 for home locations.

7. **Bike sharing supply**: The bike sharing supply aims at representing the bike sharing system that the city of Zurich plans to establish. It is planned to establish the system in 3 steps:
   (a) 100 stations (1500 bikes) in the city center
   (b) 100 additional stations (1500 bikes) to densify the North part of the city
   (c) 100 additional stations (1500 bikes) extending to further residential areas

As in most current bike sharing systems, the fare is planned to be time-dependent, with the first 30 minutes being free, before increasing every 30 minutes. Analysis of the usage of current systems showed that this results in a large majority of trips being below this time limit — 92% for instance in Paris. Hence, though it is difficult to calibrate a scenario to represent prices accurately, an approximate representation should be enough to reproduce this effect. The planned fares are included assuming that one Swiss Franc corresponds to one utility unit.

The geographical configuration is illustrated on Figure 2. The circle represent the 15 km radius, used to filter the population for analysis. The colored areas represent the zones in which bike sharing stations are located to represent stages 1 and 3 of the implementation process, which are simulated in the next section.

### Simulation Settings

Using those elements, 4 scenarios were designed:

- **Stage 1, Worst Case (1W thereafter)**: number of bikes and stations as planned for the launch, but no bike redistribution.
- **Stage 1, Best Case (1B thereafter)**: number of bikes and stations as planned for the
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During simulation, agents are allowed to adapt routes, modes, and departure times. 200 iterations are performed. After 190 iterations, agents do not generate any new plan, but just select existing plans based on their scores. This removes the noise produced by the relatively important part of plans fresh from random mutation. All agents are assumed to be member of the bike sharing system.

Simulation Results

All the graphs in this section convert the numbers from the simulation into the quantities they "represent" — given that a 10% sample is simulated, each agent "represents" 10 individuals, and each simulated bike represents 10 bikes.

Figure 3 represents the number of bikes being driven throughout the day. Without relocation, one can observe that usage of the system decreases throughout the day, as the system becomes imbalanced. In particular, it seems the symmetry of commuting trips in the morning and in the evening is not enough to provide a good supply in the evening. The amplitude is very small compared to the number of bikes in the system. In comparison, under optimal relocation, the demand for bike sharing becomes impressive, with a peak at around 1200 of the 1500 bikes being used at the same time for stage 1, and around 4000 of the 4500 bikes being used at the same time for stage 3. The demand for stage 1 exhibits the classical morning and evening peaks, while for stage 3 the demand is rather stable throughout the day — probably due to the fact that the steady demand is close to the maximum capacity of the system, forbidding a peak. Whether
this is realistic or not cannot be ascertained, due to the hypothetical nature of the system, and the absence of real system operating with optimal bike redistribution to take as reference. This however corresponds to each bike being used 50 times per day on average, dramatically higher than the 3 usages per day assumed by the Zurich City Council, or the 4 to 6 usages per day observed on average in Paris (2). The fact that the demand is overall much higher for stage 3 is probably due to the fact that the number of possible origin-destination that can be performed with the system increases quadratically with the number of stations, making a big system much more attractive.

Even more interestingly, the important difference in bike sharing use between the two relocation strategies does not result in a significant difference in personal bike use, as can be seen on Figure 4. This reproduces the observed fact that bike sharing trips mostly substitute public transport and walk trips, rather then private bike — or car (2).

![Number of “en route” bikes (bike sharing) throughout the day](image)
This comparison of bike sharing and personal bike use can be extended to the characteristics of the trips, and in particular travel time, represented on Figure 5. The pattern observed in real systems, that a large majority of the trips are performed during the free-use time (30 minutes) is reproduced here, with a clear change of slope at 30 minutes for scenario 3B. Virtually all bike sharing trips are shorter than 60 minutes, when price goes up again. Interestingly, this results in the fact that travel time distribution for personal bike is both more left-skewed (with a lower median) and has a much longer tail (around 20% of the trips are longer than 60 minutes). Indeed, a very short bike-sharing trip is not worthwhile, due to the need to walk to and from the station, and users have to pay to perform long trips.

Uphill stations being chronically empty is a typical challenge for bike sharing operators. In the simulation, the influence of altitude comes only from travel times. Figure 6 represents the daily difference between inflow and outflow per station, as a function of the station altitude (positive values indicate a station generating more trips than it attracts). The city center is located along the lake and the rivers, and thus also correspond to the lowest stations. No clear pattern can be seen, indicating that it would be necessary to add (and calibrate) a behavioral parameter to represent the aversion to ride uphill.

Overall, those results are encouraging. Though more calibration and testing (in particular for scenarios in areas where bike-sharing schemes are already implemented) is still needed, those first runs demonstrated the capability of the simulation system to represent reactions of the demand to changes in the quality of the bike-sharing supply, and overall represents known properties of bike sharing systems, for instance in terms of travel time distribution.

DISCUSSION OF RESULTS AND CONCLUSIONS

Operation of bike sharing schemes is a challenging task, in great part due to the need to balance the bike inventory across stations throughout the day. Optimization techniques in the literature
FIGURE 5  Bike and bike sharing travel times: cumulative distributions, scenario 3B

FIGURE 6  Difference between in and outflow by station altitude, scenario 3B

1 assume a fixed demand based on historical usage data, and search for optimal relocation strategies
given this demand. Though this might work reasonably well when the change in relocation
strategies does not lead to dramatic changes in the level of service, they neglect the reaction of
demand to a change in the performance of the system.
There is therefore a need to look at the problem of relocation and demand jointly. The simulation framework proposed here goes in this direction. Though it was applied only on a system yet to be implemented, and could thus not be calibrated for the specificities of bike sharing demand, its high level of detail allows to represent explicitly the influence of structural constraints on behavior: system capacity, possibility to perform one-way trips, difference of speed depending on the slope and person, and time-step-based fare resulted in patterns similar to what one can observe in already existing bike sharing systems — in particular in terms of mode substitution and travel time distribution.

However, the mere fact of considering slope and person dependent walk and cycling speeds did not allow to reproduce the well-known pattern of uphill stations generating more trips than they attract — a potentially important effect in a city as hilly as Zurich. This points the need for behavioral parameters to represent the aversion to bike uphill. This is challenging: using values of time or other parameters from mode or route choice models estimated from surveys is not really meaningful, particularly due to the fact that in a full-day approach, such as MATSim, the opportunity costs incurred by the reduction of time performing activities are explicitly taken into account, whereas they are usually implicit in mode choice experiments. Behavioral parameters are thus usually initialized to plausible values and then tuned “by hand”, which is a time-consuming and error-prone process.

This now opens the way to the possibility to experiment in silica with different bike redistribution strategies, and observe how the demand reacts and how this reaction influences the performance of the relocation. In particular, the multi-agent physical simulation allows to experiment with “reactive” relocation strategies, which react on-the-fly to events in the bike sharing system.

The simulation itself can however still be improved. First, agents currently blindly follow their plan. In particular, an agent will wait hours for a bike at a station, rather than walking to a closeby station or changing mode. Such strategies can however be implemented in a pretty straightforward way — the question then becomes what strategy should be implemented, and whether it actually helps improving the results.

Also, for time constraints, only a scenario containing 10% as many agents as the actual population was used. This forces to scale down the simulated supply. Though experience shows that this works pretty well with road capacity, scaling down the bike sharing supply might be problematic: in our runs, stations were initialized with 15 bikes initially, and a capacity of 30. This means that stations had initially 1 or 2 bike available only, and only 3 slots. The randomness of the simulation might then make the uncertainty to obtain a bike much higher than what would be observed in reality. Though time consuming, a sensitivity analysis with different sampling rates should be conducted.

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