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A dynamic simulation based model for optimal fleet repositioning in bike-sharing systems

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Abstract

In this paper a simulation model for dynamic bikes redistribution process is presented. The objective of the model is to minimize the vehicles repositioning costs for bike-sharing operators, aiming at a high level users satisfaction, and assuming that it increases with the probability to find an available bike or a free docking point in any station at any time. The proposed model considers the dynamic variation of the demand (for both bikes and free docking slot) and micro-simulate the BSS in space and time determining the optimal repositioning flows, distribution patterns and time intervals between relocation operations by explicitly considering the route choice for trucks among the stations.

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Keywords: bike-sharing; repositioning problem; decision support system; sustainable mobility.

1. Introduction

The development of Bike-Sharing Systems (BSS), in addition to the sustainability of the transport and urban systems, is mainly due to its door-to-door feature (DeMaio, 2009). BSS allow to access areas of the city that are forbidden for other transport means, including eco-friendly vehicles. BSS are also often employed to connect users to public transit networks (for ex. connection between intermodal hubs and final destination). The main components of a BSS are a bikes fleet, bike stations and a given (known) number of users. In these systems, customers arrive to bike stations (trip origin), utilize bicycles for an amount of time, and then return the bicycle to the same or to a different bike station (trip destination). Nevertheless, a greater diffusion and usage of the BSS is limited by its own drawbacks (Büttner et al., 2011). BSS is used mainly for medium-short distances and for one-way trips. Such a behaviour leads to an unbalanced distribution of the bikes over the time and space. Thus, from

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the real-time management stand point, to increase the system capacity and users satisfaction, it is necessary to properly relocate the bikes among the stations of the BBS.

As in technical literature, redistribution scheme relevant to systems operating with shared vehicles can be mainly divided into two standard categories: “user based” and “operator based” (Allouche et al., 1999; Barth & Todd, 2001; Kek et al., 2006; Vogel & Mattfeld, 2010). In the former the users are stimulated to return to a non-saturated station in order to balance the distribution of the bikes among the stations. In the latter, the relocation is assigned to the service staff. While the indirect customer base redistribution is feasible for mid-term operations, the direct operator based redistribution may be effective in short-term period.

The operator based reallocation problem is defined as Pickup and Delivery Problem (PDP). In literature several methods to solve the vehicle or resources reallocation problem have been presented (Cheung & Powell, 1996; Kochel et al., 2003; Nair & Miller-Hooks, 2011). These models are generally applied to freight transportation (Du & Hall, 1997; Crainic, 2000) or to car-sharing systems (Barth & Todd, 2001; Kek et al., 2006 and 2009; Dell’Orco et al., 2011).

Recently just a few papers have been dealing with the Bike Sharing Pickup and Delivery Problem (BS-PDP) as a variation of classical PDP. The BSS reallocation can be carried out either during the night when the bikes demand is negligible (static repositioning, as defined in literature), or during the day when the bikes distribution among the stations rapidly changes due to the high demand level (dynamic repositioning). Most of the literature presents static BS-PDP (Benchimol et al., 2011; Shu et al., 2010; Chemla et al., 2011; Forma et al., 2010). Even less authors deal with the dynamic case. In particular Contrado et al. (2012) propose a mathematical formulation of the dynamic problem on a space-time network. In general the dynamic BS-PDP is investigated without focusing at redistribution patterns and time periods (Vogel & Mattfeld, 2010). Some works propose a fixed repositioning time interval (Nair & Miller-Hooks, 2011; Sayarshad et al., 2012), a variable repositioning time interval (Caggiani & Ottomanelli, 2012) or assume redistribution vehicles moving at random from saturated stations to empty ones (Fricker & Gast, 2012).

In this paper a simulation model for dynamic bikes redistribution process is presented. The objective of the model is to minimize the vehicles repositioning costs for bike-sharing operators, aiming at a high level users satisfaction, and assuming that it increases with the probability to find an available bike or a free docking point in any station at any time. The proposed model considers the dynamic variation of the demand (for both bikes and free docking slot) and micro-simulate the BSS in space and time determining the optimal repositioning flows, distribution patterns and time intervals between relocation operations by explicitly considering the route choice for trucks among the stations. As matter of fact the model has been specified as a micro-simulation model and thanks to this features and variables considered it can be considered as a Decision Support System (DSS) for BSS design and real-time management. Furthermore the obtained results have been compared to those of the previously proposed method with variable repositioning time interval based on Fuzzy Decision Support System (FDSS) (Caggiani & Ottomanelli, 2012).

2. The proposed model

2.1. Bike sharing system simulator

In the proposed model we have represented and modelled all the operations that characterise a BSS. We assume that the system runs an advanced monitoring systems of the number of bicycles in each station as most of the current BSS.

The design variables that describe a BSS are the number of stations (Ns) and their location in the city network, the number (Nrt) and the capacity (Crt) of the redistribution pick-up or open trailers (proper carrier vehicles used to carry several bikes at the same time), for each station: the number of docking slots (Nd) and free ones (Np) and

the number of available bikes (Nb). For further detail on the architecture with relevant functions of the BSS operations simulator see the first flow-chart depicted in Caggiani and Ottomanelli (2012).

With respect to the system dynamics, we assume the operating day is divided in Z discrete time intervals. For each time interval z and for each station j, given the pickup bikes demand (Db), the model simulate the destination choice (Dp) in order to assess the arrival time for each users. The choice model is based on relative O-D attractiveness and the nature of trip (one-way or round trip). Since in this first stage we have developed the simulation for a low density stations distribution, we assume that each bike request that cannot be satisfied (empty station) turn user away (demand decreasing); as well as each give back not satisfied demand (full station) generate undesired waiting time for user.

At the begin of each interval z the number of bikes and the available docking points are updated by taking into account in-out users flow (turn-over) and the relocated bikes.

The Decision Support System (Fig. 1) is activated at constant gap time. At the end of the day (end of service time period), a static redistribution is carried out in order to restore the starting bikes distribution among the stations.

2.2. The proposed Decision Support System

The problem is to relocate the bicycles from overcrowded station to the stations with a shortage of bikes (i.e. balance the demand-supply system). The first essential data is the prediction of future demand among stations in order to forecast bikes and free docking point requests. The literature proposes different forecasting methods, in particular, for BSS, Borgnat et al. (2009) use a linear regression model; Froehlich et al. (2009) have developed a Bayesian network.

The core of the forecasting demand method in the proposed DSS is based on Artificial Neural Networks (ANN). A first advantage of this approach is that, using Neural Networks (NN), there is no need to assume explicit functions for returned or picked up bikes, because a NN learns directly from observed data. Therefore, starting from the time series of bikes requests, the NN is able to relate the hour of the day to entering or exited vehicles number. Furthermore, the high capability and the goodness of NN with respect to forecasting methods proposed for shared use vehicle has been proved by Kek et al. (2005) for the case of car sharing systems.

Differently from the FDSS model (Caggiani & Ottomanelli, 2012) the proposed DSS is activated at constant Gap Time (GT) and it starts with the forecasting module that estimates entering and exiting bikes (demand). For each station the estimation is performed on GT by two Artificial Neural Networks (NN) on the bases of given historical time series collected by the usage monitoring systems.

The first NN is used to estimate the number of entering vehicles; the second one to forecast the exiting vehicles. Both NNs are feed-forward back-propagation networks with a training function that updates weight and bias values according to Levenberg-Marquardt optimization. The NNs have three layers with five neurons for the first and the second layer and one neuron for the third. The input data of NNs are the vectors of entered and exited bicycles in the station, for each step, during the previous months of the prediction. Actually, such a formulation depends on the available data.

The outputs of the NNs are the entering (PDp) and exiting (PDb) number of bicycles dynamically forecasted for each time step and station. Other NNs variables are the day of the week, the time of the day and the weather conditions.

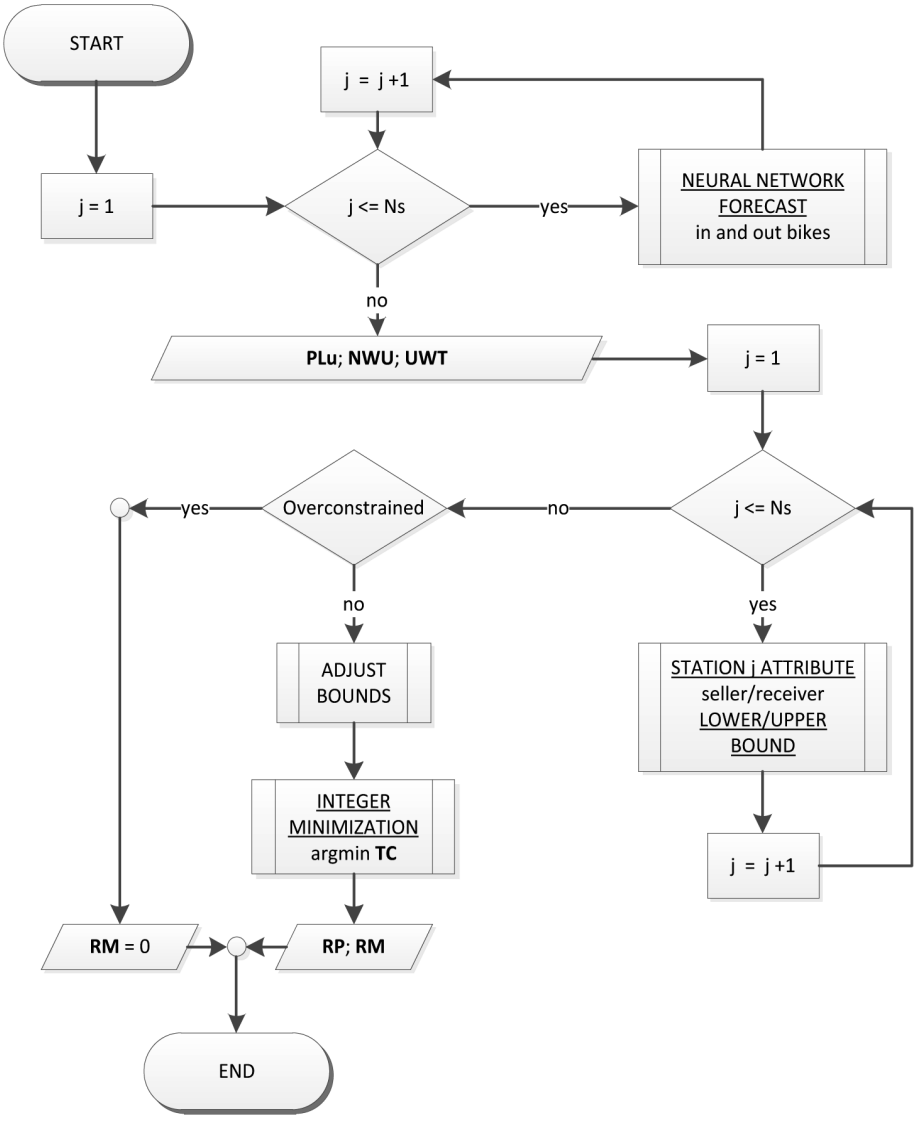


Fig. 1. Flowchart of the DSS

In other words at this stage the outputs are the estimated number of lost users PLu (i.e. users whose service request cannot be satisfied), the number of waiting users NWU (i.e. users that do not find free docking points at the desired station) as well as the estimated waiting time spent to return the bike (UWT) at each bike station. On

the basis of the forecasted in-out bikes within the GT interval, by solving the optimization problem given in eq. 1 we obtain the Relocations Matrix (RM), with rm_{ik} entries, and the Relocation Path (RelP) of the redistribution carrier vehicles that minimizes the total costs for the provider (sum of relocation costs, RelC, and lost users costs, LuC). In the proposed model the variable RelC is time dependent and it is function of the congestion level.

The RM matrix belongs to a set of matrix M such that if a station is seller it must not be receiver. The upper bound (UB with ub_k entries) and the lower bound (LB with lb_i entries) of the problem are calculated adjusting the possible maximum number of transferable bikes or free docking points. This correction is due to find the minimum number of relocated bikes that maximize the users' satisfaction. Moreover if the problem is over constrained, no relocation is feasible. For example if all station are receivers, no bikes can be delivered.

The relocation paths for carrier vehicles are obtained by solving a Travelling Salesman Problem in the same level of the optimization problem (fixed point problem). In particular the redistribution truck must previously pass through the seller stations. The lost users costs are calculated with the BSS simulation considering PDp and PDb slots and bikes demands. Differently from other approaches that use bi-level formulations, the proposed minimization problem is formulated as fixed point Non Linear Integer Optimization. The solution algorithm is based on a Branch and Bound procedure. The outputs are the optimal relocation matrix and the optimal relocation path and bikes distribution among the stations.

$$
\begin{aligned}
&\left(\mathbf{RM}^{*}, RelP^{*}\right) = \underset{\mathbf{RM}}{\operatorname{argmin}}\left(\operatorname{Re}lC\left(RelP\left(\mathbf{RM}\right)\right) + \sum_{j=1}^{Ns} LuC_j\left(PDb, PDp, RelP\left(\mathbf{RM}\right)\right)\right) \\
&s.t. \\
&\sum_{i=1}^{Ns}\sum_{k=1}^{Ns} rm_{ik} \le Crt; \\
&\sum_{i=1}^{Ns} rm_{i1} \le ub_1, ..., \sum_{i=1}^{Ns} rm_{ik} \le ub_k, ..., \sum_{i=1}^{Ns} rm_{iNs} \le ub_{Ns}; \\
&\sum_{k=1}^{Ns} rm_{1k} \ge -lb_1, ..., \sum_{k=1}^{Ns} rm_{ik} \ge -lb_i, ..., \sum_{k=1}^{Ns} rm_{Nsk} \ge -lb_{Ns} \\
&\mathbf{RM} \in \mathbf{M}_{Ns \times Ns} \\
&\mathbf{M}_{Ns \times Ns} : = \left\{ \left(a_{ik}\right)_{\substack{i=1,...,Ns \\ k=1,...,Ns}}, a_{ik} \in N \mid \exists k \in \{1,...,Ns\} : \forall i \in \{1,...,Ns\} \ \sum_{i=1}^{Ns} a_{ik} \ne 0 \wedge \sum_{k=1}^{Ns} a_{ik} = 0 \right\}
\end{aligned}
\tag{1}
$$

3. Numerical application

The proposed algorithm has been applied to a portion of a BSS. This part of the entire BSS network is made up of 5 stations that represent the typical scheme of a wider real BSS considering a larger number of central or peripheral stations. Thanks to its modular properties, the proposed algorithm can be easily scaled to the entire BSS. In the application we have considered three different level of demand and different days of the week.

The station 1 is located in the city centre while the other stations are located in the outskirts of the city. The distances in meters between the stations are reported in the Table 1. The parameters used for each station of the application reflect average values of medium-large size BSS. The method has been applied considering three working days with 24 hours/day of operations. Each day is divided into 288 steps (Z = 288), 5 minutes each long. The starting data are: the number of stations Ns = 5, the number of carrier vehicles (i.e. redistribution trucks) Nrt

= 1 with a capacity Crt = 20 bikes, the number of docking points per station (Nd_1, … Nd_5) = (40, 30, 30, 20, 20), the number of available bikes (Nb_1, … Nb_5) = (10, 10, 10, 10, 10), Gap Time = 12 steps.

Table 1. Station distances [m]

O/D	1	2	3	4	5
1	0	400	500	300	300
2	400	0	700	700	600
3	500	700	0	400	800
4	300	700	400	0	600
5	300	600	800	600	0

Since all the distances between stations (Tab. 1) are lower than one kilometer we assume that the truck travel and operation time between two stations (also in the peak hours) is lower than five minutes that is a truck movement takes place within one step. The total redistribution cost per kilometer is assumed to be 0.30 Euros (considering depreciation, taxes, fuel and tires consumption and maintenance costs); the cost for each lost user is fixed to 0.7 Euros (based on subscription and fees of the most of the major BSS). Actually, the costs for lost users should take into account all the impacts given to the consequent use of no eco-friendly transport means. The bicycles demand is distributed among the stations so that the central station (station 1) is mainly an arrival station during the morning and during the early afternoon and mainly a departure station during the rest of the day. The converse happens for the other four stations.

To evaluate the performances of the proposed model, we have tested the algorithm considering two cases and three levels of demand. The two cases are: no relocation and relocation with variable gap time (proposed DSS). Some results of the mentioned cases are reported in Table 2. In this table are depicted also the obtained result of the FDSS model with variable GT. The comparison is possible because the starting data of both model application are the same. In all considered cases, the new proposed DSS leads to a reduction of the number of lost users. Also in the case of low demand level, positive results have been reached. Assuming higher level of demand, due to the congestion of the system, the proposed method shows a lower reduced number of lost users. Making a comparison between the obtained results of the proposed model and those of the FDSS, it is clear that the model with constant relocation time intervals performs better (in terms of number of satisfied users) than the method with variable GT for the case of low demand. With increasing congestion of the system (see demand level 3) the FDSS involves, on the other hand, lower costs of relocation with slightly better average user satisfaction.

Table 2. Summary of obtained results

demand level	1			2			3		
number of day	1	2	3	1	2	3	1	2	3
pickup demand	263	302	282	477	505	494	781	720	811
Variable GT									
relocated bikes	59	88	76	156	153	172	87	83	70
lost users (no rel.)	52	76	60	161	193	188	361	304	391
lost users (rel.)	29	19	22	88	109	112	324	269	341
lost users reduction (%)	44.2	75.0	63.3	45.3	43.5	40.4	10.2	11.5	12.8
relocation costs	63.9	76.5	59.4	114.6	114.9	134.1	60.9	62.4	55.5
Constant GT									
relocated bikes	84	110	85	145	238	163	140	97	75
lost users (no rel.)	53	68	54	170	178	192	333	302	403
lost users (rel.)	11	12	22	110	118	104	286	286	350
lost users reduction (%)	79,0	82,0	59,0	35,0	34,0	46,0	14,0	5,0	13,0
relocation costs	84.6	91.2	71.7	114.9	110.1	140.1	94.2	84.0	58.8

4. Conclusions

In this paper a micro-simulation model for optimal relocation of bikes in bike-sharing systems has been presented. In particular, the proposed model jointly determines the optimal carrier vehicles route and the number of bikes to be repositioned with the relevant stations. The results show that the relocation management increases of users satisfaction in term of probability of finding available bikes or free docking point. In particular the proposed DSS is more suitable for non congested bike-sharing systems. The method is modular so that it can be used for wider systems. The proposed DSS reproduce in detailed way the system, thus it can be also used for both strategic design and/or real-time management that is to determine the optimal layout of the BSS. Additional simulations for large-scale BSS with multiple carrier vehicles are needed and are in progress in order to check the robustness of the method. Further research will deal with the implementation of the artificial NNs based model for the real-time estimation of bikes demand based on real systems with consequent model validation.

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