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A new dynamic repositioning approach for bike sharing systems

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Abstract

Repositioning operations are fundamental on bike-sharing systems. Its optimization is necessary in order to achieve the best level of service with minimum agency cost. Literature propose routing models that preventively avoid full and empty stations according to demand forecasting with good results. However, simulations show that reactive methods could improve the performance in some scenarios, because they can adapt to unexpected demand variations quicker. This paper describes a mixed repositioning model for station-based systems that includes both the preventive routing optimization and the real-time reactive adaptability. Results obtained on a simulated case of study (Barcelona 'Bicing' system) are positive. Model acts as a flexible repositioning clustering method, which breaks the cluster to control user costs if demand deviates too much from expected.

1. Introduction

Demand is not geographically even distributed. This is a common issue on mobility, and is a specially concerning problem on the operation of bike-sharing systems. Because of the uneven attraction and generation of trips, systems tend to accumulate bikes on specific zones while others get empty. If no action is taken, provided level of service worsens. Users won't find available bikes on origin or parking slots on destination. In order to avoid that, repositioning operations with trucks are used in all systems worldwide, even free-floating systems. Its optimization is fundamental to keep down agency costs.

Literature has dealt with this problem since the popularization of one-way bike-sharing systems, and currently classifies repositioning models as static or dynamic. Static models assume that demand is zero or minimum during repositioning. They focus on routing optimization, which is widely treated as a one commodity pickup and delivery problem. For that reason, they are efficient in terms of time spent. Raviv et al. (2013), Schuijbroek et al. (2017), and

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Alvarez-Valdes et al. (2016) are good examples of it. However, they can only be adapted to real-life systems if the whole repositioning takes place at night, when low demand conditions are met.

Dynamic models improve static models by considering an open system affected by users' demand while repositioning takes place. In general terms, stations inventory level is estimated through demand forecasting for the whole day. And according to that, relocation routes are optimized. Caggiani et al. (2013) and Kloimüllner et al. (2014) provide good results with different methodologies. The former even expands its methodology to free-floating systems (Caggiani et al., 2018).

Note that even dynamic models are preventive and rely completely on forecasting. This is a drawback in order to adapt those models to real-life operation on bigger systems. If demand is highly variable, forecasting accuracy will drop and the optimal repositioning route may change.

1.1. Reactive alarm-based repositioning

On a previous work, authors developed a bike-sharing simulator with two different repositioning methods (Soriguera et al., 2018). One is a routing-based method, as the aforementioned models. The other one is a reactive alarm-based method. Anytime a station is close to being full or empty, it is included in a repositioning pool. And this method assigns stations from the pool to idle repositioning vehicles.

Simulated results showed that the reactive alarm-based repositioning could work as a support or even alternative of the preventive routing-based repositioning. Repositioning was rather less efficient in terms of travelled distance. It cannot consider in advance which stations will be visited by the vehicle during the day. Therefore, it can bring to situations of crossed paths or backtracking. However, it is more adaptable and reacts quicker to unexpected demand variations. Less users were affected by no-service situations because of that. It seems clear that both have different advantages and it could be beneficial if they work together on the system.

The main objective of this paper is to define a repositioning model that includes both preventive and reactive repositioning, acting as a whole. Like current dynamic models, this one also estimates a set of repositioning routes according to demand forecast. But in addition it allows real-time modification of those routes.

In the following chapters, model is described and a case of study is presented to obtain some simulated results. Finally, the document is closed by conclusion, acknowledgements, and references sections.

2. Repositioning model description

The present model is designed to optimize day-by-day repositioning operations on a station-based bike-sharing system. In order to facilitate understanding, model is divided in three stages. On each stage a different aspect is optimized, and the resulting output will be an input of the next one. First, ideal bike distribution is calculated on any given time according to demand forecast. Given that, optimal repositioning routes are scheduled. And finally, minimum-cost criteria are defined to modify those routes in real time.

Following tables 1 and 2 describe the parameters of the model. Note that strategic variables (system layout, stations, and fleet size) are considered inputs here. They must be optimized on earlier design stages consider long term factors such as demand horizons, minimum service standards, and desired accessibility.

Table 1. Inputs.

Nomenclature	Units	Description
$\overline{m_{req,i,j}}$	bikes	Average accumulated bicycle requests on station i from t_j until 24h.
$\overline{m_{ret,i,j}}$	bikes	Average accumulated bicycle returns on station i from t_j until 24h.
β_e	€/penalty	Penalty cost of not finding available bikes on origin.
β_f	€/penalty	Penalty cost of not finding available parking slots on destination.
C_i	bikes	Capacity of station i.
γ_{repo}	€/hour	Cost of a repositioning van per time unit
δ	hours	Time spent on loading/unloading a single bike.

Table 2. Decision variables and auxiliary functions.

Nomenclature	Units	Description
t_j	hours	Instant j when a repositioning route is initiated.
$m_{i,j}$	bikes	Inventory level on station i at t_j.
$n_{i,j}^{repo}$	0/1	Indicates if station i at t_j is repositioned (1) or not (0).
V_j	vehicles	Number of repositioning vehicles working simultaneously at t_j.
$m_{i,24h}$	bikes	Gross inventory level on station i at the end of the day.
B_j	bikes	Total available number of bikes for repositioning at t_j.
$T_{route,j}$	hours	Time spent travelling on repositioning routes starting at t_j.
$€_{NSP,i,j}$	€	No-service penalty cost on station i from t_j until 24h.
$€_{ROUTE,j}$	€	Agency cost of repositioning route starting at t_j.

2.1. Ideal bike distribution

Users are penalized anytime they find no available bikes on origin or parking slots on destination. On any given time, ideal bike distribution minimizes the expected penalties for all stations of the system during the following working hours. Note that we cannot know in advanced how many of those no-service situations will happen

In order to do so, an auxiliary variable of gross inventory level is defined. This variable represents with how many bikes would each station finish the day if there weren't any capacity or fleet constraints. By definition, this value is calculated as the current inventory level (m_i) plus the average accumulated bike returns ($\overline{m_{ret,\iota,J}}$) minus the accumulated bike requests during the day ($\overline{m_{req,\iota,J}}$). Bike returns and requests on each station are considered as independent Poisson events. So, the accumulated number of those events (returns or requests) can be approximated to a Normal distribution. Therefore, the gross inventory level will follow another Normal probability as described on equations 1, 2 and 3.

$$M_{i,24h} \sim Normal\left[\mu_{i,j}, \sigma_{i,j}^2\right] \tag{1}$$

$$\mu_{i,j} = m_i + \overline{m_{ret,\iota,J}} - \overline{m_{req,\iota,J}} \tag{2}$$

$$\sigma_{i,j}^2 = \overline{m_{ret,\iota,J}} + \overline{m_{req,\iota,J}} \tag{3}$$

No-service penalties can be immediately defined as a piecewise function of the gross inventory level (equation 4). On average, each unit that gross inventory level is under zero will produce a penalty of cost β_e (users cannot find bikes on origin). Each unit that gross inventory level is over the capacity will produce a penalty of cost β_f (users cannot return their bikes). If gross inventory bike is between zero and capacity, no penalties are considered.

$$€_{NSP,i,j}\left(m_{i,24h}\right) = \begin{cases} -m_{i,24h} \cdot \beta_e & m_{i,24h} < 0 \\ 0 & 0 \leq m_{i,24h} \leq C_i \\ \left(m_{i,24h} - C_i\right) \cdot \beta_f & m_{i,24h} > C_i \end{cases} \tag{4}$$

With the previous considerations, the optimum bike distribution on any instant of time will be the result of the optimization of equation 5 subject to a fleet constraint defined by equation 6 (the sum of total bikes should be the same after the distribution).

$$Z^* = \min_{m_{i,j}}\left\{\sum_{\forall i} E\left[€_{NSP,i,j}\left(m_{i,j}\right)\right]\right\} \tag{5}$$

s.t.
$$\sum_{\forall i} m_{i,j}^* = B_j \tag{6}$$

$$E[\epsilon_{NSP,i,j}] = \int P[M_{i,24h}(m_{i,j}) = m_{i,24h}] \cdot \epsilon_{NSP,i,j}(m_{i,24h}) \cdot dm_{i,24h} \tag{7}$$

Figure 1 illustrates an example of an ideal inventory level calculation. In this case, the station receives on average more returns than requests. For that reason, the probability distribution has its center displaced to the right. (it is more likely that the gross number of bikes at the end of the day has increased). Also, the penalty function considers a higher cost for failed returns than failed requests. So, the expected value of penalties will be minimized if $m_{i,j}$ is smaller.
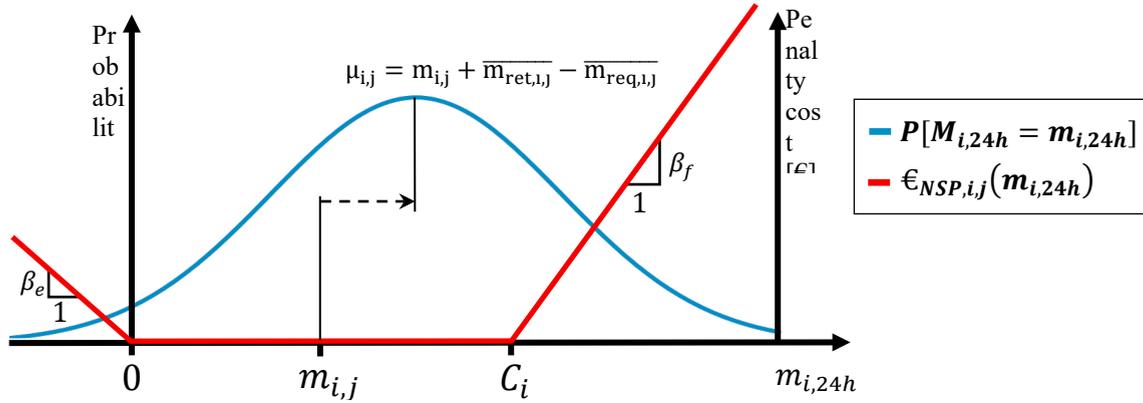

Fig. 1. Graphic depiction of an example penalty function (red) and gross inventory level probability distribution (blue).

This optimization is also adaptable without losing validity if a different goal is preferred (i.e. maximizing agency income instead of minimizing user penalty costs). In that case, the penalty function will be redefined as a revenue function and the expected value will be maximized. The rest of the problem will be the same.

2.2. Expected repositioning route scheduling

Once the ideal bike distribution is estimated, the objective of the next stage is to identify which stations should be visited during the next day. This decision is taken on several moments of the day, defining optimal repositioning routes for each moment and updating the system after that until the next one. Stations included on each route are those that maximize penalty costs savings minus the repositioning costs (which are directly proportional to time spent on loading and unloading bikes from the trucks and travelling from station to stations).

$$Z^* = \max_{n_{i,j}^{repo}}\left\{\sum_{\forall j}\left[\sum_{\forall i}\nabla\epsilon_{NSP,i,j} - \epsilon_{ROUTE,j}\right]\right\} \tag{8}$$

s.t.

$$\nabla\epsilon_{NSP,i,j} = \left[\epsilon_{NSP,i,j}(m_{i,j}) - \epsilon_{NSP,i,j}(m_{i,j}^*)\right] \cdot n_{i,j}^{repo} \tag{9}$$

$$\epsilon_{ROUTE,j} = \gamma_{repo} \cdot \left[T_{route,j}(n_{i,j}^{repo}) + \delta \cdot \sum_{\forall i}(n_{i,j}^{repo} \cdot \|m_{i,j} - m_{i,j}^*\|)\right] \tag{10}$$

$$V_j \geq \frac{T_{route,j}(n_{i,j}^{repo}) + \delta \cdot \sum_{\forall i}(n_{i,j}^{repo} \cdot \|m_{i,j} - m_{i,j}^*\|)}{t_{j+1} - t_j} \tag{11}$$

$$B_j = \sum_{\forall i}(m_{i,j} \cdot n_{i,j}^{repo}) \tag{12}$$

Equations 8, 9 and 10 show the optimization function on any instant t_j. Equation 11 constraints the necessary number of vehicles to finish the repositioning tasks. And equation 12 calculates the available bikes for repositioning.
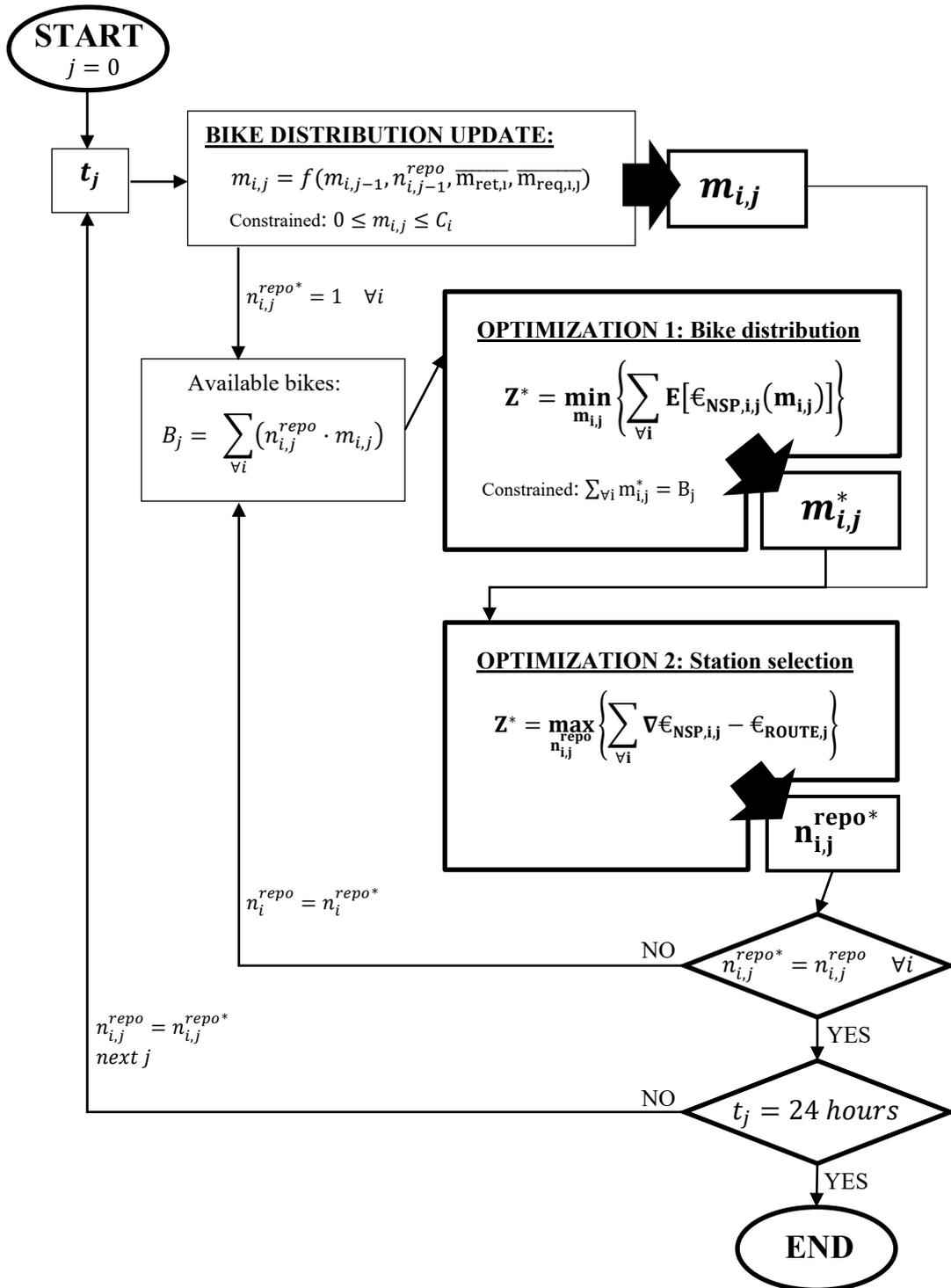
Fig. 2. Flow chart of repositioning scheduling optimization.

Figure 2 summarizes the repositioning routes scheduling optimization. Note that if visited stations vary, available bikes to be redistributed will also change. This is a constraint of the ideal bike distribution optimization previously described (equation 6), so the problem is recursive. However, the marginal variation of rebalanced bikes is smaller in terms of costs than the decision of including/excluding one station. So, result converges.

Finally, note also that the repositioning schedule optimization depends on two variables that are unknown in advance. First, the times where repositioning routes are evaluated (t_j). Headways between consecutive times should be big enough to group as much stations as possible on the same route. But also, they need to be small in case of any station needs to be visited more often. The second variable is the number of repositioning vehicles (V_j). Model should ensure that repositioning vehicles are working in full shifts.

In order to set those variables, repositioning scheduling optimization must be run in three steps:

- On a first step, small headways are considered (i.e. 30 minutes) without repositioning vehicle constraints. Optimal time steps will be defined by the most visited station.
- On a second step, a new optimization is done according to the new evaluation times still without vehicle constraints. Necessary vehicles are the minimum to finish repositioning tasks on time. Shifts are stablished here.
- The third solution is an adjustment optimization. Here, route cost is considered as given according to equation 13. This same equation must be included if repositioning vehicles and shifts are an input of the problem.

$$€_{ROUTE,j} = \gamma_{repo} \cdot V_j \cdot (t_{j+1} - t_j) \tag{13}$$

Final output will be a list of tasks for each vehicle, describing which stations must be visited and in which order. Note here that inventory level is only observable on the first time step, and therefore that would be the only repositioning route that we can assure. Then, the inventory level is forecasted and can vary.

2.3. Real-time task modification

Criteria for removing one task or adding a new one are also based on the minimization of user and agency costs. A task will be removed if the reduction of route costs (less time spent because one station is skipped) is higher than the penalty cost increase (more expected no-service situations because the station is not repositioned). In a similar way, a new task will be included if the route cost increase is less than the penalty cost savings. Figure 3 represents graphically those criteria.

Those modifications must take into account the bike balance and vehicle capacity constraints. It is not possible to refill one station if bikes were not picked previously from another station. So, route modifications will be made by pairs and only if there is enough room on the repositioning vehicle during the trip.
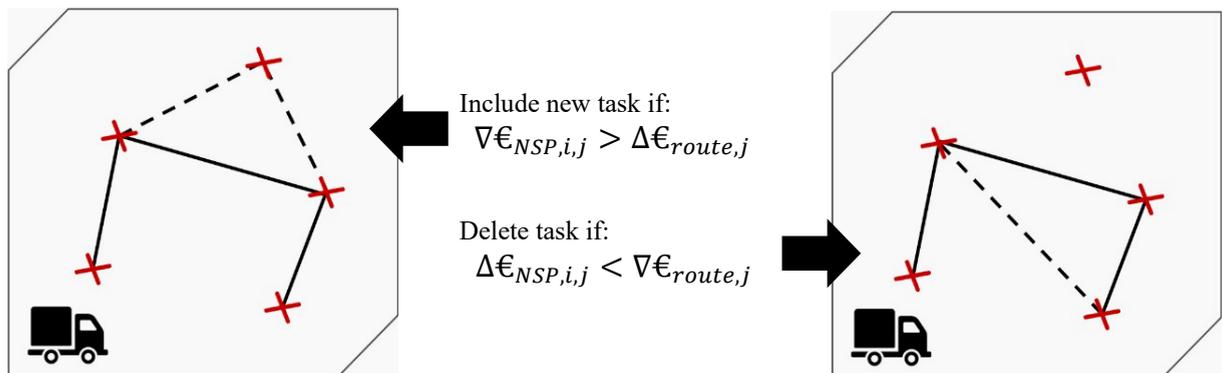

Include new task if:
$$\nabla €_{NSP,i,j} > \Delta €_{route,j}$$

Delete task if:
$$\Delta €_{NSP,i,j} < \nabla €_{route,j}$$

Fig. 3. Real-time route modification criteria.

3. Case of study

Model was applied on a case of study based on the Bicing system in the city of Barcelona. Three different repositioning scenarios were implemented on a simulator developed by our research group (Soriguera et al., 2018): only routing-based forecasted rebalancing, a pure reactive alarm-based repositioning (described in 1.1), and finally the mixed repositioning model.

Layout, stations and demand are simulation inputs and were observed directly from the real system. Repositioning resources were also an input. A fleet of 13 vehicles (with a capacity of 32 bikes) was considered working the whole day with a cost of 22.9 €/h each. Also, penalties were given a cost of €4.5 for not finding bike on origin and €9 for lack of parking slots on destination. Those values are equivalent to a delay of 10 and 20 minutes.

Two KPIs were considered to evaluate the repositioning performance (km travelled per vehicle) and the users' dissatisfaction (percentage of no-service situations). Table 3 summarizes those results.

Table 3. Simulation results. KPIs.

Scenario	Repositioning Performance [km/vehicle]	No-service situations [%]
Only routing	80.2	18.6
Only alarms	102.8	13.2
Mixed repositioning	97.3	13.8

As expected, mixed repositioning model is more efficient than the alarm-based method (less km travelled per vehicle), and reaches a better level of service than the routing-based method (less percentage of no-service situations). It is also noticeable that its performance is closer to alarm-based methods, even when the main core of the model is based on routing optimizations. This resemblance could be explained by the huge amount of alarms and route modifications made. In fact, on peak periods its behavior was almost reactive.
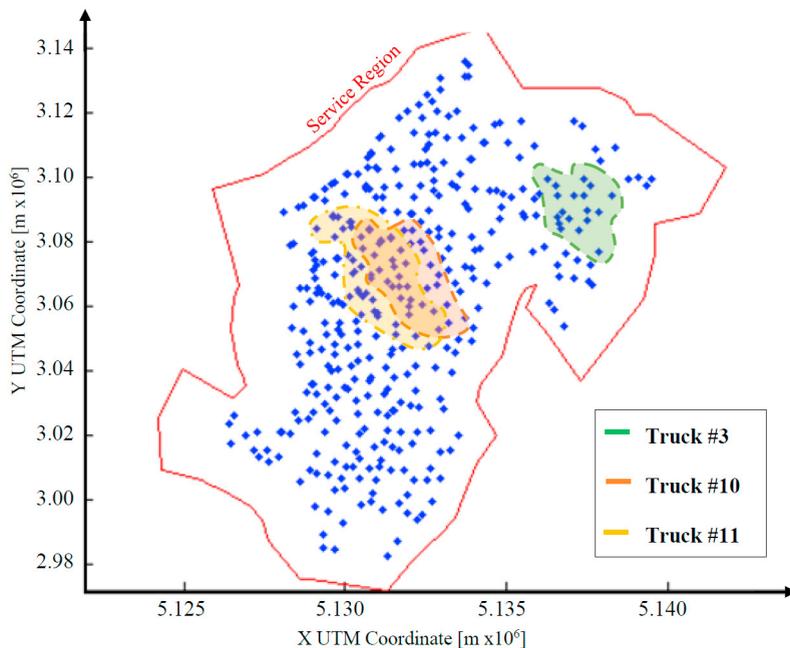

Fig. 4. Working zones of different repositioning vehicles.

Another interesting result is found after observing the trajectories of repositioning vehicles and their working areas (see figure 4 as example). During routing optimization, repositioning vehicles are split on clusters in order to minimize route distance. If demand is low and behaves as expected, cluster is maintained with little modifications and repositioning stays efficient in terms of travelled distance. But on peak period, when demand is highly variable, cluster is broken. Solving the alarms becomes more critical due to the increase of user costs. And therefore, vehicles cross paths and travel longer distances.

4. Conclusions

Results show that this repositioning model works as a flexible clustering method. It is more efficient than alarm-based systems due to routing optimization. And also provides a real-time flexibility in case of a big degree of demand variability. This is an improvement over current repositioning models, especially when applied on big bike-sharing systems like Bacelona Bicing. In those cases, even with a very good forecasting, demand variability makes impossible to predict accurately the inventory level of single stations on peak periods.

Model is also defined by stages in order to allow modular programming or further modifications. For example, ideal inventory level was defined here to minimize user penalty costs, but it could also have been defined to maximize agency income. Another possible modification is the adaptation to free-floating systems, which require a previous clustering to consider some zones as stations.

Main limitations of the model are due to its inputs. Note that some of them are in fact strategic decision variables (such as layout, stations, fleet size). This paper is focused on the operative level and therefore it assumes that those strategic decision variables are well designed in advance. Objectives here are met. The introduced model can improve repositioning efficiency. But if those variables are not optimal, another strategic design model would be necessary considering further issues (i.e. demand horizons or desired service standards).

Regarding the rest of the inputs, it would be advisable in the future to make sensibility analyses in order to evaluate the influence of those parameters. Penalty costs (β_e, β_f) are difficult to estimate. Also, some design parameters (as the repositioning vehicle capacity) are a bit hidden in the model and not subject to optimization. Future works should focus on those analyses and on evaluating different scenarios of demand variability and scale. That could help to identify in which cases model should be applied and quantify its benefits.

Acknowledgements

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