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Finding the relevance of staff-based vehicle relocations in one-way carsharing systems through the use of a simulation-based optimization tool

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ABSTRACT

This paper proposes a real-time decision support tool based on the rolling-horizon principle that manages staff activities (relocations and maintenance) of a one-way carsharing system and considers carpooling the staff in the relocated carsharing vehicles for extra cost reduction. The decision support tool is composed of three elements: a forecasting model, an assignment model and a filter. Two assignment models are proposed and tested: rule-based and optimization. The rule-based model uses simple rules to respond to system status changes, and the optimization model is a mixed integer programming (MIP) model prepared to work in real-time. A simulator was designed to test the decision support tool and an application is done to the city of Lisbon, Portugal, showing that the benefits of staff relocations can be rather low. It was verified that the number of relocations that can physically be performed by each staff member in the case study provide only a small improvement in the revenues, which is unlikely to overcome the costs associated with hiring and staff activity.

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Carsharing; relocations; maintenance; optimization; simulation

Introduction

Carsharing is becoming part of urban areas as people understand that collaborative consumption has advantages for the individual and for society. For the individual, choosing carsharing in detriment to other modes can be related mostly to convenience or saving car expenses, although for society as a whole the aggregated result of travelers migrating to this mode of transport can contribute to reducing the burden on the transportation system and the environment (Martin & Shaheen, 2016; Martin, Shaheen, & Lidicker, 2010; Shaheen, Cohen, & Roberts, 2006). This transportation service reduces car dependency and social exclusion (Millard-Ball, Murray, Schure, Fox, & Burkhardt, 2005), induces positive modal shifts (Martínez, Correia, Moura, & Lopes, 2017), and is able to bring positive financial and environmental impacts (Vasconcelos, Martínez, Correia, Guimarães, & Farias, 2017). Until recently, you needed to own a car in order to use one for a short period. With the arrival of carsharing services, travelers have the opportunity to use a car whenever they want, on a pay as you go basis, without worrying about buying one (Shaheen & Cohen, 2007). Users can avoid

fixed and some variable ownership costs (parking, taxes, insurance, and maintenance). Studies in the US and Canada showed that 15% to 32% of carsharing members sold their personal vehicles and 25% to 71% avoided the purchase of a car because of carsharing (Shaheen, Cohen, & Chung, 2009). In France, a survey revealed that each carsharing vehicle replaced 10 personal vehicles (Louvet, 2016).

Carsharing services evolved, in terms of vehicle availability location, from station-based into free-float and, in terms of vehicle movements, from only allowing round-trip movements into including one-way movements (Jorge, Correia, & Barnhart, 2014; Shaheen, Chan, & Micheaux, 2015). Station-based systems with round-trip movements have been the most used among carsharing companies during many years. A system with these characteristics is easier to manage and control, since it does not have vehicle imbalance problems, but it does not satisfy the complete range of user needs.

One-way carsharing services allow people to drop-off a vehicle in other locations (Shaheen et al., 2015). This type of movements are more convenient for the user but they require rebalancing strategies since trips

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are not self-balanced (Correia & Antunes, 2012). On the other hand, this way of operating carsharing leads to higher utilization rates of the vehicles (Jorge et al., 2014). Nevertheless the one-way movements are very often constrained, for example, the trip ending inside a predefined operating area (Car2go, 2017); or users needing to stay inside the operating area and be advised to return once the system detects the vehicle is outside the allowed boundary (DriveNow, 2017).

For systems that allow one-way movements, stations or zones with high demand will have a shortage of vehicles, while stations or zones which are major destinations will frequently have an excess of vehicles. This leads to an imbalanced distribution of vehicles' supply (Jorge & Correia, 2013). If vehicles are not redistributed the system will not be able to fully satisfy the demand, which will most likely result in a loss of customers. Therefore, in one-way systems rebalancing is necessary. The introduction of automated vehicles in the future has the potential to facilitate this task and reduce operational costs (Correia & Arem, 2016; Milakis, Arem, & Wee, 2017), although this is still an emerging technology (Nieuwenhuijsen, Correia, Milakis, Arem, & Daalen, 2018). This study considers the carsharing vehicles' technology currently in use by carsharing companies, which is mostly non-automated. Literature includes three main approaches to assist the daily carsharing system rebalancing operations: operator-based relocations, user-based relocations, and trip selection (Jorge & Correia, 2013). In operator-based relocations, staff is used to periodically drive vehicles from a station with an excessive number of vehicles to a station with a shortage of vehicles. In user-based relocations, balancing movements are performed by clients reacting to incentive mechanisms, usually based on price (Jorge, Molnar, & Correia, 2015). Trip selection consists of controlling the demand by allowing only the trips that are favorable to the balance of vehicle stocks (Correia & Antunes, 2012; Correia, Jorge, & Antunes, 2014).

Operator-based relocations are more suitable to simultaneously fulfill operators' and users' needs and to improve the perceived quality of the system. These operations do not restrict users' movements and intentions to use the service, which could decrease the potential demand and compromise the financial sustainability of the organization, and are totally controlled by the operator (Kek, Cheu, Meng, & Fung, 2009). The only drawback is that they represent an increase in cost for the operator, due to the need for hiring staff members to maintain service availability. However, staff members are also needed for other

activities, such as cleaning, inspecting vehicles, refueling, therefore relocating vehicles can be considered just part of the multi-purpose duty of staff members (Weickl & Bogenberger, 2012).

Difficult to solve mathematical models have been proposed to optimize operator-based relocation activities (Jorge & Correia, 2013), although there is a lack of understanding in what regards the real benefit of relocations in the operator's perspective. The operator is interested in the impact on profit of introducing staff to relocate vehicles (while vehicles are not automated) and the practicality of the tool it will use to manage the process.

This study analyses the relevance of the operator-based relocations in a real urban environment by recurring mainly to simulation and optimization in a rolling horizon method. It performs a profit analysis of introducing staff members to mainly relocate and maintain vehicles with the activities delineated by a real-time decision support tool. Two different assignment methods, rule-based and optimization, are tested in the real-time decision tool structure using the city of Lisbon, Portugal, as a case study.

Therefore, the contributions to the literature are:

- Proposing and applying a rolling-horizon method for planning the activities of the staff in a one-way carsharing system (relocation and vehicle maintenance).
- Comparing a rule-based and an optimization method of defining the staff activities in each horizon.
- Consider the possibility of the relocation staff traveling in the carsharing vehicles needed for relocation (carpooling).
- Working with real-time demand taking advantage of the rolling horizon method.
- Application to a real case-study city with comparison to previous studies.

The paper is structured as follows. After this introduction, we present a literature review focused on the operator-based relocations, highlighting the evolution of processes and the need for a different approach to profit analysis. Then, the real-time decision support tool is described as well as the two assignment models that are proposed: rule-based and optimization model. The simulator designed to test the real-time decision support tool is detailed afterward. This is followed by the description of the application of the simulator together with the real-time decision support tool to the case study of Lisbon, detailing the needed data, the simulated scenarios, and the corresponding results. Different fleet sizes were tested and the analysis was focused on the scenarios with the number of vehicles

that led to higher profits for each level of demand that was considered. Based on that, the relevance of operator-based relocations is discussed including a comparison with the study from (Jorge et al., 2015) where the impacts of vehicle relocations were very promising. The paper ends with the main conclusions taken from this work.

Literature review

Going through the research on carsharing operations, it can be seen that operator-based is the most studied vehicle rebalancing approach. The reason is that the use of operator-based relocations gives a competitive edge to organizations since it assures privacy, simplicity, and convenience to users (Kek, Chen, & Chor, 2006).

Some studies proposed the use of towing or platooning to perform relocations, by considering that a truck could tow several vehicles between stations at the same time, or that the vehicles could group in platoons and move under their own power, respectively (Barth & Todd, 1999; Dror, Fortin, & Roucairol, 1998). This has been, in the meantime, dropped due to its technical difficulties. Instead, operator-based relocations were considered to be done by personnel hired by the carsharing organizations. However, the use of staff cannot be limited to driving the vehicles into favorable locations because there are other tasks such as refueling, cleaning, and vehicle inspection that need to be accomplished, making the existence of a team a necessity to maintain the level of service provided to the clients. Simple relocation mechanisms tested by means of simulation, and based on forecasted demand were the focus of Kek et al. (2006) and Wang, Cheu, and Lee (2010) research.

Other authors, resorted to Mathematical Programming models to achieve the best outcome in terms of vehicle relocations, which were then tested using simulation (Kek et al., 2009; Nair & Miller-Hooks, 2011; Nourinejad & Roorda, 2014; Smith, Pavone, Schwager, Frazzoli, & Rus, 2013). Kek et al. (2009) innovated by optimizing all staff related movements and tasks in the same linear programming model. Nair & Miller-Hooks (2011) used a stochastic MIP model involving chance constraints to generate optimal redistribution plans, which overcame the prior work that assumed static or known demand. Smith et al. (2013) presented a process to obtain an optimal solution by solving two different linear programs: a rebalancing of vehicles and rebalancing of drivers. Nourinejad and Roorda (2014) proposed two models

part of a dynamic tool able to work in real-time for supporting relocation decisions: a benchmark model (static) assuming that all daily user requests were known in advance, and a dynamic model that reacts to online user requests.

A recent study by Boyaci, Zografos, and Geroliminis (2017) proposed an integrated optimization-simulation framework for vehicle and personnel relocations of electric carsharing systems with reservations. In their model, demand served is prioritized over relocation cost and profit, because they are aiming at providing a high quality of service and maximize the vehicles' availability for the users. Moreover, demand is either known a priori or it is rejected/accepted one trip at a time, which can present limitations in scenarios in which bundling is advantageous.

Nevertheless, none of the previous works assessed the financial relevance of performing relocations using the mathematically elaborated tools that they presented for the optimization of the carsharing operations. One of the few studies that did such an analysis was Jorge et al. (2014), which presented a cost-revenue analysis of having operator-based relocations in a simulated environment for a one-way station-based system. The authors concluded that relocations would allow a daily profit increase from a negative value of 1161 Euro to a positive value of 855 Euro for the Lisbon case scenario and using the best relocation policy considered. The work assumed static travel demand, staff resources were unlimited and outsourced, and that the number of vehicles was dimensioned in such a way that only those needed would be part of the fleet. Another study assessing the relevance of performing carsharing relocations was done by Weikl and Bogenberger (2015). The authors introduced a practice-ready integrated relocation model for free float carsharing systems and applied it to a real testbed. The application led to a profit increase between 4.7 and 5.8%. Those values were taken from different time periods of the real system (October 2013, February and May 2014), and most probably are affected by the evolution of the acceptance of such system by the population, leading to increased demand. Also, the prices and number of vehicles changed during this period, which can also affect profit. Therefore, we believe that there are more factors to consider than just the improvement of relocation algorithms. A work from Huang, Correia, and An (2018), proposed a mixed-integer non-linear programming model to solve the carsharing station location and a capacity problem for a large one-way carsharing system and was applied to Suzhou, China. The

authors ignored the personnel allocation problem considering that there were unlimited people to carry out relocation operations, and only specified a cost value per time of relocation.

In the literature, there seems to be missing a profit analysis using a controlled testbed of the staff-based relocation operations in a carsharing system with its own staff members (not outsourced), which is the most common, with a more realistic approach in terms of operator conditions (e.g. fixed fleet size, stochasticity of demand) and with a rolling horizon method that can divide the problem in pieces which can then be handled in a real-time decision support tool. The rolling horizon approach was chosen due to its simplicity, and it is classified by Sayarshad and Chow (2017) as a dynamic policy without look-ahead, since it does not use Markov decision processes to explicitly account for the dependency of future states on future decisions. This research is focused on trying to understand the real benefit for carsharing organizations of having hired staff personnel performing relocations through applying realistic simulations with optimized movements designed by a mathematical model. An organization or company is focused on the balance between revenues and costs (profit) and needs to understand from an operation standpoint if employing more staff to perform relocations is beneficial or not for their operation. We consider the possibility of saving extra costs with carpooling the staff together in carsharing vehicles that contribute to the relocations.

Real-time decision support tool

A real-time decision support tool is proposed to be applied to a one-way free-float carsharing system based on an operational area, having no limitations concerning parking (vehicles can park at any public parking space inside the operating area). This decision support tool is designed in such a way that it could be used by a carsharing company. It includes all the elements necessary to perform in a real situation. And the optimization process timely retrieves the output plans. Therefore, by running it with realistic trip data we aim at emulating what would be the operation of such a system on a typical day.

The main characteristics of the system we are considering are the following:

- The operating area is subdivided by zones to allow spatial differentiation and aggregation in state variables, easing the complexity level of a mathematical

model design, while facilitating the definition of operational borders. Each zone of the operational area has a walkable size (this guarantees that a client can walk to a vehicle if both are at the same zone of the operating area);

- Vehicles serve movements of clients but can also serve movements of staff between zones. All the vehicles share the same characteristics including capacity. It is considered that vehicles need a certain type of maintenance and refueling. Refueling is mainly supported by clients, and maintenance is performed by employees of the carsharing company. Two possible status are attributed to vehicles: available and needing maintenance;
- Clients use the service for their personal transportation needs. Only available vehicles are used by clients. Vehicles are rented on an on-demand basis, and mobile communication devices are used by clients as a means to locate the vehicles. The client is not required to announce in advance his/her destination. Although in-vehicle communication and GPS systems allow tracking each vehicle position in real-time;
- It is considered a constant number of staff elements working simultaneously to perform maintenance tasks and relocations. But that does not mean that the same workers are used for the entire day since the salary is by the hour. Breaks or rest time for the same staff employee can be introduced a posteriori as the hours can correspond to different employees.
- The maintenance procedures are based on the staff activities of service providers currently in operation. The activities are related to client incorrect check out: intervention to correct vehicle parking, intervention to turn off lights, intervention to close doors (including rear door), intervention to close windows, intervention to enable parking brakes, simple cleaning, intervention to refuel an empty tank, and intervention to solve discharged battery.
- Vehicles have sensors to diagnose incorrect check-outs and malfunctions and have the ability to transmit this information to the central. The service provider receives the information related to client incorrect checkout procedure and sends orders to staff to perform the corrective measures. Each staff member is considered to have a mobile communication device in permanent contact with the headquarters to receive instructions about the next tasks. The maintenance tasks are performed locally (it is considered that the equipment transported by staff does not affect its mobility).

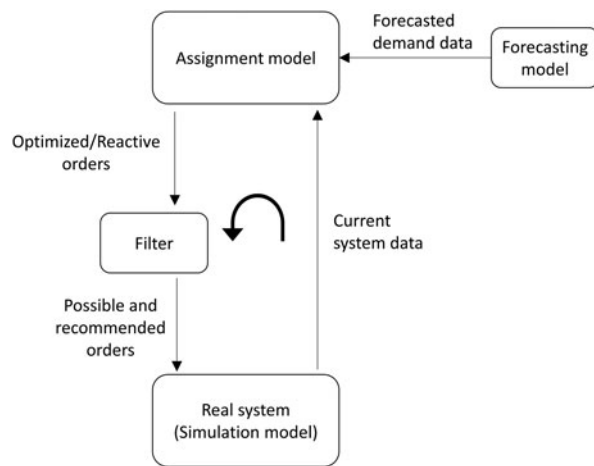


Figure 1. Real-time decision support tool scheme.

- The relocation movements of vehicles are determined based on the current location of vehicles and demand forecasts.
- Public transport is an alternative option to move staff inter-zones. Regarding intra-zonal movements, it is considered that staff members move towards the vehicle by walking, since each zone has a walkable size.

As referred the decision support tool is composed of three elements: a forecasting model, an assignment model, and a filter (see Figure 1).

The forecasting model allows predicting the demand for the immediate future, in order to allow better planning of the staff activities and of the vehicles' stocks. This process uses historical data from the carsharing system to produce an estimate of the expected demand for each zone. In this study, the seed demand data is the same used to generate the real-time trips, but generation and forecasting are independent processes otherwise we would be considering perfect information.

The assignment model designs a reaction plan for the staff activities based on forecasts and the current status of the system, in order to optimize the staff activities at that time interval. Two assignment models were developed. The first is a rule-based process using routines triggered by the system status. The second is an optimization process, through a Mixed Integer Programming (MIP) model, which delineates optimized staff activity scheduling. Both are prepared to work in real-time.

Some staff orders included in the output plan may not be applicable due to differences between predicted and real demand, therefore, the orders go through a filter to discard the ones that cannot be fulfilled. For example, a relocation movement may not be fulfilled

using a carsharing vehicle due to the fact that there is no car at the zone of origin because this has been taken by a client in the meantime. This is a result from considering that the available vehicles (not needing maintenance) are allocated for client usage, not being previously reserved for the staff-related movements advised by the new output plan. In short, the filter works to prevent possible errors from the output plan retrieved from the model when applied to reality.

The entire procedure is cyclic and based on a rolling horizon approach allowing the system to adapt to the real-time demand. This reduces the processing time and allows including a forecast view, which was a drawback from previous works, namely Kek et al. (2009) and Jorge et al. (2014). This is suboptimal when compared with considering the entire day, but at the same time computing an optimal solution for a whole day is not a realistic objective since demand is not known a priori.

At each rolling horizon, the assignment of tasks is decided using a fore view regarding the forecasted demand. The adopted framework was the rolling horizon planning with fixed interval (Wang & Kopfer, 2013). In this work, it was considered that each horizon period is subdivided into two planning periods. The orders for the first planning period are fixed and sent immediately, while the orders for the second planning period can change when the activities for the next horizon are designed using the more updated system status. The horizon rolls one planning period at a time, which is subdivided into six time steps for the use of the optimization model which is time discrete (see Figure 2). The operation period in this paper is considered to be 12 hours, from 8 a.m. to 8 p.m.

Rule-based assignment model

The rule-based model is an algorithm that uses simple rules to respond to changes of the system status (staff location, vehicle location, and forecasted demand). It is based on the minimum and maximum stock levels defined for each zone (process adapted from Jorge et al., 2014).

At each planning period, movements are defined for staff, based on the needs of each zone. First, the status of the system is determined, being the data aggregated by zone. For each zone, the number of available staff members is also computed. Comparing the available vehicles with the minimum and maximum stock levels, zones are classified as in-need or givers.

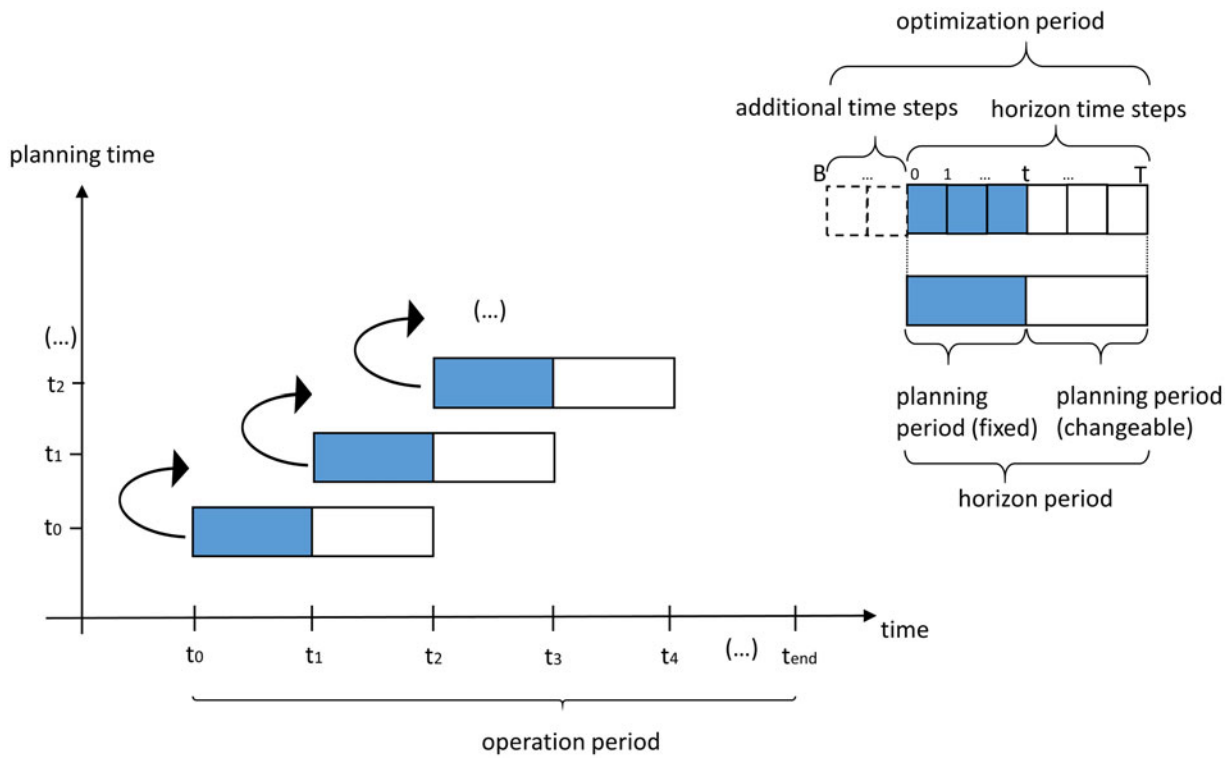


Figure 2. Representation of horizon, operation and planning periods.

The staff activities are ordered by priority level. The main priority is to perform maintenance, and secondly to relocate vehicles. Activities are attributed to staff according to their availability and location relative to the vehicles. Four sets of orders are assigned according to the following priority:

1. Order sent to the available staff member in the same zone where a vehicle is in need of maintenance to maintain that vehicle;
2. Order sent to the nearest available staff member in relation to the zone where the vehicle needing maintenance is located. The order is decomposed into two tasks: first to move to the zone where the vehicle is in need of maintenance using public transport; second to perform the needed maintenance task;
3. Order sent to the available staff member located at a giver zone to move a vehicle from that zone to the closest in-need zone. After the order is sent, the temporary stock of available vehicles is updated, as well as zones' classifications (in-need or giver).
4. The remaining available staff members receive orders to move to the closest giver zone by public transport, and then to move a vehicle into the closest zone that needs vehicles. The temporary difference between available vehicles and the existing demand and zones' classifications are once again updated.

Table 1. Example of the process to determine minimum and maximum limit values for stock of vehicles for a given zone.

Planning periods in a day	1	2	3	4	5	6	7	8	9	10
Forecasts:										
#arrivals	8	8	0	1	2	0	1	3	0	0
#departures	0	1	0	3	0	3	4	0	4	0
#arrivals-#departures	8	7	0	-2	2	-3	-3	3	-4	0
#in-need	0	0	0	2	0	3	3	0	4	0
<hr/>										
in-need										
Average (μ)	Std. Dev. (σ)		Min threshold = μ		Max threshold = $\mu + \sigma$					
1.2	1.62		1.2 \approx 1		2.82 \approx 3					

The minimum and maximum vehicle stock levels are based on the demand forecast data (see Table 1). Having the set of forecasted arrivals and departures per planning period, for the entire period of operation, we determine the difference between arrivals and departures. From this difference, the number of vehicles that are needed to satisfy all forecasted demand is computed, for each planning period of the considered operation day. Using the data of in-need vehicles for each planning period, the average and standard deviation are determined for each zone considering the operation day.

The minimum limit for the vehicles stock is the rounded average of the in-need vehicles from all the planning periods contained in the operation period. The maximum limit considered is the sum of the average with the standard deviation. Assuming that the number of in-need vehicles is a random variable

that follows a normal distribution (Central Limit Theorem), we can state that, by guaranteeing the minimum number of vehicles equal to the average, half of the likely needs are covered. And, by setting the maximum number as the average plus one standard deviation, the action of letting excess vehicles leave the station above that threshold will only lead, on average, to vehicle depletion in 16% of the cases. The maximum and minimum vehicle stock levels obtained by this method are reference values that can be, in a real situation, overridden by the operator.

Optimization assignment model

A mixed integer programming (MIP) model designed to work in real-time to help in the management of one-way carsharing staff operations is proposed. This MIP model is an evolution of the model presented by Santos and Correia (2015), and it includes three main improvements when compared with the work of Kek et al. (2009). First, the model is prepared to be used in a rolling horizon planning approach by allowing the incorporation of staff tasks ongoing at the start of the current horizon. Second, it considers that staff movements are performed using carsharing service vehicles or public transport according to what is best for cost minimization. And third, it allows trip joining of staff, meaning that staff members that share the same origin and destination zone can travel in the same vehicle, benefiting from the use of the available vehicle seats to reduce costs. The trip joining of staff is an adaptation from the user-based relocation mechanism proposed by Barth, Todd, and Xue (2004).

The optimization process is repeated during the operation day, for each horizon, to allow an acceptable data update rate from the system, and produce a real-time interaction between requests and the staff activities. To accommodate the tasks that were initiated previously to the current horizon, the lower limit of the optimization period is extended to the beginning of the earliest incomplete staff activity (instant B), considering that the first time instant of the current horizon is equal to one (see Figure 2).

Therefore, the set of time instants considered is $I = \{B, \dots, t, \dots, T\} \subset \mathbb{Z}$. The set of zones is $N = \{1, \dots, i, \dots, S\} \subset \mathbb{N}$, being S the number of zones in the region where the system operates (if the space is discretized in stations, each zone can be considered as a station). The set $V = \{1_B, \dots, i_t, \dots, S_T\}$ denotes the time-space network constituted by all the $S \times I$ nodes. The set of arcs between the nodes defined in V is designated by A , and represents all the possible time-space movements and activities.

A set of staff members $L = \{1, \dots, k, \dots, W\}$ is available to carry out the maintenance and relocation activities. Members of staff are identified by an ID number and each member is assigned to perform only one activity at a time. The possible activities of staff members are the following: idling, moving inside a carsharing system vehicle, moving by using public transport, and performing maintenance.

Staff uses carsharing vehicles or public transport to move in the network according to maintenance needs and to perform relocation activities. The travel time between zones using a carsharing vehicle is defined by the variables t_{ij} , and the travel time using public transport is defined by the matrix t_{ij}^P . The maintenance procedures performed by a staff member k have a fixed duration (t_z).

The number of vehicle requests and the number of vehicle arrivals by clients for the given horizon denoted as $d(i_0)$ and $r(i_0)$, respectively, are defined, for each zone i , using a forecasting method. Moreover, the number of available vehicles $a(i_0)$ and the number of vehicles needing maintenance $b(i_0)$, are retrieved from the system before each optimization process. These forecast and status values are included in the instant zero of the optimization period.

The number of vehicles at the beginning of the horizon period in each zone, $a(i_0)$, is converted into a number of overstocked vehicles $o(i_0)$. The number of overstocked vehicles at each zone equals to the number of vehicles located at zone (i) at the beginning of the planning period $a(i_0)$, plus the difference between the forecasted vehicle arrivals $r(i_0)$ and vehicles taken by clients $d(i_0)$:

$$o(i_0) = \begin{cases} 0, & \text{if } a(i_0) + r(i_0) - d(i_0) \leq 0 \\ a(i_0) + r(i_0) - d(i_0), & \text{otherwise} \end{cases} \quad (1)$$

The number of vehicles needed in each zone $n(i_0)$ derives from the demand for vehicles by the clients, $d(i_0)$, and the number of vehicle arrivals brought by the clients, $r(i_0)$, whose values are forecasted:

$$n(i_0) = \begin{cases} 0, & \text{if } d(i_0) - a(i_0) - r(i_0) \leq 0 \\ d(i_0) - a(i_0) - r(i_0), & \text{otherwise} \end{cases} \quad (2)$$

In Figure 3 we present an example of the calculation of $n(i_0)$ and $o(i_0)$.

The values of $o(i_t)$ and $n(i_t)$ are updated with real system values at the instant zero of the optimization period which corresponds to the beginning of each horizon.

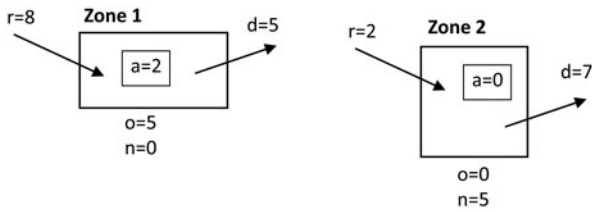


Figure 3. Calculation of o and n for two zones at the instant 0 of the optimization period.

The fulfilled component of the needed vehicle demand, $n(i_t)$, at each zone and instant ($\forall t > 0$) is denoted by $k(i_t)$. Clients (forecasted demand for $t > 0$) can only use the available vehicles $o(i_t)$ to move. Staff can also use those vehicles or public transport. The vehicles requested by clients are discounted from the $o(i_t)$ vector during the optimization period, vehicles returned by clients are only accounted for when system status is updated at the beginning of the next horizon, after new data has been retrieved from the system running. Vehicle movements by staff are described in aggregated variables, denoted as $v(i_t, j_{t+t_{ij}})$.

Therefore the problem formulation has six sets of decision variables:

- $v(i_t, j_{t+t_{ij}})$: discrete variables quantifying the number of vehicles moving from zone i at time instant t to zone j at time instant $t + t_{ij}$;
- $u^k(i_t, j_{t+t_{ij}})$: binary variables associated with a staff movement inside a vehicle, taking value 1 if staff k moves from zone i at time instant t to zone j at time instant $t + t_{ij}$, and 0 otherwise;
- $s^k(i_t, j_{t+t_{ij}^p})$: binary variables associated with a staff movement using public transport, taking value 1 if staff k moves from zone i at time instant t to zone j at time instant $t + t_{ij}^p$, and 0 otherwise;
- $y^k(i_t, i_{t+1})$: binary variables associated with a staff member waiting for the next task, taking value 1 if staff k is waiting at zone i from time instant t to time instant $t + 1$, and 0 otherwise;
- $z^k(i_t, i_{t+t_z})$: binary variables associated with maintenance activity, taking value 1 if staff k is maintaining a vehicle at zone i from time instant t to time instant $t + t_z$, and 0 otherwise;
- $n(i_t)$: number of vehicles needed at zone i at time instant t .

With three additional sets of dependent variables:

- $o(i_t)$: number of vehicles available at zone i at time instant t ;
- $b(i_t)$: number of vehicles needing maintenance at zone i at time instant t ;

- $q(i_t)$: number of fulfilled client requests at zone i at time instant t , $\forall t > 0$.

The known constants are:

- g : vehicle capacity in number of available seats. It is considered that all vehicles have the same capacity;
- t_{ij} : travel time between zones using a car;
- t_{ij}^p : travel time between zones using public transport;
- t_z : time to complete maintenance procedure;
- $n(i_0)$: number of vehicles in need to balance zone i at time instant $t = 0$;
- $o(i_0)$: number of vehicles available to perform movements at zone i at time instant $t = 0$;
- $b(i_0)$: number of vehicles needing maintenance at zone i at time instant $t = 0$;
- $c_v(i, j)$: cost of a vehicle movement by staff between zones i and j ; which is based on distance and fuel cost. It is assumed that staff hours and other vehicle costs are fixed, therefore not optimizable;
- $c_s(i, j)$: cost for staff movement using public transport between zones i and j , which is based on tariff price;
- $c_d(i)$: penalty for not fulfilling or delaying one client request, which is related to the potential profit outcome allowing the optimization process to be smart and give more importance to more profitable zones when relocating vehicles;
- c_b : penalty for maintenance not fulfilled or delayed to the next time instant, which is a value higher than the average revenue per vehicle for the period between time instants.

The objective function of the problem is:

$$\begin{aligned} \min(\Pi) = & \sum_{(i_t, j_{t+t_{ij}}) \in A} c_v(i, j) \cdot v(i_t, j_{t+t_{ij}}) \\ & + \sum_{k \in L} \sum_{(i_t, j_{t+t_{ij}^p}) \in A} c_s(i, j) \cdot s^k(i_t, j_{t+t_{ij}^p}) \\ & + c_d(i) \cdot \sum_{i_t \in V} n(i_t) + c_b \sum_{i_t \in V} b(i_t) \end{aligned} \quad (3)$$

Subject to:

$$\begin{aligned} & \sum_{t=B}^{t=0} \sum_{i \in N} y^k(i_t, i_{t+1}) + \sum_{t=B}^{t=0} \sum_{i \in N} z^k(i_t, i_{t+t_z}) \\ & + \sum_{t=B}^{t=0} \sum_{\substack{i, j \in N \\ i \neq j}} u^k(i_t, j_{t+t_{ij}}) + \sum_{t=B}^{t=0} \sum_{\substack{i, j \in N \\ i \neq j}} s^k(i_t, j_{t+t_{ij}^p}) \\ & = 1, \quad \forall k \in L \end{aligned} \quad (4)$$

$$\begin{aligned}
 & y^k(i_{t-1}, i_t) + z^k(i_{t-t_z}, i_t)_{(i_{t-t_z}, i_t) \in A} + \sum_{(j_{t-t_{ij}}, i_t) \in A} u^k(j_{t-t_{ij}}, i_t) \\
 & + \sum_{(j_{t-t_{ij}^p}, i_t) \in A} s^k(j_{t-t_{ij}^p}, i_t) - y^k(i_t, i_{t+1}) - z^k(i_t, i_{t+t_z})_{(i_t, i_{t+t_z}) \in A} \\
 & - \sum_{(i_t, j_{t+t_{ij}}) \in A} u^k(i_t, j_{t+t_{ij}}) - \sum_{(i_t, j_{t+t_{ij}^p}) \in A} s^k(i_t, j_{t+t_{ij}^p}) \\
 & = 0, \quad \forall i_t \in V | t > 0, k \in L
 \end{aligned} \tag{5}$$

$$\sum_{k \in L} u^k(i_t, j_{t+t_{ij}}) \geq v(i_t, j_{t+t_{ij}}), \quad \forall (i_t, j_{t+t_{ij}}) \in A \tag{6}$$

$$\sum_{k \in L} u^k(i_t, j_{t+t_{ij}}) \leq g \times v(i_t, j_{t+t_{ij}}), \quad \forall (i_t, j_{t+t_{ij}}) \in A \tag{7}$$

$$o(i_t) \geq v(i_t, j_{t+t_{ij}}), \quad \forall (i_t, j_{t+t_{ij}}) \in A | t > 0 \tag{8}$$

$$o(i_t) = o(i_{t-1}) + \sum_{(j_{t-t_{ij}}, i_t) \in A} v(j_{t-t_{ij}}, i_t) - \sum_{(i_t, j_{t+t_{ij}}) \in A} v(i_t, j_{t+t_{ij}})$$

$$+ \sum_{\substack{(i_{t-t_z}, i_t) \in A \\ k \in L}} z^k(i_{t-t_z}, i_t) - q(i_t), \quad \forall t \in T | t > 0 \tag{9}$$

$$b(i_t) = b(i_{t-1}) - \sum_{\substack{(i_t, j_{t+t_{ij}}) \in A \\ k \in L}} z^k(i_t, i_{t+t_z}), \quad \forall t \in T | t > 0 \tag{10}$$

$$n(i_t) = n(i_{t-1}) - q(i_t), \quad \forall t \in T | t > 0 \tag{11}$$

$$\begin{aligned}
 & u^k(i_t, j_{t+t_{ij}}), y^k(i_t, i_{t+1}), z^k(i_t, i_{t+t_z}), s^k(i_t, j_{t+t_{ij}^p}) \\
 & \in \{0, 1\}, \quad \forall k \in L
 \end{aligned} \tag{12}$$

$$v(i_t, j_{t+t_{ij}}) \in \mathbb{N} \cup \{0\}, \quad \forall (i_t, j_{t+t_{ij}}) \in A \tag{13}$$

$$o(i_t), b(i_t), q(i_t), n(i_t) \in \mathbb{N} \cup \{0\}, \quad \forall i_t \in V \tag{14}$$

The objective function (3) minimizes the generalized cost function Π for this particular interval of time which includes: the cost of vehicle movements used for staff operations, the cost of staff moving by using public transport, the potential profit losses of not fulfilling demand, and a penalty for maintenance requests not executed. The potential profit losses are included in order to consider the demand attended by the system. Notice that it only makes sense to consider the profit of the system along a day and not in one time interval.

Constraints (4) impose the initialization of the variables according to the previous cycle by limiting the staff operations initiated before instant $t = 0$ to only one task per staff member. Constraints (5) assure the conservation of staff activities at each node of the time-space network. It restricts staff to start a new activity only after ending the previous one. Constraints (6) and (7) relate in-vehicle staff movements with the vehicles moving by imposing a

minimum and a maximum number of staff traveling in each vehicle. A minimum of one staff is needed to drive a vehicle and the maximum number is related to the vehicle's capacity in a number of seats. This allows having trip joining in staff movements. These two sets of constraints also assure that the vehicle movements initiated before $t = 0$ fulfill the same criteria, being the domain $(i_t, j_{t+t_{ij}}) \in A$. Constraints (8) impose that a vehicle can only depart from a station where vehicles exist. Constraints (9) and (10) update the values of the variables between time instants. Constraints (11) are conservation equations related to demand. Constraints (12) set the domain of the binary variables, and constraints (13) and (14) the non-negative integer variables.

Simulator

A simulator was designed to test the real-time decision support tool. It emulates a free-float one-way car-sharing system, allowing to test different scenarios, by including the necessary procedures that characterize the interaction between demand and supply. The simulator works in a hybrid way. It is time driven, to set the beginning and end of each considered planning time, and event-driven to initiate and finish movements of staff, cars, and clients. To reduce the level of complexity, since no animation is required, the simulator is built on top of a database by using data arrays and is additionally connected to Xpress (Commercial software produced by FICO used to solve the MIP model).

Simulation process

The simulation process initiates by building the simulation environment using the static input data (see Figure 4). The basic data vector and zones' data arrays give the information about simulation parameters and the necessary information to build the geographic space. The system data is initiated by the staff and vehicles initial positions from the respective static input data arrays. In the beginning, the arrivals array is empty.

Starting the simulation

For the first iteration, the simulator runs the assignment model (rule-based or optimization) to produce the first assignment plan. The plan is then applied to the first planning period by using the forecast values (in a number of requests for the respective horizon

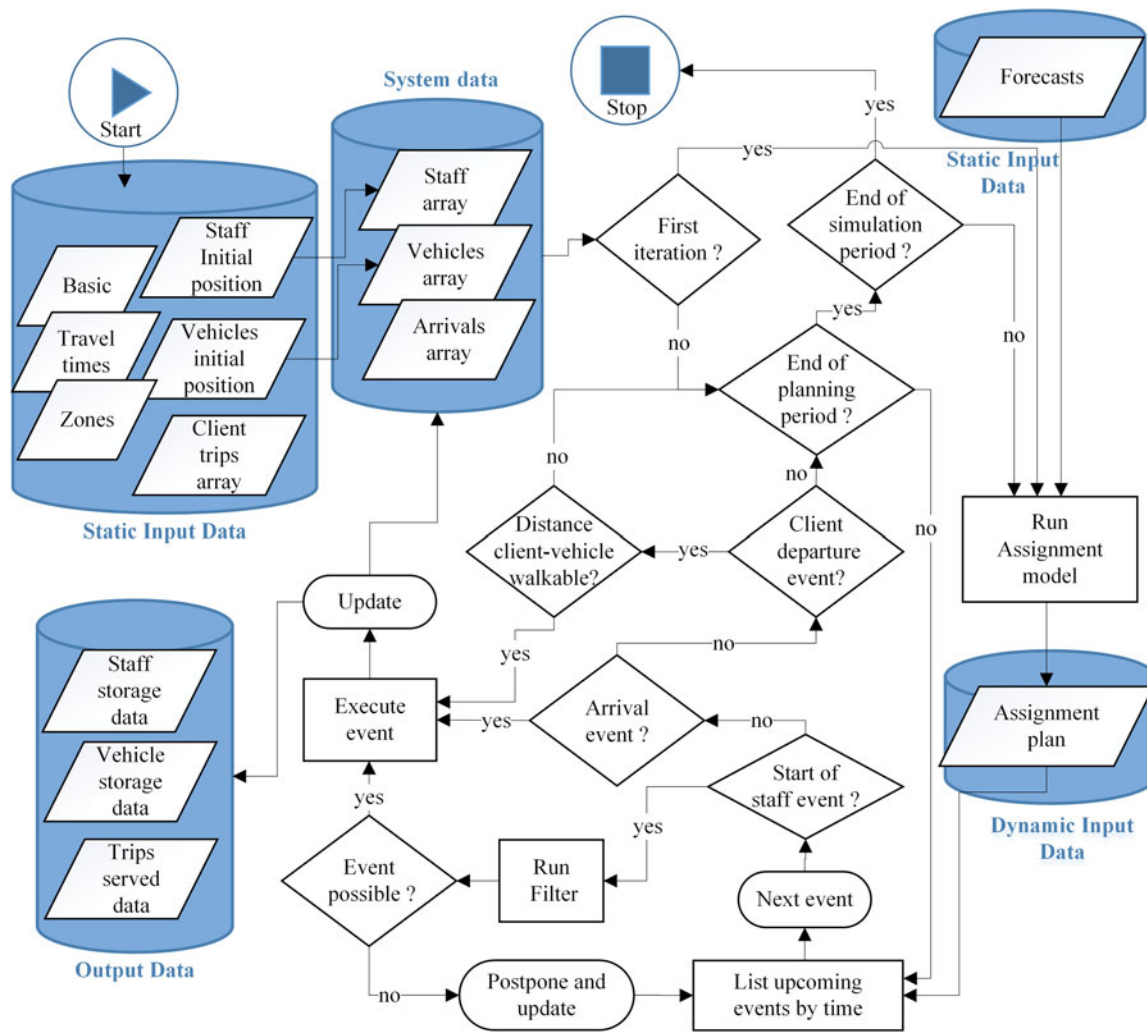


Figure 4. Simulator flow chart.

period) retrieved from the static input data. The activities of the staff for the first planning period are merged with the client trips in order to populate a list of upcoming events. The list is then ordered by time of occurrence.

Processing events

The travel events are processed by chronological order. Three questions must be answered: “it is the start of staff event?”, “is it an arrival event?”, “is it a client departure event?”.

- If the next event is the “start of a staff event”, the simulator runs the filter of the real-time decision tool to check if the event is possible. If yes, the event is executed, otherwise, the staff activity is postponed and the list of upcoming events updated.
- If the next event is an “arrival event”, the simulator executes the event. The arrival events are updated

at the time a client trip or staff event is started, as it is further discussed.

- If the next event is a “client departure”, the distance between the client and the vehicle is determined to assess if the distance between the two entities is walkable (vehicles and clients’ positions are registered in coordinates). In case the answer is positive the event is executed (demand is accepted), otherwise demand is rejected.

Updating system arrays and adding new entries on output tables

When an event is executed (start or arrival), the system data arrays are updated and the replaced data is stored in the correspondent output data tables. The possible events are: “departure of client”, “arrival of client”, “staff starting movement”, “staff finishing movement”, “staff starting maintenance”, and “staff finishing maintenance”. The events are described next:

- **Departure of client**
When a client starts a trip, the vehicle system data is changed (remember that system data virtually controls what is happening inside the system). The vehicle that the client uses changes its status from “available” into “used by client” and the data related to the origin, destination, duration, and distance are added. At the same time, the arrivals array and output data are updated. A new entry is added to the arrivals array with the time of arrival of the vehicle and the coordinates of the location of the arrival, where the client ends the rental period. Lastly, one new entry is added to the vehicles’ storage table of the output data with the previous vehicle status.
- **Arrival of client**
On the arrival of a client, the client and vehicle new positions are updated in the client and vehicle arrays. A Bernoulli trial with a probability p , in this work designated by maintenance generation factor, is applied to decide if the vehicle was left in a state of needing maintenance. As a consequence there are two outcomes, the status of the vehicle in the system database changes into needing maintenance or into available, depending on the Bernoulli process result. Once the status of the vehicle changes this is updated in all relevant databases.
- **Staff starting movement**
Movements of the staff are subdivided into two types: movement in a carsharing vehicle and movement by using public transport. When a staff member initiates a movement the mode used, zone of origin, destination, vehicle used (in the case of using a carsharing vehicle) time of departure and time of arrival, are identified in the staff array of the system database, and the previous values registered in a new entry in the staff storage table of the output database. Simultaneously a new entry is added to the arrivals array and the list of upcoming events is updated. If the staff is using a car-sharing vehicle, the status of the vehicle used by staff changes and, consequently, the respective values in the vehicles array of the system data are updated. The previous status is stored in the vehicles storage table of the output database.
- **Staff ending a movement**
When a staff member finishes a movement the new position is updated, the status changes into idle, and the staff array of the system data is changed in accordance. The previous status information is stored on the staff storage table of the output data. For movements in a vehicle, the status

of the vehicle is updated to available, the vehicles’ array is updated, and the information related to the previous status stored in the vehicles’ table of the output database.

- **Staff starting maintenance**
Status of the vehicle changes from “needing maintenance” into “being maintained” and the values of the vehicle array of the system data are updated. The assigned staff status also changes into “maintaining a vehicle” and the values of the staff array are updated accordingly. The previous status of both vehicle and staff are stored in the respective tables of the output database.
- **Staff finishing maintenance**
When staff finishes maintenance, the status of staff changes into available, and the status of the vehicle into available, being both staff and vehicle arrays updated. The former statuses are stored in the staff and vehicles tables of the output database.

Assessing conditions to move to the next planning period or stop the simulation process

After processing each event two conditions are assessed. The first one marks the end of the planning period and allows the simulator to run the assignment model once more for the new system data values and using the correspondent forecast values. This produces a new action plan for staff, whose entries are included in the list of upcoming events. The second condition marks the end of the simulation period.

Application to the case study of Lisbon

The real-time decision tool was tested for a simulation environment with the characteristics of Lisbon municipality.

Setting up the experiments

To assess the daily movements inside the Lisbon municipality, a survey was applied to its area of influence, amplifying the spatial analysis, but containing it to the limits of the Lisbon Metropolitan Area. The survey, Web-based complemented with CAPI, was oriented to produce a synthetic population including the daily activity log of each individual, in order to characterize the mobility inside the Lisbon municipality. The implemented survey is detailed in Santos, Martínez, Viegas, and Alves (2011).

The data needed to use the real-time decision support tool can be subdivided into the following categories: basic data, zones, staff and vehicles’ initial

positions, travel times, client trips (“real demand”), demand forecasts, and minimum and maximum stock limits (rule-based model).

Basic data

The start and end time of the simulation is the working period of the staff, which was considered to be from 8 a.m. to 8 p.m. The duration of the horizon and planning periods were 60 and 30 min, respectively. The planning periods were subdivided in time instances of 10 min. Every vehicle has a maximum capacity of four seats. The duration of a maintenance activity was considered to be fixed and equal to 30 min, which corresponds to walking to the vehicle, solve the problem and send a report. This duration is assumed and was established for planning purposes, that is, to design an activity plan. In simulated reality, if it is concluded earlier than that, the vehicle availability happens earlier.

The price charged for using the service is the same as what the company Citydrive is charging in Lisbon, which is 0.29 €/min (Citydrive, 2016). The salary cost for the staff is 3.5 €/hour (based on a 40 hour working period and a monthly wage of 560 €, which is 30€ higher than the considered Portuguese minimum wage established for the year 2016 (DN, 2015)).

It is considered that the cars cost 15,000 € and will be used in the system for an average of three years, having a depreciation of 20% per year, leading to a depreciation value of 8.22€/day. The fuel cost was considered to be 0.09 €/km, based on a mixed fuel consumption of 6.9 liters of petrol per 100 km (values for an Opel Adam) and a price of 1.21 €/l of unlead petrol 95 (average price in Portugal for January 2016 (DGEG, 2016)).

The municipality of Lisbon charges 50 € per month per carsharing vehicle for conceding unlimited parking inside the city, which corresponds to 1.67 € per day (CML, 2014). It is considered that the carsharing company provides a transit pass for every employee. The individual title covering the city of Lisbon named *Navegante*, costs 35.65€ for a 30 day period (Transportes de Lisboa, 2015), which represents 1.19 €/day and per staff. Finally, the maintenance generation factor is considered to be 0.5%, for which there is no data available.

Zones

The zones are squares with 1500 m side, resulting in 46 zones for the operating area (see Figure 5). This assures a walkable range between a staff member and a vehicle if both are inside the same zone. Note that for the simulation of clients there are no discretization

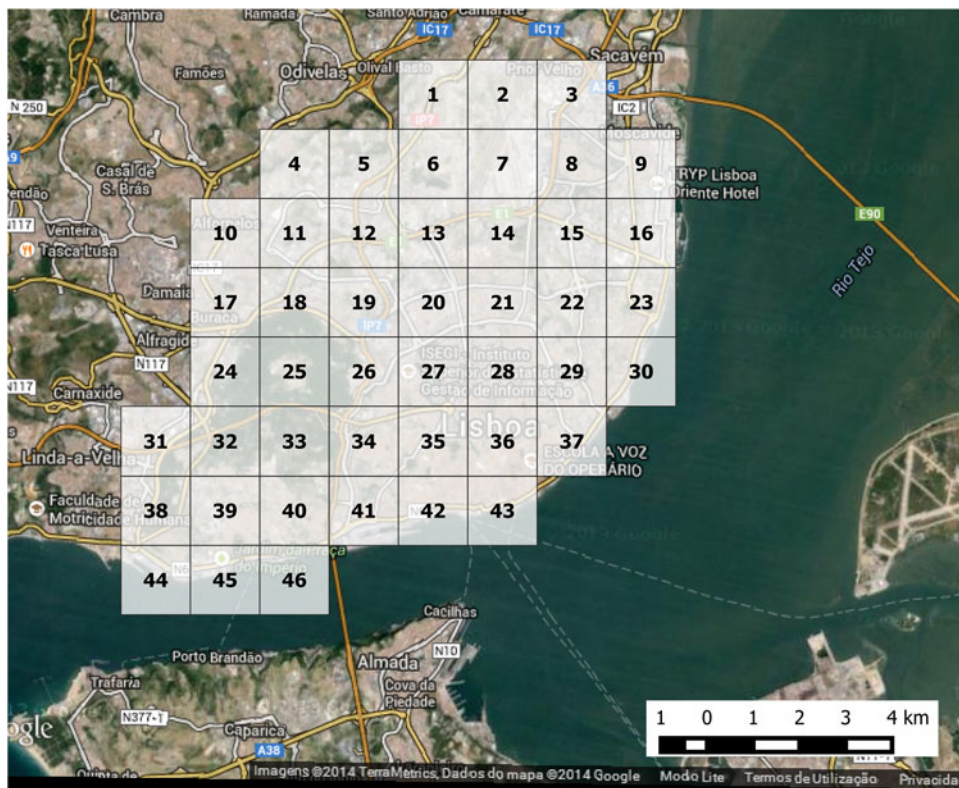


Figure 5. Defined zones with the grid cells in the background.

in zones. Clients use the nearest vehicle and are willing to walk 1000 m for a car. Zones constitute a simplification used only for planning staff movements.

Staff and vehicles' initial positions

All the staff is located at the staff headquarters in the beginning of the day. The chosen zone is zone 28 which is central to the operation area (Figure 5), well served by public transport, close to the main urban avenues, and has the highest demand.

The vehicles initial positions were determined using a process with two stages. Firstly, the vehicles were distributed by each zone proportionally to all the daily demand as the origin for the entire operation period. With those vehicle stocks, the simulation model was run for a warm-up period. The movements of clients between midnight and 8 a.m. were simulated to get the positions of vehicles close to what most likely would be found by staff when starting the working period (from 8 a.m. to 8 p.m.). With this, it is assumed that when the staff starts working at 8 a.m., it faces a scenario of imbalanced vehicle positions, which is a result of client movements during staff off hours.

Travel times

The car and public transport travel times were obtained from a traffic macro-simulation of Lisbon using real data. The in-vehicle time depends on the mode chosen by the staff member, and this simplification allows the definition of a time window after which the staff member is supposed to be at the destination.

Client trips

The client trips are used to simulate client movements of the real system and were obtained from the car-sharing potential demand estimated in previous research by Eiró (2015) for the same city, using the survey detailed in Santos et al. (2011). The application of an agent-based model together with a discrete choice process for the city of Lisbon resulted in 26,025 potential daily trips for carsharing (considering that a car is always available within 10 min access), which represents 4.1% of the trips done in the Lisbon municipality by people with a driver's license (short trips are excluded). This process is depicted in Santos (2016). Taking into consideration the difficulties of a new carsharing system entering the market (not having enough vehicles, not having enough visibility), conservative scenarios are analyzed in which the simulated demand is only part of the potential demand

previously obtained. By using Bernoulli trials with 8%, 15% and 25% of success, we reduced the demand into 2108 trips, 3929 trips, and 6414 trips, respectively (78% starting between 8 a.m. and 8 p.m.). The 8% share of the demand, returned a number of trips close to the demand considered by Jorge et al. (2014) for the same study application area which was obtained through another database. These were the three samples used as real demand (client trips) for simulation. The necessary trip data for simulation retrieved from this process includes origin, destination, start time, time duration and distance.

Demand forecast

The demand forecast, part of the real-time decision support tool (see Figure 1), is used to allow a better planning of the staff activities and vehicles' stocks, and is based on client arrivals and departures for each zone. The forecast is computed using a homogeneous Poisson process. It is considered that the inter-arrival and inter-departure times of clients are independent and identically distributed following exponential distributions. To apply the Poisson generation process we used the average hourly vehicle departure and arrival rates defined for each zone, and for each of the twelve hours operation period. The Poisson generation process was applied separately for departures and arrivals, in order to generate the necessary forecasts (see Figure 6).

The simplistic use of a homogeneous Poisson process is due to the absence of historical values (a consequence of studying a nonexistent system), affecting the significance level of the considered rates. The consideration of more advanced sampling algorithms should be regarded for real applications (e.g. Ichoua, Gendreau & Potvin, 2006; Matteson, McLean, Woodard, & Henderson, 2011; Sayarshad & Chow, 2016; Weinberg, Brown, & Stroud, 2007).

Minimum and maximum stock limits

The stock limits for the rule-based model were obtained using the process previously described for the forecasted demand values of arrivals and departures (see Table 1).

Simulated scenarios

A total of 272 scenarios were simulated in order to test the real-time decision support tool and conclude about the impact of the relocations. Several replications were done for three levels of demand: starting by the 8% demand level (similar to the demand

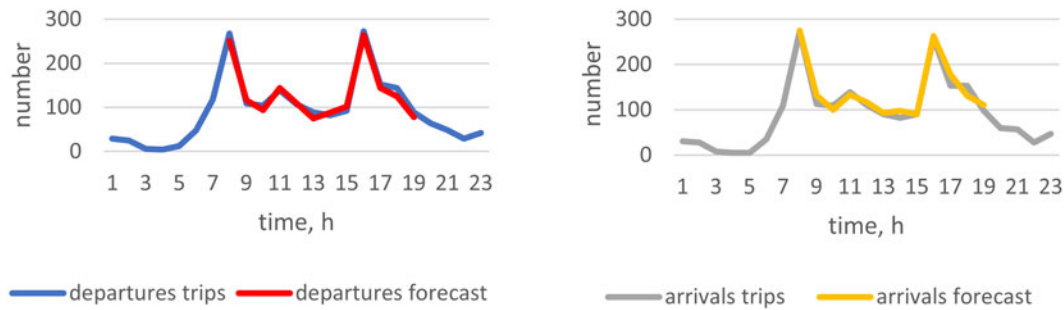


Figure 6. Client arrivals and departures for the 8% level of demand along one day period.

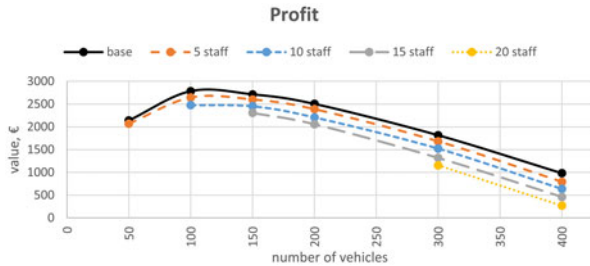


Figure 7. Profit for the scenarios with maintenance requests, 8% of demand, considering 0, 5, 10, 15 and 20 staff members and the optimization of their activities.

considered by Jorge et al. (2014)), followed by a demand level two times higher, and a level three times higher. The number of cars considered in each scenario, had a lower and an upper limit. The lower limit allows to have a fulfilled demand above 50%, and the upper limit is the next 100 cars increment that satisfies more than 95% of demand (previous simulation tests were run to choose these scenarios). A base model was additionally developed to collect the system performance indicators when staff operations are not used in the system, that is, when only the movements of clients are simulated. The base model is run for all the scenarios described before (see Table 2).

For the rule-based and the optimization model of the real-time decision support tool, staff members are added. The number of staffs considered for the rule-based and optimization model is related to the number of vehicles, varying from 1 staff member per 10 vehicles to 1 member per 80 vehicles. In all cases, two scenarios were tested with vehicle maintenance needs: a maintenance generation factor of 0.5% and no maintenance events.

Results

In general, from the simulations, it could be observed that the use of staff in the carsharing system normally reduces the value of the daily profits due to the fact that the increase of costs associated to staff salaries

are not compensated by the increment of profits generated by the vehicle relocations and the solving of the maintenance requests. As an example, we show the profit for the scenarios with maintenance requests, 8% of demand level, considering 0, 5, 10, 15 and 20 staff members and the optimization of their activities (Figure 7). It's possible to see that the increment of staff members is reducing the profit of most of the fleet dimensions.

To analyze in detail what caused the reduction of profits we compare the results of having staff and not having staff for the scenarios with higher profit: 8% of demand with 100 vehicles, 15% of demand with 200 vehicles, and 25% of demand with 300 vehicles (see Table 3). All the scenarios have a 0.5% maintenance generation factor.

The introduction of staff members results in a reduction of the profits in relation to the base scenario for the demand levels of 8% and 15%, and an increase for the 25% demand level independently on how relocations are planned (rule-based or optimization).

In terms of costs, the introduction of staff members has two fixed components: the salary of 3.5 €/h and the 1.19 € daily parcel of the monthly pass per staff member. This leads to daily fixed costs of 216 € for 5 staff members. Additionally, there is a variable cost component related to the movement of staff in vehicles for relocation or maintenance purposes, which ranges from 16 to 43 € per operation day for the scenarios in Table 3.

The benefit of having staff activity is that it increases the revenue due to the relocation of vehicles, and also by making cars available after maintenance operations. However, for the 8% and 15% demand level scenarios, this is not enough to overtake the costs increase. For the 8% demand scenario, the increase in revenues of having 5 members of staff is 38.56 € for the rule-based model and 72.89 € for the optimization model. For the 15% demand level scenario, the increase in daily revenues is 168.94 € for the

Table 2. Overview of simulated scenarios.

Demand	Number of cars	Number of staff	Maintenance gen. factor	Models	Total Sims
8% (reference)	50	5	0 and 0.5	• Base	6 × 2
	100	5, 10		• Rule-based	17 × 2
	150	5, 10, 15		• Optimal	17 × 2
	200	5, 10, 15			
	300	5, 10, 15, 20			=
	400	5, 10, 15, 20			80
15%	100	5, 10	0 and 0.5	• Base	6 × 2
	150	5, 10, 15		• Rule-based	20 × 2
	200	5, 10, 15		• Optimal	20 × 2
	300	5, 10, 15, 20			
	400	5, 10, 15, 20			=
	500	5, 10, 15, 20			92
25%	150	5, 10, 15	0 and 0.5	• Base	6 × 2
	200	5, 10, 15		• Rule-based	22 × 2
	300	5, 10, 15, 20		• Optimal	22 × 2
	400	5, 10, 15, 20			
	500	5, 10, 15, 20			=
	600	5, 10, 15, 20, 25			100

Table 3. Performance indicators for selected scenarios (maintenance requests included).

Model	8% demand			15% demand			25% demand		
	base	rule-based	optim.	base	rule-based	optim.	base	rule-based	optim.
Number of cars	100	100	100	200	200	200	300	300	300
Number of staff	0	5	5	0	5	5	0	5	5
Profit (€/day)	2784.39	2619.03	2645.59	5489.25	5437.24	5447.28	9272.52	9328.51	9339.14
Revenues (€)	4165.56	4204.12	4238.45	8260.99	8429.93	8461.32	13526.77	13812.87	13836.87
Costs (€)	1381.17	1585.09	1592.86	2771.74	2992.69	3013.74	4254.25	4484.36	4497.73
- Car depreciation	822.00	822.00	822.00	1644.00	1644.00	1644.00	2466.00	2466.00	2466.00
- Parking cost	167.00	167.00	167.00	334.00	334.00	334.00	501.00	501.00	501.00
- Staff wage	-	175.00	175.00	-	175.00	175.00	-	175.00	175.00
- Staff movements pt	-	5.95	5.95	-	5.95	5.95	-	5.95	5.95
- Client movements in car	392.17	398.22	398.74	793.74	812.76	812.73	1287.25	1318.12	1320.58
- Staff movements cars	-	16.92	24.17	-	20.98	42.06	-	18.29	29.20
Number of accepted trips	1248	1262	1270	2424	2475	2486	4086	4153	4169
Number of rejected trips	400	386	378	609	559	548	825	759	743
% accepted trips	75.7	76.6	77.1	79.9	81.6	81.9	83.2	84.5	84.9
Average dist. car client Euclidian (m)	461.9	470.6	469.3	389.2	392.7	376.8	343.8	338.3	338.6
Total maintenance requests	3	6	11	14	10	21	23	23	21
Number of fulfilled maint. req.	-	6	10	-	10	17	-	23	15
Car downtime (h)	16.1	6.3	15	93.1	14.9	46.4	139.1	27	40.9
	(1.3%)	(0.5%)	(1.3%)	(3.9%)	(0.6%)	(1.9%)	(3.9%)	(0.8%)	(0.9%)
Car time mov. Clients (h)	239.4	241.6	243.6	474.8	484.5	486.3	777.4	793.8	795.2
	(20.0%)	(20.1%)	(20.3%)	(19.8%)	(20.2%)	(20.3%)	(21.6%)	(22.1%)	(22.0%)
Car time mov. Staff (h)	-	9.2	6.7	-	8.8	11.2	-	7.5	8.2
	(-)	(0.8%)	(0.6%)	(-)	(0.4%)	(0.5%)	(-)	(0.2%)	(0.3%)
Car time idle available (h)	944.5	943	934.7	1832.1	1891.8	1856.2	2683.5	2771.7	2755.8
	(78.7%)	(78.6%)	(77.9%)	(76.3%)	(78.8%)	(77.3%)	(74.5%)	(77.0%)	(76.8%)
Total car distance (km)	4357.4	4612.7	4699	8819.3	9263.8	9497.7	14302.8	14849.1	14997.6
- with clients	4357.4	4424.6	4430.4	8819.3	9030.7	9030.3	14302.8	14645.8	14673.1
- with staff	-	188.1	268.6	-	233.2	467.4	-	203.2	324.4
Staff time maintaining (h)	-	3	5	-	5	8.5	-	10.8	7.2
	(-)	(5.0%)	(8.3%)	(-)	(8.3%)	(14.2%)	(-)	(18.0%)	(9.2%)
Staff time moving in car (h)	-	9.2	8.2	-	8.8	12.8	-	7.5	10
	(-)	(15.3%)	(13.6%)	(-)	(14.7%)	(21.3%)	(-)	(12.5%)	(17.0%)
Staff time moving in pt (h)	-	20.7	25.7	-	17.3	29	-	18	27.3
	(-)	(34.4%)	(42.8%)	(-)	(28.9%)	(48.3%)	(-)	(30.0%)	(42.8%)
Staff time idle (h)	-	27.2	21.2	-	28.8	9.7	-	23.7	15.5
	(-)	(45.3%)	(35.3%)	(-)	(48.1%)	(16.2%)	(-)	(39.5%)	(31.1%)
Number of car trips with staff	-	55	48	-	50	67	-	42	60
Number of staff PT trips	-	59	72	-	50	87	-	53	81
Num. of trip join passengers	-	-	9	-	-	10	-	-	11
- Car distance saved (km)	-	-	58.8	-	-	82.3	-	-	83.7
- Car time saved (h)	-	-	1.5	-	-	1.7	-	-	1.8

rule-based model and 200.33 € for the optimization model. For the 25% demand level the increase in revenues is 286.10 € for the rule-based model and 310.10

€ for the optimization model, which, in both cases, allows overtaking the fixed costs of staff by a small margin thus producing more profit.

The results obtained using the rule-based model (reactive) assignment are close to the ones obtained for the optimization model, meaning that it may be difficult to get better profits by optimizing these operations. For the optimization model considering 8% of demand level with 100 vehicles, the increase of profit in relation to the rule-based model is 26.56 €, for the scenario with 15% demand level the difference is 10.04 €, and for the scenario with 25% of demand the increase in profit is 10.63 € (see Table 3).

There are some other differences between both assignment models which need to be highlighted. The main difference is that the rule-based model gives priority to maintenance requests while the optimization model defines staff activity plans based on an overarching objective of improving the financial performance of the operator. This has impacts on the performance indicators, namely on the share of fulfilled maintenance requests and vehicle downtime. The number of fulfilled maintenance requests for the rule-based model is higher, lowering the downtime of the vehicles when compared to the optimization model. For example, the share of fulfilled maintenance requests for the scenarios on Table 2 varies from 71 to 91% for the optimization model and is 100% for the rule-based model in all demand scenarios. The car downtime varies from 0.5 to 0.8% of the total car time for the rule-based model, and 1.1 to 1.9% for the optimization model.

Giving priority to maintenance leads to higher vehicle availability, but not necessarily to an increase of the number of accepted trips, since vehicles might not be available at the right places. The simplicity of the rule-based model by establishing relocation movements using stock limits defined for the entire day also contributes to having less accepted trips than the optimization model. For the 8% demand level, the rule-based model leads to 8 fewer trips accepted than the optimization model, for the 15% demand the difference is 11 trips, and for 25% demand level the difference is 16 trips (see Table 3).

The optimization model is based on forecasts for the horizon period (equal to one hour for the application to the case study) and decides if it is more profitable doing relocations or performing maintenance, resulting in more movements of staff to perform relocation of vehicles. Since forecasts can be different from what happens in reality, the relocated vehicles not always result in trips served, and consequently in an increase in revenues. This can be seen in the 8% demand scenario where base and optimization model have similar car downtime (time that the vehicle is

unavailable to clients due to maintenance request) allowing to discard the contribution of maintenance on the number of accepted trips. For that scenario, there are 48 trips with staff, and the increase in accepted client trips relatively to the base model is only 22, therefore it can be said that the efficiency of these relocations could be lower than 50%.

Trip joining (staff carpooling) was considered to be advantageous for the performance of the system however during the simulation process it was verified that the savings due to trip joining were not significant. For the 8% demand scenario, the saving of 58.8 km corresponds to 5.29 € only, which is 0.1% of the total revenues, for the case of 15% of demand there were savings of 82.3 km, corresponding to 7.41 € (0.09% of the total revenues), and for the case of 25% demand level, there is a reduction of 83.7 km, which corresponds to 7.53 €, (0.05% of the total revenues) (see Table 3).

On the impact of operator-based relocations

The body of literature on carsharing operations preconizes the operator-based relocations as a mechanism that could solve the imbalance problems on vehicle stocks in one-way carsharing systems, therefore, improving the quality of service and eventually improve the financial performance of the system. During the previous analysis, it has been shown that the revenues obtained with the introduction of the full-time employed staff were, in general, not enough to significantly improve the profit and in some cases, they could even lead to worse results given the costs of keeping a staff team to take care of relocations and maintenance.

To understand what would happen if staff members were only focused on relocations, we can analyze the scenarios without maintenance requests. For these scenarios, the number of vehicle movements resulting from staff intervention is directly associated to relocations, with the exception of the optimization model, where vehicle movements can, in some cases, be associated with staff joining inside the same vehicle if it represents a favorable situation for the objective function.

We can see that for those scenarios the movement of vehicles performed by 5 members of staff, do not suffice for increasing the profits in relation to the base scenario (see Table 4). The maximum number of vehicle movements verified for these scenarios is 66, for the 8% demand level rule-based model and for the 15% demand level optimization model scenarios. For

Table 4. Performance indicators for selected scenarios not considering maintenance requests.

Model	8% demand			15% demand			25% demand		
	base	rule-based	optim.	base	rule-based	optim.	base	rule-based	optim.
Number of cars	100	100	100	200	200	200	300	300	300
Number of staff	0	5	5	0	5	5	0	5	5
Profit (€)	2797.09	2614.65	2659.00	5625.81	5440.41	5475.36	9455.79	9341.69	9365.36
Revenues (€)	4179.48	4201.15	4266.48	8411.54	8436.19	8494.39	13728.09	13834.94	13872.74
Costs (€)	1382.39	1586.50	1607.48	2785.73	2995.78	3019.03	4272.30	4493.25	4507.38
Number of accepted trips	1252	1263	1280	2469	2481	2497	4142	4168	4181
Number of rejected trips	396	385	368	564	553	537	769	744	731
% accepted trips	76	76.6	77.7	81.4	81.8	82.3	84.3	84.9	85.1
Car time mov. clients (h)	240.2	241.4	245.2	483.4	484.8	488.2	789	795.1	797.3
Avg client trip time (min/trip)	12	12	12	12	12	12	12	12	12
Car distance with clients (km)	4371	4419.6	4493.2	8974.8	9014.5	9080.4	14503.3	14672	14708.3
Avg car dist with client (km/trip)	3.5	3.5	3.5	3.6	3.6	3.6	3.5	3.5	3.5
Number of car trips with staff	-	66	57	-	62	66	-	61	58
Car time mov. staff (h)	-	11	9.5	-	11	11.3	-	10.8	9.7
Avg. time car staff mov. (min/mov.)	-	10	10	-	10.6	10.3	-	10.6	10
Car distance with staff (km)	-	208.7	368.2	-	283.6	476.1	-	275.7	396.4
Avg car dist. with staff (km/staff)	-	3.2	6.5	-	4.6	7.2	-	4.5	6.8
Num. of trip join passengers	-	-	23	-	-	13	-	-	23
- Car distance saved (km)	-	-	94.3	-	-	78	-	-	110.2
- Car time saved (h)	-	-	2.3	-	-	2.2	-	-	2.5

the 8% demand level rule-based model scenario, the 66 movements are converted into 11 additional accepted trips, while for the 15% demand level optimization model scenario, the same number of vehicle movements by the staff is converted into 28 additional accepted trips. Ideally, if all 66 movements were converted into accepted trips, the increase in revenues would be around 215 Euro taking the average revenue into account, which is 1 € lower than the fixed cost of having 5 members of staff (216 € per operation day), therefore it is not surprising that results are so disappointing.

Realistically the maximum possible number of relocations per staff per hour is between 2 and 3. The staff member needs to move towards the vehicle, drive it to the new location, park it and leave it there. Weikl and Bogenberger (2015) measured 0.7 to 1.1 relocations performed per hour on the field tests in Munich, Germany. Taking an average of two relocations per hour per staff member into consideration, in a 10h period of operation, each staff member would only be able to perform 20 relocation movements.

Assuming the average cost for staff relocation equal to 0.72 € (consisting in 8 km per movement in Lisbon with a fuel cost of 0.09 €/km) and the average revenue per accepted trip equal to 3.26 € (based on the average time and distance of client trips in Lisbon, respectively 12 min and 3.5 km), we can estimate the maximum possible profit increase considering 5, 10, 15, and 20 elements of staff which can be seen in Table 5.

In ideal conditions of every car being used by clients after being relocated and staff having had no other activity besides relocation, allowing 2 vehicle

Table 5. Possible profit increase from relocations considering that all relocations are converted into accepted trips with no maintenance requests all through the day.

Number of staff	5	10	15	20
Number of relocations	120	240	360	480
Possible revenue from clients (€)	+379.2	+758.4	+1137.6	+1516.8
Salary costs (€)	-210	-420	-630	-840
Public transport costs (€)	-6	-12	-18	-24
Relocation movement cost (€)	-86.4	-172.8	-259.2	-345.6
Possible profit variation (€)	+76.8	+153.6	+230.4	+307.2

relocation movements per hour per staff, the potential increase in profit varies from 77 € for 5 elements of staff to 307 € for 20 elements of staff per 12 h of operation. This would represent a profit increase from 2.7% to 11% for the 8% demand level, 1.4% to 5.5% for the 15% demand level, and 0.8% to 3.2% for the 25% demand level (see Table 6). The impact of the potential increments is eliminated as the demand increases, due to the fact that relocation revenues are limited by the number of staff elements.

For the results presented in Tables 5 and 6, it was assumed that all relocation movements would be converted in accepted trips. In a real situation, this is unlikely to happen if we look at what happens in the simulation model. Considering all the simulated scenarios without vehicle maintenance needs (136 of the 272 simulated scenarios described in Table 2), the percentage of relocations that are converted into accepted trips is on average less than 65%, varying from 63.5% for a level of demand satisfied (part of the potential carsharing demand that was able to match with a nearby available vehicle) between 60 and 70% to an average of 39.6% for a level of demand satisfied between 90 and 100% (see Table 7). As expected, the number of successful relocations decreases when the

Table 6. Percent profit increase for the considered scenarios by adding the relocation potential profit for ideal conditions to the base scenario.

Potential profit increase (€)	Number of cars	Base Profit (€)	Number of staff				
			5	10	15	20	
			+76.8	+153.6	+230.4	+307.2	
Demand level	8%	100	2797.1	+2.7%	+5.5%	+8.2%	+11.0%
	15%	200	5625.8	+1.4%	+2.7%	+4.1%	+5.5%
	25%	300	9455.8	+0.8%	+1.6%	+2.4%	+3.2%

Table 7. Average and standard deviation of the percentage of successful relocations for different percentages of potential demand satisfied.

% Demand satisfied	% of successful relocations	
	Average	Standard deviation
60–70	63.5	44.1
70–80	43.3	14.7
80–90	41.5	11.9
90–100	39.6	17.7

accepted demand gets close to the potential total demand since there is no more demand gap to explore.

In summary, providing relocation movements in a system with similar characteristics to the one that was simulated would very unlikely have a positive influence on the profits, since its benefits can only compensate the costs by a short margin in very few cases.

Comparison with the literature

The question that arises is why this was not concluded by other researchers. From the literature review, we see that Jorge et al. (2014) performed a detailed analysis of the operator-based relocations potential using simulation and optimization. The authors applied a relocation optimization model to the same case study used in this research (city of Lisbon), using a demand pattern that is similar to the 8% demand scenario that we considered. The authors proposed a mathematical model that maximizes the profit of running a one-way carsharing system by applying optimized relocations with exact knowledge of the demand in the operation period. They also proposed real-time rule-based relocation policies in a simulator. Both models were compared to the results of a base model without relocations that had been studied in (Correia & Antunes, 2012).

From the three different station network size scenarios analyzed in Jorge et al. (2014) the one that can be used to compare with the present research work is the scenario with the full city covered (69 stations) whereby every zone with potential demand was considered to be open for service and all demand in the city had to be attended by the system. Having studied

a station-based this requires having parking spaces explicitly modeled. The parking spaces increase the fixed costs of running the system when compared to the situation of having free-float. The cost per parking space, considered by the authors, was 2 €/day (assuming the city would subsidize the system). The staff was considered to be hired per relocation trip, and the authors did not consider a limit on the number of staff working simultaneously. This has the advantage of not having staff idle time and of being able to execute many operations at peak times. Nevertheless, it can be argued that it could be difficult to find people wanting to work in these conditions. The depreciation cost per vehicle is higher, authors considered 17 €/day for three years of vehicle usage, which were bought using credit with an interest rate of 12%, having a residual value of 5000 €. This reveals a more expensive vehicle chosen (price with interests equal to 23,615 €) and a more accelerated yearly depreciation rate (26%). The different characteristics between this research and the research carried out in Jorge et al. (2014) are presented in Table 8.

The authors concluded that relocations allow the increase of profit in 2015.6 €/day, for the best policy real-time relocation policy considered, which is very different from what was obtained in this paper (see Table 9). Analyzing the original values presented in Jorge et al. (2014), shown in Table 9, it can be seen that this improvement is reached due to a decrease in the number of vehicles and parking places needed, made only possible by the introduction of relocations that allowed to continue to fulfill all demand requests. The constraint of trying to satisfy all demand in their research leads to a high number of vehicles and consequently a need for more parking spaces, which can be reduced with adding relocations.

We also adapted the original results in Jorge et al. (2014) by applying the same unitary costs, with the exception of the costs related to staff activity (due to the fact that staff is hired using a different process). The costs of client movements were introduced to the adapted version using the average cost of 0.028 €/min. Moreover, the adapted results from Jorge et al. (2014) and simulated results using the developed tool do not

Table 8. Comparison between this research and Jorge et al. (2014) – main characteristics.

	Jorge et al. (2014)	This research
Allowed movements	One-way	One-way
Location of vehicles	Station-based (69 stations)	Free-float (46 zones)
Staff number	Unlimited and hired per service	Limited and hired for the operation period
Period of operation	6 a.m. to midnight (total of 18 h)	8 a.m. to 8 p.m. (total of 12 h)
Demand (compared to forecasts)	Without uncertainty	With uncertainty
Full demand trips	1777	1648 (8% demand level)
Full demand minutes	23,711	19,177
Parking cost	Payed by parking space 2 €/day per space	Payed by vehicle 1.67 €/day per vehicle
Vehicle depreciation cost	17€/vehicle per day (20,000 € vehicle + interests)	8.22 €/vehicle per day (15,000 € vehicle without interests)
Relocation and maintenance cost	Payed by vehicle minute	Includes staff wage, public transport title cost, and fuel cost of vehicle movement
Revenues (client usage)	0.30 €/min	0.29 €/min
Cost of fuel for client trip	Not considered	0.09 €/km (0.028 €/min)

Table 9. Comparison between this research and Jorge et al. (2014) – Best profit scenarios.

	Best relocation policy (2.A) with 267 vehicles	Optimization model with 100 vehicles and 5 staff members
Increase in profit (compared to base model)	+2015.6 €	-139€ (it decreases)
Staff time (min)		
- Movements	2967 (relocations)	2034 (relocation + maintenance)
- Maintenance	Not referred	300
- Idle	None	1272
Staff cost		
- Wage	-	42€ per day per staff
- Relocations	0.20€ per minute of relocation	0.09€/km (0.028€/min) fuel cost
- Maintenance	0.007€ per minute of vehicle usage	-
Base model	Different number of vehicles, different number of parking spaces	Same number of vehicles

Table 10. Comparison between this research and Jorge et al. (2014) ceteris paribus.

	[Jorge et al.2014] Original		[Jorge et al.2014] Adapted for comparison		Simulated results With the same number of vehicles	
	Base	Policy 2.A	Base	Policy 2.A	Base	Optimization
Operation period (h)	18	18	18	18	12	12
% relocation	-	100	-	100	-	(58 movements)
% accepted trips	100	100	100	100	97.3	93.3
Number of vehicles	390	267	390	267	390	267
Number of staff	Paid by service (maintenance)	Paid by service (maintenance + relocations)	0	Paid by service (only relocations)	0	5
Parking	739 spaces	480 spaces	Paid by vehicle	Paid by vehicle	Paid by vehicle	Paid by vehicle
Time driven by clients (min)	23,711	23,711	23,711	23,711	18,816	17,886
Time of relocations (min)	0	2967	0	2967	0	2292
Depreciation cost of vehicles (€)	6630	4539	3205.80	2194.74	3205.80	2194.74
Parking cost (€)	1478	960	651.30	445.89	651.30	445.89
Staff costs (€)	165.98	759.38	-	593.4	-	216.15
Client movement costs (€)	-	-	663.91	663.91	527.60	497.52
Revenues (€)	7113.30	7113.30	6876.19	6876.19	5456.64	5186.94
Profit (€)	-1160.7	854.9	2355.2	2978.3	1071.9	1832.6
Profit improvement (€)		2015.6		623.1		760.7

include maintenance requests (to be at the same level of comparison). Results can be seen in Table 10.

Clearly, it can be verified that the profit improvement between base and relocations scenario from the research published in Jorge et al. (2014) adapted for comparison and the simulations using the tool

developed in the present work are similar (623.1 vs. 724.9 €) and these are due to the decrease in the number of vehicles, which leads to a decrease in depreciation, and to parking costs that overtake the cost of the introduction of the staff relocation services.

Therefore, the conclusion of the authors in the referred paper is specifically applied to the situation of having one-way, station-based carsharing systems where:

- staff is outsourced and paid by the minute, not having a limit on the number of elements working simultaneously;
- the stock of parking spaces is paid per unit regardless of its use;
- the depreciation cost of vehicles is high;
- and, all demand needs to be served.

The increase in profit verified by the authors is due to the reduction of costs related to the decrease in the number of vehicles and parking spots leveraged by relocations when trying to serve 100% of the potential demand for carsharing in a city, which causes great stress in the system.

Conclusions

One-way free-floating carsharing systems have been receiving great attention in recent years, namely in solving the vehicle imbalance problem that naturally results from letting clients freely move inside a service area. With the aim at contributing to understanding the real effect of staff-based relocations on the financial performance of such system, a real-time decision support tool was developed for the staff movements, based on the concept of rolling-horizon, with the objective of improving the financial performance of the carsharing operator. This was lacking in the literature since either relocations were considered to happen without the need to define staff activities, or staff activities have been the focus of mathematical models that are difficult to solve and are mostly ignoring the company perspective. Moreover, the stochasticity of the demand of such systems has rarely been considered, or, when considered, it was for small systems.

A test application was performed in a virtual environment with the characteristics of the Lisbon municipality (Portugal). A potential upper bound of demand was obtained for carsharing in previous research from which an 8%, 15%, and 25% scenario was extracted to conduct tests on the performance of the decision support tool and as a consequence on the performance of carsharing operator.

The different levels of demand were tested for two distinct ways of defining staff operations: rule-based and optimization. A base scenario was also simulated with only the client trips (thus not considering

relocations). Using different vehicle fleets, a different number of staff members, and considering or not maintenance requests, 272 scenarios were run.

It was verified that the use of staff (employed full-time) in the one-way carsharing system normally reduces the profits. This happens due to the costs associated with staff activity and only small increases in revenues resulting from extra trips. There were few exceptions where the profit values were similar between scenarios with and without staff.

The results of the rule-based model (real-time policy) were close to the results from the optimization model. The savings of having trip joining (carpooling of staff) associated with the optimization model were not significant, ranging from only 0.05% to 0.1% of the total revenues.

A thorough analysis of the results leads to the conclusion that the number of relocations that can physically be performed by each staff member in the case study, adding to the fact that not all relocations end up in accepted demand, provide only a small improvement in the revenues, which is unlikely to overcome the costs associated with staff activity (salaries, public transport title, fuel spent in relocation movements). This is a major limitation of the relocation approach, at least while vehicles still need to be driven by humans. In a future scenario of vehicle automation, it will be more likely that relocations will have a much more effective effect on the carsharing operator profits as had been found in previous research (Jorge et al., 2015).

We conclude that the best practice from a profit point of view is to keep enough members of staff to respond to maintenance requests and fill their idle time by having them performing prioritized relocations (e.g. vehicles not being used for an extended period of time). Responding to maintenance requests is of the utmost importance in order to guarantee that the vehicle unavailability does not escalate with time, generating a loss in reliability and interest for users.

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