# Predictive dynamic relocations in carsharing systems implementing journey reservations

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# 1 Introduction

Carsharing is an on-demand shared-mobility service that aims at providing a level of service similar to private vehicles while mutualizing the transportation resources. Several benefits linked to its implementation have been identified both at user and society scale ([1, 2]). In this study, we focus on station-based carsharing systems which allow one-way rentals, namely vehicles can be picked-up and dropped-off at different stations. In addition, the system imposes a reservation policy denoted as complete journey reservation policy, in which both a vehicle and a parking spot have to be reserved at the booking time. Reservations can be made up to one hour in advance and the corresponding resources are kept reserved until the pick-up and drop-off times, respectively. Note that the exact times are not known to the system as users are not required to specify them in advance. Such rental conditions are attractive to customers but they result in a less efficient use of vehicles and spots due to extended reservation locking. In order to maximize resource availability in the system, the operator may introduce dynamic relocation schemes. Two main approaches exist in the literature: staff-based relocations, where car-sharing system employees move vehicles ([3, 4, 5, 6, 7, 8, 9]) and user-based relocations, where customers adapt their trips according to the operator's suggestions ([10, 11]).

This study presents a new proactive dynamic staff-based relocation algorithm tailored for the type of systems considered, which aims at both reducing present imbalances in vehicle and spot availability and preparing the system for the future demand. The algorithm is based on a Markovian model that incorporates reservation information and historical data in order to estimate the near future expected demand loss at a station. Through a collaboration with the car-sharing system in Grenoble, France, we have conducted field experiments and extensive simulation experiments based on data retrieved from the system. The outcome of the experiments demonstrate the superiority of the proposed algorithm over other existing approaches.

# 2 A Markovian estimation relocation policy

We apply a Markov chain based modeling approach to quantify the impact of relocation choices on the expected demand loss due to shortages in vehicles or parking spots. This approach was initially proposed by [12], and was later adopted by several studies in the vehicle sharing literature. However, in this work we utilize for the first time reservation information in the model. Such information is important especially for short term estimation periods as it reduces uncertainty regarding vehicles and parking spots that are about to become available. On the one hand this leads to a more complex model, on the other, it allows us to enhance near-future estimations.

Consider a single station with $C$ parking spots. Under the complete journey policy, the inventory state of each station can be described at any time by the triplet $(x_{av}, x_{rv}, x_{rp})$, where $x_{av}$ is the number of available vehicles, $x_{rv}$ the number of reserved vehicles and $x_{rp}$ the number of reserved spots. As capacity is fixed, the number of available parking spots is $C - x_{av} - x_{rv} - x_{rp}$. The transitions between the inventory states of the station are due to four events: (i) reservation of an available vehicle with mean vehicle inter-reservation duration $\lambda_v^{-1}$, (ii) pick-up of a reserved vehicle with mean time between booking and pick-up $\mu_v^{-1}$, (iii) drop-off of a vehicle with mean time between booking and drop-off $\mu_p^{-1}$ and (iv) reservation of an available spot with mean spot inter-reservation duration $\lambda_p^{-1}$. Transition rates out of state $(x_{av}, x_{rv}, x_{rp})$ are detailed in Table 1.

| **Event** | **Current state** | **Next state** | **Transition rate** |
|---|---|---|---|
| Booking of available vehicle | $(x_{av}, x_{rv}, x_{rp})$ $x_{av} > 0$ | $(x_{av} - 1, x_{rv} + 1, x_{rp})$ | $\lambda_v(t)$ |
| Pick-up of booked vehicle | $(x_{av}, x_{rv}, x_{rp})$ | $(x_{av}, x_{rv} - 1, x_{rp})$ | $x_{rv}\mu_v(t)$ |
| Drop-off of vehicle | $(x_{av}, x_{rv}, x_{rp})$ | $(x_{av} + 1, x_{rv}, x_{rp} - 1)$ | $x_{rp}\mu_p(t)$ |
| Booking of available spot | $(x_{av}, x_{rv}, x_{rp})$ $x_{av} + x_{rv} + x_{rp} < C$ | $(x_{av}, x_{rv}, x_{rp} + 1)$ | $\lambda_p(t)$ |

Table 1: Transitions between states in the independent station Markov chain model

Let $(x_{av}^t, x_{rv}^t, x_{rp}^t)$ be the state of the station at a decision time $t$, $\delta$ the estimation horizon and $\pi_{x_{av},x_{rv},x_{rs}}^{x_{av}^t,x_{rv}^t,x_{rp}^t}(\tau)$ the probability that the station is in state $(x_{av}, x_{rv}, x_{rs})$ at time $\tau$, $t \geq \tau \geq t + \delta$. The expected demand loss due to vehicle and parking shortage at station $s$ during $\delta$ is:

$$EL_{t,\delta}^s(x_{av}^t, x_{rv}^t, x_{rp}^t) = \int_t^{t+\delta} ((\sum_{i=0}^{C}\sum_{j=0}^{C-i} \pi_{0,i,j}^{x_{av}^t,x_{rv}^t,x_{rp}^t}(\tau))\lambda_v(\tau) + (\sum_{i=0}^{C}\sum_{j=0}^{C-i} \pi_{i,j,C-i-j}^{x_{av}^t,x_{rv}^t,x_{rp}^t}(\tau))\lambda_p(\tau)d\tau$$

The first (resp.second) term in the integral represents the rate of requests that cannot be fulfilled due to shortages in available vehicles (resp. spots), obtained by multiplying the probability for vehicle shortage (resp. spot shortage) at time $\tau$ by the arrival rate of requests for vehicles (resp. spots) $\lambda_v(\tau)$ (resp. $\lambda_p(\tau)$). The evaluation of the expected demand loss is numerically obtained with the approximation method of [12]. In a single run of the procedure, expected demand losses for all stations, all initial states and the desired estimation horizon $\delta$ are obtained and stored to be used later in the on-line relocation algorithm.

The output of the model is applied in real-time decision making as described in the following. In the considered operation mode, relocators are required to reserve a vehicle and a spot as users do. If a station in state $(x_{av}, x_{rv}, x_{rp})$ at decision time is selected as the origin of the next relocation task assigned (and therefore has $x_{av} > 0$), it transitions to state $(x_{av} - 1, x_{rv} + 1, x_{rp})$ and the resulting avoided expected demand loss at this station is:

$$O_{t,\delta}^s(x_{av}, x_{rv}, x_{rp}) = EL_{t,\delta}^s(x_{av}, x_{rv}, x_{rs}) - EL_{t,\delta}^s(x_{av} - 1, x_{rv} + 1, x_{rp})$$

Equivalently, if this station is the destination of the next relocation task assigned (and therefore is such that $x_{av} + x_{rv} + x_{rp} < C$), it transitions to state $(x_{av}, x_{rv}, x_{rp} + 1)$ and the resulting expected avoided demand loss is:

$$D_{t,\delta}^s(x_{av}, x_{rv}, x_{rp}) = EL_{t,\delta}^s(x_{av}, x_{rv}, x_{rs}) - EL_{t,\delta}^s(x_{av}, x_{rv}, x_{rp} + 1)$$

At a decision point, deciding to relocate a vehicle from station $s_1$ to station $s_2$ represents an expected avoided demand loss of $O+D$. If $O+D$ is negative for any pair of stations, no relocation is triggered. In selecting an origin-destination pair for a relocation task, we wish to balance the expected avoided demand loss against the time required to execute the relocation task. In order to do so, we calculate the expected avoided demand loss per time unit spent relocating. Let $move(s)$ be the time required for the relocator to move from his current location to station $s$, and let $drive(s_1, s_2)$ be the driving time from station $s_1$ to station $s_2$. The selected relocation pair $(o^\star, d^\star)$ is the one with the highest positive expected avoided demand loss per time unit spent relocating:

$$(o^\star, d^\star) = arg \quad max_{(s_1,s_2)\in P} \frac{O^{s_1}_{t,\delta}(x^{s_1}_{av}, x^{s_1}_{rv}, x^{s_1}_{rp}) + D^{s_2}_{t,\delta}(x^{s_2}_{av}, x^{s_2}_{rv}, x^{s_2}_{rp})}{move(s_1) + drive(s_1, s_2)}$$

Practically, the decision process is initiated any time a relocator completes a relocating task or when the state of the system is changed while some relocators are idle.

# 3 Case study and results

A collaboration with the car-sharing system in Grenoble has provided us unique opportunity to test our proposed algorithm in the field. In addition, we were able to base our simulation analysis on trip transaction data obtained from the system. The Grenoble car-sharing system consisted of 27 stations, each with 3 to 8 parking spots adding up to a total of 121 parking spots. The available fleet size varied frequently between 40 to 55 vehicles, due to maintenance issues.

In the experiments, we compared the Markovian estimation policy to the operators' relocation policy, to a no-relocation policy and to a purpose-built state of-the-art reactive inventory rebalancing relocation policy (OVOS). The latter smartly combines the policies introduced in [4], namely inventory rebalancing and shortest-time relocations. In addition, we adapted a centralistic full-knowledge relocation model [5] to generate an approximated upper bound on the performance of the dynamic relocation policies.

A three weeks field experiment conducted in June/October 2017, has shown that the OVOS and the Markovian estimation policy performed significantly better than the operator's policy and the no-relocation policy. In addition, it demonstrated the ability to implement of our policies in the field and built knowledge to enhance the simulation framework. In the simulation experiment, we considered cases with 40, 60 and 80 vehicles in service. The daily demand levels investigated ranged between 100 and 400 and the staff size ranged between 1 to 3 relocators working simultaneously. For each demand level, 100 demand realizations consisting in 10 consecutive days of operation were drawn from real data. The simulation results have shown that the Markovian policy served on average 1.3% to 4.5% more requests than the OVOS policy. As compared to the OVOS policy, which by itself resulted with high performance, the Markovian policy was able to close 10% to 30% of the gap to the approximated upper bound. As this bound is based on decision making using full information of the demand, the relative improvement is much higher than it seems.

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