On-line proactive relocation strategies in station-based one-way car-sharing systems

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1 Introduction

One-way car-sharing systems are nowadays operating in many cities around the world. They have proved to reduce vehicle ownership and greenhouse gas emissions [1,2,3] leading towards a more sustainable mobility [4]. The planning and operation of one-way car-sharing systems entail complex decision processes at strategic [5,6], tactical and operational levels [7,8,9,10,11,12,13].

The operational level focuses on increasing vehicle and parking availability where and when needed to improve the quality of service provided to the users. In this work, we study the integration of relocations and system regulations. Specifically, we consider the on-line proactive planning of relocations in a one-way station-based electric car-sharing system implementing complete journey reservation policy [9]. In such a system, a user request is approved only if there exists an available vehicle at the origin station and an available parking spot at the destination station. In that case, a vehicle and a spot are immediately blocked in these stations until the rental start and the rental end, respectively. As users do not announce their return time when booking, the exact start and end times of the trip remain unknown to the system. Nevertheless, reservations provide information regarding stations in which parking spots and vehicles will soon be available. We propose to utilize this information in the planning of relocation activities.

The contributions of this study are as follows: we formulate a Markovian model that uses reservation information to derive decisions regarding vehicle redistribution and we implement it in staff-based and user-based relocation algorithms. We test these algorithms in a simulation environment using data derived from real-world car-sharing system and in field experiments through a collaboration with a car-sharing operator.

2 A Markovian model

In this section, we formulate a Markovian model that utilizes reservation information in order to estimate near-future shortages of vehicles and parking spots. Under the complete journey reservation policy, each parking spot may be in one of the four following states: empty free spot, empty reserved spot, available vehicle and reserved vehicle.

Considering a single station with *C* parking spots, we denote the state of the station by the triplet (x_{av}, x_{rv}, x_{rs}) corresponding to the number of available vehicles, the number of reserved vehicles and the number of reserved spots, respectively. The number of available spots is then given by $C - x_{av} - x_{rv} - x_{rs}$. We model the evolution of a station using a continuous time Markov chain. For this purpose, we assume that at any station, booking rate for vehicles at the station and return rate of vehicles follow a station-specific time heterogeneous Poisson process with rates $\lambda_v(t)$ and $\lambda_s(t)$ respectively. The time between the users' reservation and their arrival at the origin station is assumed to be exponentially distributed with mean $1/\mu_v(t)$. Travel time is also assumed to be exponentially distributed with mean $1/\mu_s(t)$. The transition rates out of state (x_{av}, x_{rv}, x_{rs}) are summarized in Table 1.

Given the current state of the station, the expected vehicle and parking spot shortages during a predefined planning horizon is approximated. For this end, we use an approximation procedure similar to the one presented in [14]. We next describe how these estimations are used in real-time decision making.

Table 1: Continuous time Markov chain - transition rates

Event	Current state	Next state	Transition rate
Available vehicle reserved	(x_{av}, x_{rv}, x_{rs}), $x_{av} > 0$	$(x_{av} - 1, x_{rv} + 1, x_{rs})$	λ_v(t)
Reserved vehicle taken	(x_{av}, x_{rv}, x_{rs})	$(x_{av}, x_{rv} - 1, x_{rs})$	$x_{rv}\mu_v(t)$
Vehicle returned to station	(x_{av}, x_{rv}, x_{rs})	$(x_{av} + 1, x_{rv}, x_{rs} - 1)$	$x_{rs}\mu_s(t)$
Parking spot reserved	(x_{av}, x_{rv}, x_{rs}), $x_{av} + x_{rv} + x_{rs} < C$	$(x_{av}, x_{rv}, x_{rs} + 1)$	$\lambda_s(t)$
-	(x_{av}, x_{rv}, x_{rs})	Any other	0

3 Staff based and user based relocations

To select promising relocations, we identify the stations that would benefit the most from the introduction or removal of a vehicle in the following time-periods. Using the Markovian model, we calculate for each station independently, the gains in the expected shortages obtained by removing/adding a vehicle from/to the station. As relocators (staff or users) need to book a vehicle at origin and a spot at destination, the gain of relocating a vehicle from a station (resp.

to a station) corresponds to the difference in expected shortages between the current state (x_{av}, x_{rv}, x_{rs}) and state $(x_{av} - 1, x_{rv} + 1, x_{rs})$ (resp. $(x_{av}, x_{rv}, x_{rs} + 1)$). The value of a relocation between an origin station and a destination station is the sum of the gains at the two stations.

The calculated gains are utilized both in staff-based and user-based relocations. For staff relocations, the origin and destination are selected such that the relocation has a high impact while relocation distance is short. This approach can be extended to accommodate the planning of multiple relocation tasks at the same time. Independently, the calculated gains are also used to generate lists of recommended origin and destination stations suggested to users. They may select stations from these lists if they are neighboring their wished origins and destinations.

4 Results

During this study, we had the unique opportunity to examine the proposed algorithms in the field through a collaboration with a car-sharing operator. In parallel, we tested the policies using a purpose-built simulation framework. This allowed us to further assess insights derived in field. Results from these two types of experiments are presented hereafter.

The case-studied system consisted in 27 charging stations with capacity varying from 3 to 8 spots (121 spots in total) and a fleet of about 50 electric vehicles. Over the three weeks of field tests, demand was artificially increased from an average of 40 demands per day to 100 demands per day by (i) generating additional requests with hired drivers and (ii) offering free usage to targeted frequent users. One to two staff members performed staff-based relocations. Statistics were retrieved from the operator's information system. In addition, hired drivers were requested to log their requests in order to reveal the proportion of denied requests due to shortages, which cannot be derived from the information system.

In the simulation framework, we tested 4 demand levels (50/100/200/400 demands per day), 3 fleet sizes (40/60/80 vehicles) and 3 staff numbers (1/2/5 employees relocating at the same time). For each configuration, results were averaged over 100 demand realizations in order to obtain statistically meaningful values. Each realization represents the demands over 10 consecutive days.

Alongside a benchmark policy which consisted in performing no relocations, 3 relocation algorithms were tested and compared: 1) the current relocation strategy of the system, 2) a simple threshold policy that aims at having at least one available parking spot and one available vehicle at each station and 3) the Markovian prediction relocation policy. We also tested the demand shifting recommendation strategy based also on the previously presented Markovian model for different compliance levels in users.

On the field, we observed that using relocations had a positive impact and led to a 10-15% decrease in denied demands, as compared to no relocations. This came with a 30% average increase in the number of stations having a free spot and a free vehicle, namely ready to serve the following request. Yet, the small number of replications made it impossible to compare the relocation policies with certainty. Eventually, origin and destination shifting recommendations to the hired drivers, who were fully complying with them, reduced the previously refused demands by half.

Simulation experiments reconfirmed the benefit of demand shifting as it improved in average the demand service ratio by 5 to 8% depending on the compliance level of the users. Concerning relocations, Table 1 shows the user acceptance rates for several combinations of demand levels and relocation policies with one personnel working and 60 vehicles in the system (i.e. half of the spot capacity). The benefits of relocations are again highlighted. However, the Markovian prediction-based policy has not shown to perform significantly better than a simple inventory rebalancing threshold policy, an unexpected result.

		Demand levels (users/day)			
		50	**100**	**200**	**400**
Policies	**No Relocations**	71.6%	69.2%	65.6%	58.2%
	Threshold Policy	96.3%	88.5%	77.0%	63.8%
	Markovian Prediction	96.1%	88.3%	76.2%	62.6%

Table 1: Acceptance rates as a function of demand level per day for three relocation policies

We are currently investigating various hypotheses that may explain the results obtained up to now. In particular, we examine the impact of the complete journey policy on resource availability and the interaction with inadequate system dimensioning. This way, we hope to identify system settings in which reservation information can be utilized to improve system performance.

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