

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

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Abstract

In this work, we study the integration of relocation activities and system regulations in the operation of one-way car-sharing systems. Specifically, we consider the on-line proactive planning of relocations in a one-way station-based car-sharing system that implements a complete journey reservation policy. Under such policy, a user's request is accepted only if at the booking time, a vehicle is available at the origin station and a parking spot is available at the destination station. If a request is accepted, the vehicle is reserved until the user arrives at the vehicle and the spot is reserved until the user returns the vehicle. Each parking spot may be in one of the following states: empty free spot, empty reserved spot, available vehicle and reserved vehicle. The reserved vehicles/spots provide additional information regarding spots/vehicles that are about to become available. We thus propose utilizing this information in order to plan relocation activities and implement impactful demand shifting strategies. We devise two relocation policies and two demand shifting strategies that are based on the evaluation of the near future states of the system. Using a purpose-built event based simulation, we compare these policies to a state-of-the-art inventory rebalancing policy. An extensive numerical experiment is performed in order to demonstrate the effectiveness of the proposed policies under various system configurations.

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 utilize this information in the planning of relocation activities and in passive regulations, i.e. origin and destination shifting mechanisms.

The contributions of this study are as follows: we specifically 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. The model is presented in section 2 and we describe its integration in the decision process in section 3. In section 4, we introduce more relocation methods for comparison purpose. Specifically, we present there the second relocation policy based on prediction, which relies on the estimation of future station inventories, alongside a benchmark approach where no relocations are made and a reactive inventory rebalancing policy based on triggering thresholds at stations. We test all 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	$(x_{av}, x_{rv}, x_{rs}), x_{av} > 0$	$(x_{av} - 1, x_{rv} + 1, x_{rs})$	$\lambda_v(t)$
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 refusals due to 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 lost demands 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 and a destination 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. First, a pool of candidate stations, i.e. stations in the worst states according to model estimates, is identified. Then, a simple process selects the best origin-destination pair among the candidates in order to minimize relocation time, namely access time plus driving time for the relocator. This two-step process, consisting in (1) an identification of candidate stations according to the key indicator of the relocation impact model used and then (2) a minimum relocation-time pairing among the previously pre-identified stations, is also used in the other policies presented in section 4. In the present research state, only one relocation decision is considered to be taken at a time although the process can be easily extended to accommodate the planning of multiple relocation tasks.

Independently, in the context of user-based relocations, the calculated gains are 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. Case study

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 in this section.

4.1 System description

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 in normal working order. Most stations were located in the city center while 7 of them had been put in more remote regions of the urban area. The range of the vehicles was stated to be 50km with a maximum speed of 50km/h. A relocation process was already implemented as the project started and

involved two relocators working from 9 am to 5 pm, performing not only relocations but also maintenance and cleaning tasks. The observed demand was around 40 rentals a day with days where demand could reach up to 100 rentals per day thanks to some promoting actions. In general, users book their trips through a smartphone app or on the website using an interactive map showing the availability of spots and vehicles at every station.

4.2 Policies

Alongside a no relocations benchmark policy, 5 relocation algorithms were tested:

- 1) The current relocation strategy of the system (CU). In this policy, the relocators are assisted by an on-line tool monitoring the number of available spots and vehicles at each station. Knowing this information, they use their own judgement and schedule of tasks (cleaning, maintenance...) to select the most relevant relocation to perform next. As this behavior could be hardly reproduced in simulation, it was only used as a comparison in the field.
- 2) A simple threshold policy (TH). In this policy, the operator aims at having at least one available parking spot and one available vehicle at each station. In such a system state, any incoming demand will be accepted as it appears. Therefore, whenever, a station sees its spot or vehicle resources fall under 1, a relocation should be triggered.
- 3) A variant of TH strategy, called THK, was also implemented. In THK, the numbers of available spots and available vehicles targeted at each station (set to 1 in TH) are modified according to in advance knowledge of the demand. To that end, we consider that a certain percentage of the users will communicate their trip characteristics in advance. The system can then provide a better level of service by anticipating. In both TH and THK and as explained in section 3, decision making follows a two-step process where stations in shortage of spots and vehicles according to the target values set are first identified. Then an origin-destination pair is then selected among them as to minimize relocation time. The TH and THK policies were tested both in the field and in simulation. They were only implemented for staff-based relocation.

- 4) An inventory-based prediction policy (AP). By using reservation information and historical data, the number of available vehicles and spots in the near future can be derived at each station. The number of available vehicles (spots) in the future is equal to the current number of vehicles (spots) plus the number of reserved spots (vehicles) plus the number of expected returns (rentals) minus the number of expected rentals (returns). Expected returns and rentals can be obtained from historical data. Based on these future inventory estimates, stations that will need vehicles and/or spots are identified and sorted accordingly. Once the worst stations in terms of future inventory are determined, the origin-destination pair minimizing relocation time is chosen for relocation, as detailed in section 3. The future inventory calculation principle is also used in a demand-shifting strategy where users are advised to start their trips at stations with future high vehicle inventories and end them at future low spot inventory stations. AP policy was tested in the field and in simulation.

- 5) The Markovian prediction relocation policy (MK) presented in section 2 and integrated in a decision process as explained in section 3. We also tested the demand shifting recommendation strategy (for different compliance levels in users) where suggestions are selected according to the Markovian model indicator. Users are encouraged to start and end their trips at stations such that the expected demand loss overall is most reduced. Neither the demand shifting version nor the relocation process using the Markovian prediction model were tested in the field. They were later introduced in the simulation framework though and compared with the other policies.

4.3 Field test: settings and results

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. Approximately one third of the total demand during the experiment corresponded to hired drivers' demand, another third could be linked to offered free usage to targeted users and the last third was the usual demand. 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. This proportion could not

indeed be found in the information system as there is no straightforward and precise correspondence between users opening the app and users making a reservation. Some users may open the app without meaning to travel and therefore, this action cannot be strictly categorized as a refusal due to resource shortage. This uncertainty vanishes for hired drivers in the field-test conditions.

In the field, we observed that using relocations had a positive impact and led to a 10-15% decrease in observed denied demands, as compared to no relocations case. This came along 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. Besides, origin and destination shifting recommendations, communicated to the hired drivers through a specifically developed online application, reduced the number of previously refused demands by half on the days when it was applied. Meanwhile, regular customers were following the normal reservation process they were accustomed to through the app.

Yet, the small number of replications made it impossible to compare the relocation policies with certainty as the variance in demand between days with the same policy configuration was quite important and the experiment duration quite reduced. Specifically, it remained unclear whether policies based on prediction (in this case only AP) outperformed simpler policies such as the threshold one (TH).

4.4 Simulation settings and results

In the custom-built 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 demands and operations over 10 consecutive days.

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 users, i.e. what proportion of them actually follow the recommendation from the operator. The more users comply, the better even if the observed marginal improvement decreases quickly with the compliance rate. As a trade-off, the higher flexibility required from the users may not be worth the small gains observed in the level of service, especially in cases where a vast majority of the users has to comply.

About 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). These parameters were among the best ones after performing a sensitivity analysis as they yielded good performance with a reasonable amount of resources. Specifically, using 60 vehicles raised the performance by 10% in average compared to the 40 vehicles case while an additional 20 vehicles (i.e. 80 vehicles in the system) did not further improve the level of service and even worsened it in some settings. Besides, the marginal gains brought by additional relocators working are positive but decrease with the number of relocators. The very highest gain is obtained when hiring the first relocator.

The benefits of relocations are highlighted as in the test field but the higher number of replications allows us to derive firmer conclusions. The Markovian prediction-based policy (MK) has not shown to perform significantly better than a simple inventory rebalancing threshold policy (TH), an unexpected result. The other prediction-based policy, (AP), also performs less well than TH. The only policy outperforming TH is its variant, THK, in which precise and complete information regarding users' trip characteristics is given. Nevertheless, the amount of information requested from the users in this variant, i.e. communicating desired origin, destination, start and end times a day in advance, seems heavy compared to the small gains observed on the level of service.

		Demand levels (users/day)			
		50	100	200	400
Policies	No Relocations	71.6%	69.2%	65.6%	58.2%
	Threshold Policy (TH)	96.3%	88.5%	77.0%	63.8%
	Threshold policy variant (THK) with 50% of users communicating trip information in advance	97.4%	90.5%	79.4%	65.2%
	Markovian Prediction (MK)	96.1%	88.3%	76.2%	62.6%
	Aggregate Prediction (AP)	94.3%	86.7%	75.8%	62.8%

Table 1: Acceptance rates as a function of demand level per day for three relocation policies with 60 vehicles in service and one relocator working from 7 am to 8 pm

5. Conclusion and further research

This study presents a model of station evolution for one-way station-based car-sharing systems to be used for dynamic decisions regarding relocation and/or demand shifting. It aims at better adapting supply to demand and vice-versa by taking advantage of information existing in the system. This information consists in current vehicle and spot reservations in stations and historical demand. However, as we incorporated more information and historical data to the relocation decision-making process, no clear improvement trend was observed. The two prediction policies studied, MK and AP, designed to proactively act on the system, do not perform better than a smart reactive threshold policy, TH. We are currently investigating various hypotheses that may explain these results in order to understand better what is at stake and overcome the limitations met by the prediction policies.

In parallel, we applied the same prediction models in user-based relocation processes to propose impactful origin and destination shifts to customers, for the greater good of the system. We were able to demonstrate a significant improvement in the level of service, both due to an extended station choice set to serve complying customers and an overall better spreading of resources (spots and vehicles) in the system.

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