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Availability-based dynamic pricing on a round-trip carsharing service: an explorative analysis using agent-based simulation

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Abstract

Carsharing companies aim to customize their service to increase fleet usage and revenues with different pricing schemes and offer types. Dynamic pricing policies can be designed to adjust and balance temporally and spatially cars availability but may pose some question on customers' fairness. In this paper, we propose an explorative analysis of how an availability-based dynamic pricing scheme impacts the demand and the supply performance. The policy is simulated in MATSim and compared to a fixed pricing policy scheme. This simulation consists of analyzing the behavior of a synthetic population of car-sharing members for Berlin and the surrounding region in which is applied an availability-based dynamic pricing in which price depends on vehicle availability in booking stations. Results show that when the dynamic pricing is applied there is a light decrease in the number of bookings and people with low value of time tend to abandon the carsharing mode in favor of other modes of transportation.

Keywords: Carsharing; MATSim; Dynamic Pricing; Value of Time; Round-Trip.

1. Introduction

The assumption behind carsharing services is straightforward: through a membership, individuals can get access to a lease car without the burden of owning it. Vehicles are accessible for a short-term rental on an as-needed basis by

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paying a usage fee (1). The spread of mobile technology meant a second birth for carsharing: mobile applications are often used to book carsharing services on the fly allowing fast payment, a personalized experience for users and continuous supervision and usage data collection and analysis for companies (2). In North-America This flexibility contributed to an increasing car utilization rate in favor of the carsharing service (3) whereas daily usage of cars is only about 10% (4); this evidence makes clear the effect of a paradigm shift in which the user tends to avoid the burden and the expense of ownership but benefits of the flexibility and the accessibility of a car service. At the same time, besides mitigating negative externalities caused by land occupancy, carsharing helps offering a last mile service in areas with low public transport accessibility (5).

In the last two decades, carsharing acquired more and more importance in various research fields thanks to investigations made on pricing, market analysis, location, travel behavior, and sustainability (6), (7).

Regarding the one-way system, simulation using Vienna taxi data proved a dynamic incentive scheme to be effective in equilibrating the fleet state at the station (8). With the goal of maximizing company profits, dynamic pricing was applied on the one-way system in a theoretical case study on the city of Lisbon. Results demonstrated that trip pricing can be used to increase profit through a more balanced system (5). The influence of vehicle distribution on the carsharing areas pricing computation was also addressed by a creation of a digitized decision support system. The support of an information system using the dynamic pricing method helped reducing the need for vehicle relocation enhancing the vehicle availability (9).

Different pricing strategies were also applied in free-floating carsharing (10). The problem of how round-trip and free-floating carsharing demand varies with different pricing strategies was applied to a case study on the metropolitan area of Zurich, Switzerland. Results found the spatio-temporal profile of carsharing demand to be sensitive to pricing structures.

However, the literature concerning the pricing topic is still fairly unexplored. Situations of 'local monopoly' that lasted for years didn't produce any pricing competition and the non-existence of any competitor in terms of modal offer made pricing schemes for carsharing not a popular research topic (10).

Even though carsharing is a quite an established concept (11), models able to assess their functionality have not yet been fully exploited until these last years: traditional four-step models tend to use data that is too aggregated to allow researchers to grasp the singularity typical of a carsharing service, and dynamic traffic assignment approaches usually deal with a demand which is typically given as fixed-period OD matrices that cannot adapt to a dynamic pricing scheme (12). The simulation of innovative transport modes with agent-based models has been proven useful because of their microscopic nature. For example, regarding the carsharing, the peculiarity of the services offered can be estimated in a realistic way and can capture car availability in a given space at a given time. Among other agent-based models, MATSim (Multi-Agent Transport Simulation), while acting on large-scale scenarios, is capable to catch disaggregated data at single user level (13). Focusing on pricing schemes, different active pricing strategies were already tested in MATSim for what concerns traffic road tolls. Starting from the fact that in most cases activities have a higher importance than the trip itself, meaning that a commuter cannot always choose where to carry out its activities or change its trip destination, a full daily plan for a population in the city of Zurich was simulated in order to test time-dependent tolls applied at the city center border (12).

Applying policies on round-trip carsharing supply systems, this paper studies the implementation of an availability-based dynamic pricing (ABDP) strategies: a diversification of the price based on the number of remaining cars at the station when the rental starts. The goal in the analysis of this strategy is, first of all, to assess the equity of the system from the user's perspective (e.g. if a measure like dynamic pricing happens to be socially fair) and, secondly, what are the repercussions on the supply. On one hand, the pricing offer is expected to lead to a more balanced rental performance since renting a car in a station with all available vehicles at disposal allows to take advantage of cheaper fees, to trigger a shifting of the rental starting time in order to pick up cars when availability is higher but, on the other hand, the utility increment due to a lower cost should lead to a trade-off because of the creation of a disutility due to the shifted activity schedule. In the end, a variable use of the carsharing for the same offer is also expected since the spending power varies from user to user (14). In this paper, we describe the first steps of that analysis by exploring if various pricing policies impact the demand and what are the trends we can observe.

2. Methodology

In the practice, the most typical model used to represent travel demand is still the classic four-step model (15). Forecasts are made considering one area as a whole and flows are dealt with in an aggregated way and usually measured in vehicles/hour (flows). Regarding the round-trip carsharing, it rapidly leaps out how an aggregate, trip-based model cannot be able to asses important KPIs such as the availability at a precise point in space and time (16). Temporal and spatial resolution becomes of paramount importance when assessing the capability of a carsharing service. Disaggregated methods are necessary to describe activities executed by users at different locations and at different times; this is what is defined as the user behavioral component. Agent-based modeling is the most natural way to apply this criterion. Hence, in this work we adopt an agent-based simulation approach to analyze carsharing systems, following a well-established stream of research in the field (17)(18)(19).

Multiple agent-based simulators were examined before choosing which simulation approach was more suited to our work. SimMobility (20), is an integrated simulation platform designed to be activity based, multi-modal, multi-scale and fully modular, unfortunately a contribution on carsharing is still missing. PTV MaaS Accelerator Program (21) was investigated since its implementation of ride-sharing and multimodality. The close-source essence of the software and the poor literature on it became an essential issue. Mezzo (22) simulates road traffic at the level of individual vehicles but with an aggregated behavior on links. The absence of the carsharing mode and very few publications made us opt for another simulator. In the end we selected MATSim since up to today, it is one of the fewest tools that allow to simulate carsharing services interacting with other transportation modes, hence allowing to consider explicitly the elasticity of the car sharing demand towards other modes of transport. In research, since after its deployment, the carsharing contribution to MATSim is one of the most widely used platform to simulate carsharing scenarios through an agent-based model.

2.1. Scenario Setup

MATSim is an open-source software, written in Java, for implementing large-scale agent-based transport simulations (13). People's behavior is represented in form of activity chains and differentiates depending on a number of attributes (e.g. age, gender, driving license, …) derived from empirical data. The simulation consists of a typical day in which every agent performs its daily tasks (plan), generating the daily travel demand. In each iteration agents evaluate how "good" the execution of their plan was with a utility score and try to modify it according to predefined rules in order to improve it. By adopting this approach an equilibrium is reached, subject to constraints, where the agents cannot further improve their plans unilaterally (13). The three basic input used by MATSim consist of:

Network: The network is obtained importing the OSM (Open Street Map) map of the Berlin and Brandenburg region into JOSM (Java Open Street Map) which is an extensible editor for OSM and for Java (23). Once the map is loaded, a plugin developed ad-hoc for MATSim converts it in a network readable by the software with basic attributes for links and for nodes. Carsharing stations were located randomly within the Berlin area as shown in Fig.1.

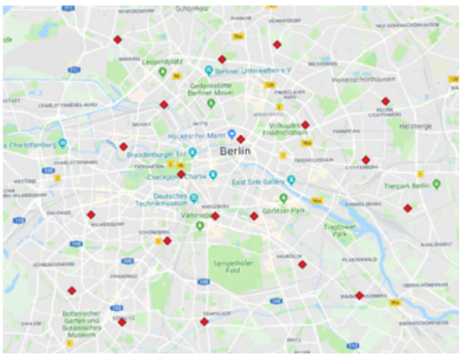

Fig. 1. Carsharing station distribution.

Plans: A *plans* file (or *population* file) consists of a synthetic population that can be generated from census data, and included in this file there is the complete agents' list with their respective activity-chains. Furthermore, every agent is portrayed with a system of attributes (e.g. person ID, gender, age, license, car availability and employment status). The plans file used in this work is based on the one used in (24), which consists of a 10% sample of the federal state of Berlin and the federal state of Brandenburg population. Every agent is described by its personal activity schedule with attributes such as activity type, coordinates of the location where the activity takes place, time duration of the activity and mode of transport used to reach a determined facility. Since this population is lacking of some essential information such as car availability, employment status and income, information were gathered from another population file described in (25); here a 1% sample of the federal state of Berlin and the federal state of Brandenburg population is used to export the following attributes for every agent: gender, age, driving license, car availability and employment status. Furthermore, this data is univocally linked to a set of GPS coordinates. Once obtained the distribution for every attribute given the district, using a GIS software, we linked the agents' GPS coordinates with the districts shapefile, that resulted in an assignment of every attribute to a specific agent in the 10% population sample. To meet the goal of this paper two new attributes were introduced into the population file: income and Value of Time (VOT). Since the main intention of this paper is to evaluate the user behavioral change after the introduction of the dynamic pricing, a variable like the VOT, which is sensible to travel price (14), was needed. Carsharing demand is considered elastic. Carsharing is a membership program, that means customers can use the service only if they meet some specific requirements (e.g. hold a driving license). In this study every agent holding a driving license is allowed to use the carsharing as an additional mode of transportation and, moreover, this mode can be used for a subtour or for the complete trip chain.

Configuration: A *config* file is the connection between the user and MATSim. A list of parameters, divided by their logical group, are set up in order to run the simulation. The constants used to model the scoring function below are here defined with other parameters allowing the agents to use different strategies in order to modify their plans.

2.2. Carsharing Model

In order to use the MATSim transport modeling toolkit for evaluating the effect of the introduction of different pricing schemes, an additional module for simulating carsharing was needed. The work made by Ciari to integrate this service in MATSim started in the 2009 is still ongoing and maintained by Balac (17,26). The score used in MATSim for the evaluation of agents' plan considers both the undertaken activities and the performed trips.

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \tag{1}$$

With N as the number of activities and q as the trip that follows the activity. The first term represents the utility of executing the set of activities, the second one represents the disutility of travelling with a given mode. The second component of this relationship is specific to each mode of transport supported by MATSim. In (27), the carsharing custom utility function is defined as in equation (2) in order to evaluate the travel disutility for choosing carsharing.

$$S_{trav,q,cs} = \alpha_{cs} + \beta_{c,cs} * c_t * t_r + \beta_{c,cs} * c_d * d + \beta_{t,w}(t_a + t_e) + \beta_{t,cs} * t_{trav} \tag{2}$$

This relationship is the sum of the following elements: the first term α_{cs} is a calibration parameter, specific to different carsharing types, the next two groups $\beta_{c,cs} * c_t * t_r$ and $\beta_{c,cs} * c_d * d$, refer to the cost associated to reservation duration and distance travelled, respectively. $\beta_{t,w}(t_a + t_e)$ introduces the walking time needed to reach and leave the station, while the last part $\beta_{t,cs} * t_{trav}$ treats the travel duration with carsharing.

In the proposed contribution, we believe that linking this utility term to the agents' characteristics would be a significant improvement of the carsharing representation within MATSim. We propose to include a term associated to the income in equation (2).

2.3. Value of Time

In order to determine which effects are possible to evaluate from changing specific pricing policies, it is important to include a variable sensitive to this transformation. Using only the income as sensitive variable would not be sufficient. What could make one choose for a mode of transport instead of the others is the value of the time saved by doing that choice. For this reason, the VOT is chosen as parameter.

We separated the population in eleven different income groups, in accordance with their characteristics. Before the simulation, it is really difficult to determine the VOT for each agent because it generally depends on the mode of transport, the trip purpose and the trip length. To address this, the VOT used is a marginal value ($VOT_{marginal}$ = 4,83[€/h]) obtained from (28), which is linked to the income by the relationship (3) where VOT_f is the VOT factor.

$$VOT\left[\frac{€}{h}\right] = VOT_{marginal} * VOT_f \tag{3}$$

Based on values retrieved from (28) the dependence between income and VOT_f is estimated through a logarithmic regression, see Fig. 2.

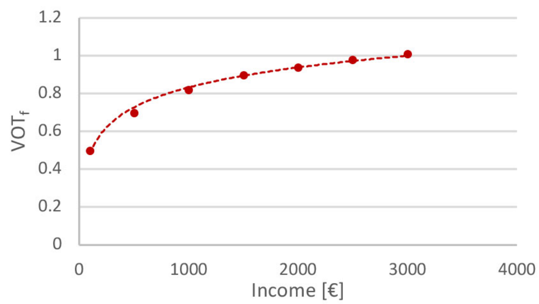

Fig. 2. Income Dependence from VOTf.

The function (4) obtained this way is:

$$VOT_f = 0{,}1522\ ln(Income) - 0{,}218 \tag{4}$$

2.4. Dynamic Pricing

A scenario is built in which the carsharing price is meant to vary accordingly to the car availability: the trip becomes more expensive the fewer cars are available at the station at booking time. This strategy seeks for a more even distribution of cars and vehicle usage in time and space, and is only indirectly dependent on the actual demand, which on the other hand can be sensitive to pricing if demand elasticity is considered explicitly.

The two concepts described above (VOT and dynamic pricing) are integrated inside MATSim by updating the carsharing travel scoring function (2) in order to make the general scoring function (1) and agents' choices sensible to different VOTs.

$$S_{trav,q,cs} = \alpha_{cs} + \beta_{c,cs}\left[\frac{c_t(t) * t_r}{a^j} + (c_d * d) + \left(\ \beta_{VOT} * VOT_{cs}^i\right)\right] + \beta_{t,w}(t_a + t_e) + \beta_{t,cs} * t_{trav} \tag{5}$$

Equation (5) is obtained introducing β_{VOT}/VOT_{cs}^i where β_{VOT} is a calibration parameter (usually negative) and i refers to the i-th simulated agent and a^j is the number of cars available at the station j. Since the goal of this paper is to analyze how an ABDP scheme impacts the demand and the supply performance of a carsharing service, the VOT has been implemented only in the carsharing score. Future studies could see the VOT implemented even for other modes.

3. Results

Six different scenarios are built according to table 1. While the scenario 1 and 3, are created to check if the introduction of the VOT has an impact on the simulation, the other scenarios are divided between the "base" ones (4 and 6), where a fixed price rate is applied, and those where the ABDP is activated. To increase the number of vehicles per station limits the impact of results that could depend from a specific reason related to the single user and gives a better understanding of which behavior is triggered by the competition for resources.

Table 1. Scenarios

Simulation code	VOT	ABDP	Vehicles per station
1	O	O	10
4	I	O	10
7	I	I	10
3	O	O	100
6	I	O	100
9	I	I	100

3.1. Temporal effect on demand

The first observation we can do by comparing scenarios 4 and 7 is the impact of ABDP on the distribution of the demand in time. Once the ABDP is applied, the total number of bookings tend to increase from 201 to 222 leading to a different profile as shown in Fig.3.

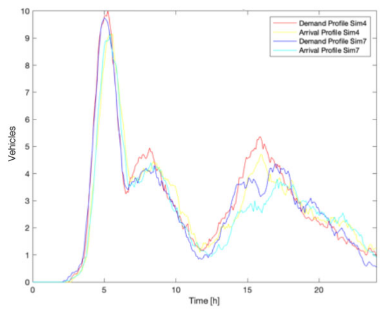

Fig. 3. Demand and Arrival profile Sim4-Sim7.

The demand profile goes from 3 peaks (red) to 4 peaks (blue) due to the return of the carsharing vehicles to the station, thus lowering the price. Furthermore, all peaks have a lower maximum and are spread over a longer period.

Table 2. Distance Travelled and Number of Bookings

	Distance Travelled [Km]	# Bookings	Avg Distance Travelled per Vehicle [Km]
Sim4	7000.81	201	34.83
Sim7	7450.20	222	33.56
% Difference	6.03%	9.46%	-3.79%

We assume that the introduction the ABDP pushes in particular agents with a low VOT to behave differently and equilibrate cars availability in their surrounding stations. An additional confirmation is found in table 2: while the number of bookings and the distance travelled with the carsharing tend to increase, the average distance per vehicle tends to decrease resulting in shorter bookings. In order to see how the shift in demand is correlated to these individual attributes of agents, we also analyze the economic effect on the demand.

3.2. Economic effect on demand

The shift in reservation number in the scenarios with VOT activated and with both VOT and ABDP activated are shown in Fig.4. People with the lowest VOT tend to abandon the carsharing mode in favor of other modes of transportation (Fig. 4a) while the carsharing resource tend to be exploited more by people with an average VOT (2-3 [€/h]). Population with a high VOT (>3[€/h]) tend to not be affected by the ABDP. Moreover, in the case of 100 vehicles per station (Fig. 4b), the "competition" factor is not present anymore and all the VOT classes have a systematic positive shift in reservations number due to abundant supply. For this reason, the following comparison focuses on scenarios 4 and 7, where competition exists.

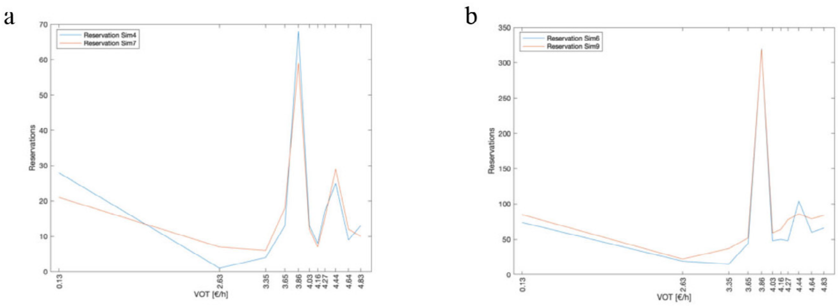

Fig. 4. (a) Shift in Reservation Sim4-Sim7; (b) Shift in Reservation Sim6-Sim9.

In addition to the difference in number of reservations, an explanatory indicator is the duration of booking. While they tend to book more, the population with an average VOT tend to strongly lower the booking time in order to keep a cheap rental, while people with the lowest VOT, have a softer decrease. This behavior can be ascertained by Fig.5. Stations (red diamonds), carsharing users (blue dots) and a heatmap layer describes the VOT distribution. It is possible here to notice how the areas in which a major density of medium-high VOT tend to have more users once the ABDP is applied.

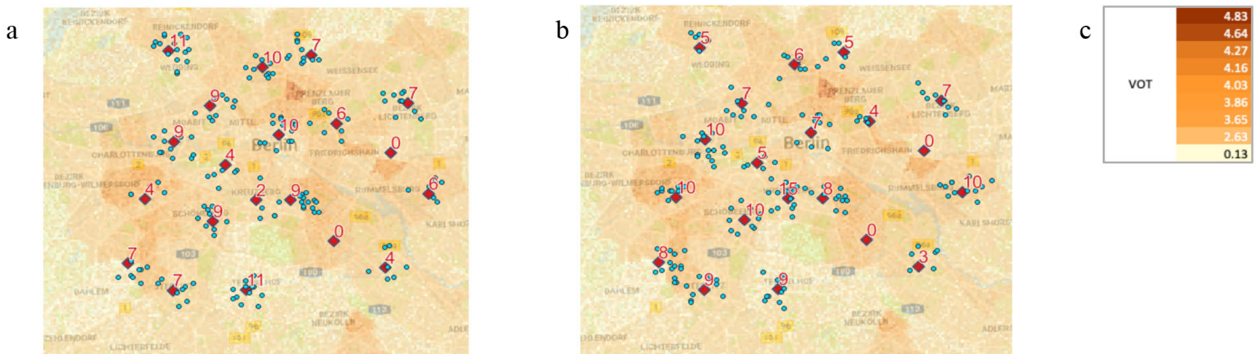

Fig. 5. (a)VOT Heatmap Sim4; (b) VOT Heatmap Sim7; (c) Heatmap Scale

4. Summary and outlook

The work here presented is motivated by the need to model the behavior of carsharing users with socio-economic attributes in order to investigate on which supply attributes impact the demand and how. The explorative analysis here proposed has identified trends and shows interesting potential. However, given the complexity of the phenomena, they will in the future be inspected further.

One of the main contributions is the introduction of the VOT to characterize the carsharing demand. The introduction of this variable influences the users' response to price schemes and helps to better simulate the behavior of different groups of users. The second main finding is that carsharing users with an average VOT tends to take resources from users with a lower VOT that will migrate to other means of transportation while pricing only slightly affects high VOT users.

At a strategic level, future developments will focus on the reduction of some degrees of freedom fixing some variable (e.g. the station location choice) in order to better estimate the influence of the ABDP on the demand more systematically and quantitatively.

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