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Born on 29 May 1987 in Rome (Italy)

DYNAMIC PRICING STRATEGIES IN THE CARSHARING BUSINESS, PROFIT MAXIMIZATION AND EQUITY CONSIDERATIONS

"It would have been nice to have a bit of cosmic explanation at this point, but the universe never gave you explanations, it just gave you more questions."

- *Terry Pratchett, Unseen Academicals*

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Summary

In the last two decades the development of mobile technology and the ease of access to an internet connection helped the consolidation of the sharing economy paradigm. This new way of purchasing goods and services differs from old traditional business models since it enables a shared use of resources in order to save money and generate profit. As an important player in the sharing economy, sharing mobility continues, nowadays, to shape urban mobility with the introduction of different modes of shared transport such as carsharing, bike sharing, ride sourcing, and other collective mobility services. Different stakeholders participate in the creation and exploitation of these new mobility services: governmental agencies, customers, and private companies. Each of them has a specific purpose that can affect and stir the benefit of sharing platforms. Focusing on the carsharing service, on the business side and on the user side, profit and customer satisfaction are usually the main goals even if, at times, both difficult to pursue together. Competition on today's landscape leaves little room for both established and less established businesses. Opportunities to increase corporate profit become scarcer and more refined systems to better manage carsharing operations are needed to guarantee commercial viability.

Evaluating business models for carsharing is no trivial task. Several methods are used for assessing the quality of changes in some operations or to evaluate possible approaches. Combinatorial and stochastic optimization are used to answer decision-making problems in the case of deterministic or uncertain problems. The shortcoming of these approaches is that they are limited at solving problems related to fleet management or service planning as it is more difficult to have an overview in which multiple properties (e.g., demography, territorial distribution, specificity of the fleet, ...) of both supply and demand are considered. This happens because car sharing is a highly complex service that has many interdependent factors. Given this complexity, a more favorable approach to estimate the demand for the service - together with all its peculiarities - and to help operators in the decision-making process, is the simulation one. This criterion allows the interaction of multiple factors which, through functional relationships between the decision-making parameters of the supplier, can introduce indicators to evaluate the quality of the solutions that cannot be easily derived analytically.

This dissertation focuses on a simulation-based approach that aims to create a decision support system for carsharing business. This decision support system aims to use demographic and land use data as input, once the provider's needs are known, and to return solutions regarding the optimization of the carsharing service. The development of this thesis is conceived from the point of view of the service provider, even if considerations regarding the equity of the various strategies proposed therein for the service customers constitute an integral and fundamental part of the construction of this system of support for decisions.

In this manuscript, we discuss the introduction of different dynamic pricing strategies that aim to increase the profit of the carsharing service, along with other indicators such as the number of bookings and utilization time of vehicles. By developing different price models, the introduction of dynamic prices based on the quantity of vehicles present in the station at the time of booking is evaluated and the output of the implementation of a dynamic price based on the time of the day is examined. In the first part of this thesis, we discuss how it is possible to evaluate the quality of a carsharing service from the point of view of its members, focusing on how different strategies generate or can reduce inequalities due to different wages or purchasing powers. Furthermore, using data collected by a car-sharing company operating in Germany and the United Kingdom, Oply, we implement these same strategies in a scenario calibrated with real data. Finally, we propose a methodology for calibrating carsharing scenarios in an agent-based environment.

Moreover, we use these scenarios to demonstrate how it is possible, once there is complete knowledge of the demand and the status of the offer, to attribute a certain price to a single booking that maximizes the profit of the service.

The overall results show that the introduction of dynamic pricing strategies does not always benefit all segments of the population and that the goals of a carsharing company are not always compatible with those of its members. Furthermore, they show how it is possible to increase the profit of a carsharing company accordingly to its position on the market, whether it has a total knowledge of the territory or not, whether it is an established company or not yet fully established. As we will also see in the final chapter of this thesis, the product of this work does not consist only in a practical contribution aimed mostly at carsharing companies, but also in a scientific counterpart that outlines new research directions.

Acknowledgements

Giving myself the time to take a breath and to look back to these four wonderful years spent at the University of Luxembourg, I realize the tremendous number of battles, adventures and challenges I have faced and overcame. And if I managed to be so brave to get to the end of this path, I want to express immense gratitude to those who brightened my days, those who showed me the way, those who helped me broaden my horizons.

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I. Introduction

This part sets out the context and rationale for this dissertation. It defines the purpose and objectives and then underlines the contribution of this thesis with the related research questions. Finally, it presents an outline of the work defining its structure.

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1
Introduction

Carsharing is a service that provides a fleet of cars and offers short-term rentals. The offer of the carsharing service has different variations. Companies provide different types of vehicles with prices that can be based on time, space travelled, or a mix of the two. Nowadays, the use of car sharing is on the rise; despite this, and despite the large opportunities for growth, this market still presents many challenges and is still attracting a relatively small share of the modes used by travellers.

This dissertation focuses on the challenges a private car sharing company faces in increasing its financial capabilities and the efficiency of its fleet. Furthermore, this work aims to assess the impact that the pursuit of these goals will have on service members.

In this chapter we introduce the context and motivation of this dissertation. We describe the objectives of the thesis and the research questions.

1.1 Context and Motivation

Mobility is one of the various human activities with the highest economic and social significance. The European population tends to concentrate in urban areas, exacerbating congestion phenomena that lead to important losses estimated over one percent of the European GDP (*1*). Although the authorities try to reduce the number of cars, the number of vehicles in use in the European Union has increased by 1.08% in the last five years (*2*) along with the number of passengers per kilometer (*3*). While it is probably too early to talk about a paradigm shift towards the private car (*4*), Europe must reduce emissions from transport further and faster with a goal of 90% reduction of greenhouse gas emissions generated by transport by 2050 (*5*). The transition to more sustainable modes of transport is taking place using different modes of transport, smart traffic management methods and smart applications. In order to tackle this critical issue, both companies and public institutions are showing an increasing interest in new collaborative mobility solutions, in particular sharing services (car sharing, carpooling, parking sharing), on-demand services (Call-a-bus, Uber, etc.) (*6*) and Mobility-as-a-Service (MaaS) systems (*7*). Carsharing and carpooling have the additional advantage of offering a flexible service without the burden of ownership. In addition, these strategies have the potential to reduce the negative social costs of private cars, by reducing overall car ownership rates while promoting car occupancy rates (*8*).

The term sharing mobility refers to the phenomenon proper of the sharing economy. This paradigm consists of transfers that take place with "shared" vehicles: people do not use their own cars, bicycles or scooters, but use rental services offering them these vehicles. In sharing mobility, technology is an indispensable support. Mobile apps are needed to enable the collaborative service model and make it useful and scalable. Digital platforms then make it possible to facilitate relationships and exchanges beyond physical borders, in a faster and more effective way. All innovative shared mobility services pre-existed the advent of the Internet, the development of intelligent transportation systems (ITS) and the more recent mass diffusion of the use of mobile devices such as tablets and smartphones. However, are these innovations that have allowed, on one hand, that some niche practices have begun to establish themselves as forms of mass consumption, and, on the other, that some consolidated business models have been upscaled and have gained new market shares.

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 paying a usage fee. Currently, peer-to-peer (P2P) and business-to-customer (B2C) are the two most important carsharing models. The first model consists in having private cars as shared vehicles. These cars are owned by individuals who decide to rent their vehicle using a platform made available to them by a third-party company (*9*). Otherwise, the B2C model consists of having a company (usually private) that offers a fleet of vehicles that are shared by the users of the service. Referring to the latter model described, we can further describe this service through its different formats (*10*, *11*):

- Station-Based Round-Trip or Two-Way carsharing: customers can pick up a vehicle from any station, but it must be returned to the same station where the rent started.
- Station-Based One-way carsharing: customers can pick up a vehicle from any station and it can be returned to any available station.
- Free-floating carsharing: pick up and drop off can happen in a vast operation area designated by the carsharing provider without any predefined station.

Thanks to the recent growth in popularity of carsharing, there has been a boom in the number of carsharing companies that enter the market every year (*12*). In recent times, the revenue generated by the carsharing service has seen a stable increase even if the recent pandemic has halved the annual income of the global market (*13*) (Figure 1). Nonetheless, the revenue generated by the service is set to grow in the coming years. Given the short duration of the pandemic event, the number of users has not decreased, and a slight inflection of future trends is expected in the face of a consolidation of the market which is however far from being saturated.

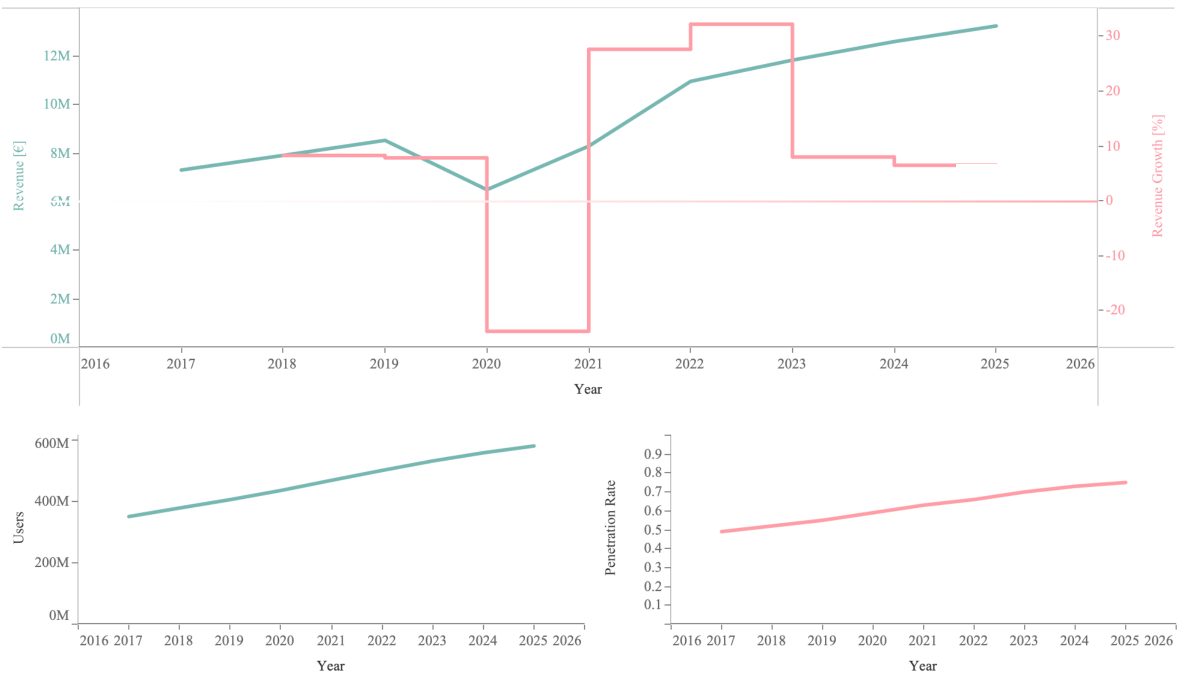

Figure 1. World Revenue and Users Trends of Carsharing

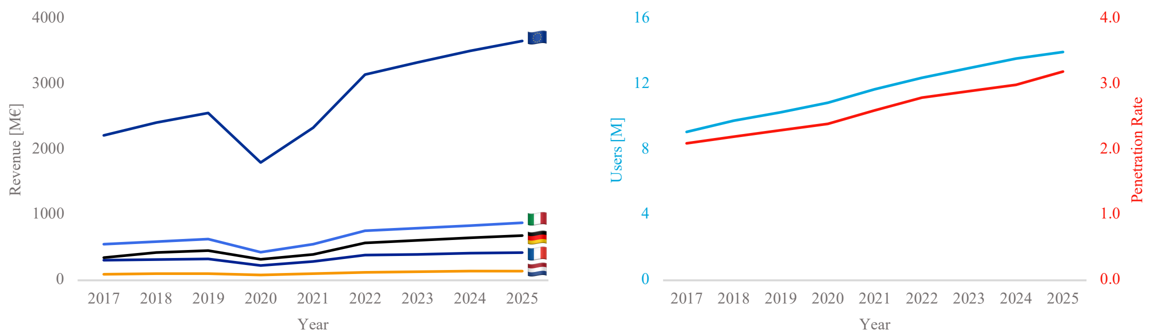

Figure 2. EU Revenue and Users Trends of Carsharing

An important hint given by the first graph in Figure 1 and Figure 2 is given by the future growth trends of carsharing: even if the revenue is destined to grow, it will grow much slower. At the moment, several carsharing companies have started a collaboration both at the level of private (e.g., Daimler AG and BMW) and public partnerships (i.e., cooperation with local authorities for granting parking space/permits) in order to face this relatively lower generation of revenues and still guarantee a growing profit. Specifically, with regard to car sharing in Germany, the size of the fleet in the twenty main German cities by number of carsharing vehicles is shown in Figure 3 (*14*). In the 2019, in Germany, there were 2,46 million registered carsharing users for an offer of 20200 vehicles (*15*). The number of vehicles and members is constantly growing. The two main German cities of Munich and Berlin appear to have the largest car-sharing offer in terms of fleet: respectively 5,814 and 3,133 vehicles for a total of 1.60 and 1.61 vehicles per 100,000 inhabitants.

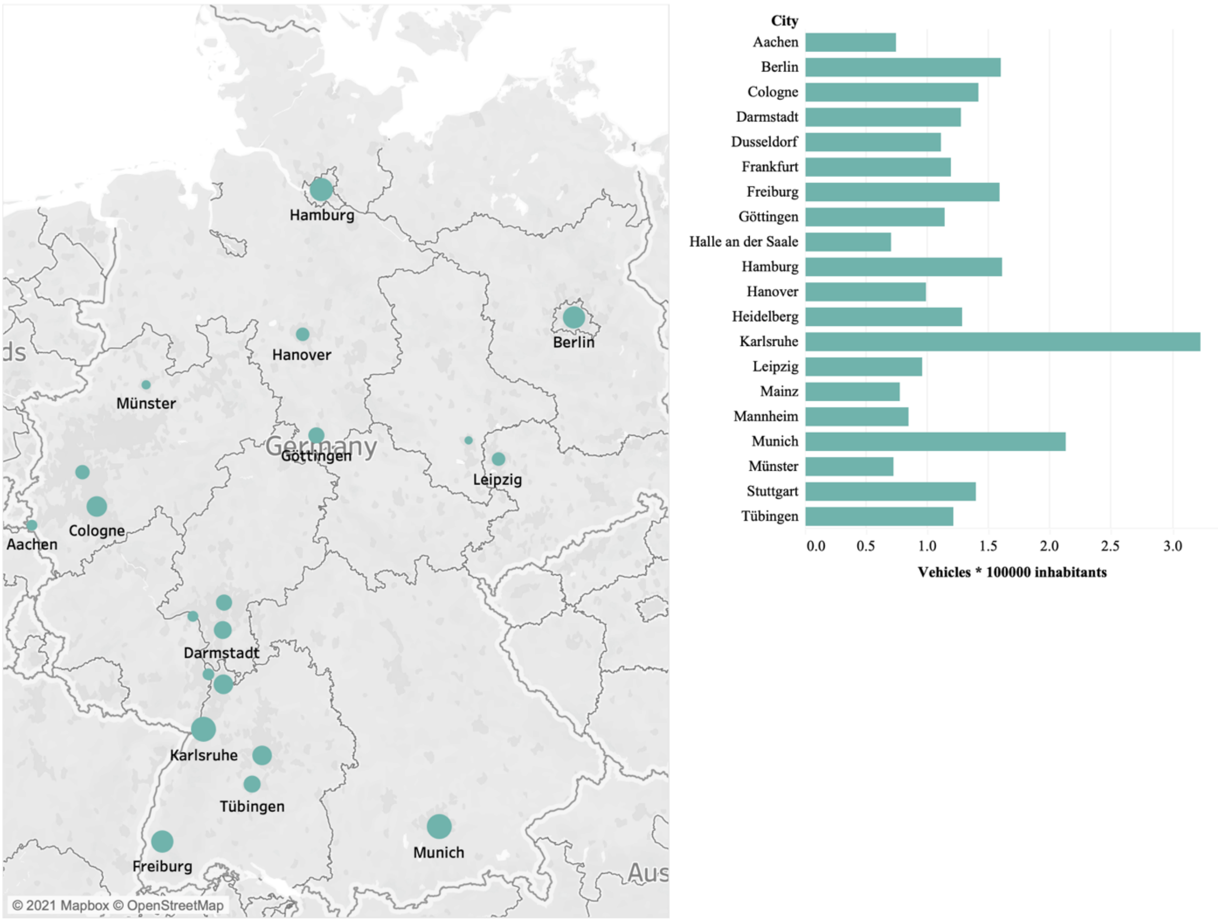

Figure 3. Size of German Carsharing Market

There are four key factors that need to be considered to make a carsharing company successful: Location, availability, pricing, and fleet. The complex interdependence of these factors, the low profit margins due to strong competition, and a high diversity of the various business models adopted by the carsharing companies, make this mode of transport a weakly profitable business. Even though carsharing is no longer an innovative solution, a business model that ensures its long-term stability is still far from being identified (*16*).

Carsharing is a service that, given the presence of various stakeholders with different objectives, is complex. The main stakeholders of carsharing are the public sector, private companies, and the end user. The complexity of the service is due to the different objectives that these stakeholders have. First of all, the public sector, which may be more or less involved in the service that will be introduced in a broader transport planning scheme, has the power to dedicate specific parking areas or propose incentives to establish parking areas for car sharing. Usually, the goal of this stakeholder is to make the introduction of carsharing in the urban area more harmonious. The private company, on the other hand, is part of a context in which, usually, there is already a substantial competitive component that naturally makes profit margins low. Also counting the various types of existing carsharing models, a service designed by analogy with other companies is difficult, especially considering that the territory in which this mode of transport is introduced can vary noticeably from city to city. Finally, the users. Even within the same carsharing model, members of the service can have very different behaviors caused by lifestyle and their ability to pay. The interaction of these actors and the different reasons that can make such a service useful (benefits similar to those of the private car, weather conditions that favor the use of a more comfortable vehicle, lack of other modes of transport, etc.) create a complex system in which it is often difficult to summarize all the variables with an analytical approach.

In this context, our main goal is to develop a tool to be used as a decision support system (DSS) based on a simulation approach to create realistic what-if scenarios based on different characteristics of the territory and the service. Furthermore, the DSS will be employed as a tool to advise on the best pricing model and lay the foundations for creating a business modeling system for carsharing companies.

1.2 Emerging Behaviors and Agent-Based Modeling

Agent-based models aims at simulating the actions and interactions of autonomous agents with the goal of evaluating their effects on the system as a whole. Unlike more traditionally used models that employ traffic flow assessments as vehicles per hour, agent-based models allow for a strongly disaggregated description of demand. The core concept of carsharing, the fact that it contributes only to a small (but not negligible) part of the modal choice, its peculiarity of being available in a specific place at a specific time, make agent-based models more suitable to the simulation of this mode of transport, thanks to their high precision capable of representing single entities: agents. When representing the movements of a group of people using different means of transport, one of the main aspects is to understand and interpret their reasons. Movements derive from a need that a particular person has to go to a place where he can carry out a specific activity. The trips are therefore the result of activities that must be carried out and that will be chosen according to the characterization of the people and their behavior. The description of a user's behavior is the fundamental paradigm of agent-based models. These models have the ability to have rules that can be inserted at a microscopic scale level which, however, result in an influence on behavior at the system level, therefore at a macroscopic scale. The outputs generated by the implementation of these models make it possible to interpret emerging behaviors. This is a fundamental skill needed when trying to describe new modes of transport of which one does not have sufficient knowledge of the behavioral patterns that lead people to choose them.

At the time of writing this thesis there are multiple agent-based simulators. TRANSIMS (TRansportation ANalysis SIMulation System) (*17*) is «an integrated set of tools developed to conduct regional transportation system analyses». SimMobility (*18*) is «a simulation platform that integrates various mobility-sensitive behavioral models within a multi-scale simulation platform». MATSim (*19*), «an activity-based, extendable, multi-agent simulation framework implemented in Java designed for large-scale scenarios». Anylogic (*20*) which incorporates three different simulation methods concerning system dynamics, discrete event, and agent-based modeling, giving the user the possibility to use multi-method models. Besides these agent-based simulators there are also several simulators defined as activity-based demand modelers. frameworks such as ALBATROSS (*21*) or FEATHERS (*22*) which, despite helping the development of dynamic activity-based models, still fail to fully implement the integration of the different aspects of transport modeling.

For this reason and for the fact that it was an open-source simulator and therefore more easily extendable, for the fact that a first extension for carsharing already existed, MATSim was chosen as a framework for the studies performed and subsequently reported in this thesis. MATSim is a dynamic activity-based agent-based modeler built on a mesoscopic transport modeler. The basic idea is to use a synthetic population generated through data derived from censuses that can move and act in a virtual reality. it is based on a co-evolutionary principle in which each agent tries to optimize his plan at each iteration of the simulator, while competing with other agents, adhering to his chain of activities. The main purpose lies in an iterative approach that proceeds until the score, that is generated in each iteration of the simulation, and which describes the usefulness that a particular agent draws in carrying out its daily activities, increases. One of the additional reasons for choosing MATSim as a simulator was the presence of data regarding the cities of Berlin and

Munich. The importance of these scenarios is given by the fact that this doctorate was carried out in the context of a partnership between private and public. The private stakeholder was Oply, a two-way carsharing company which operates, among other cities, in Berlin and Munich.

1.3 Objective and Scope

Carsharing brings with it numerous benefits. From the point of view of sustainable development, the vehicles used by this service are usually more efficient in terms of consumption bringing a reduction of the emissions in the urban field. Typically, carsharing can also help reduce congestion and the need for more parking spaces (*23*). Given the benefits of this mode of transport, researchers have focused on several branches with the aim of deepening the knowledge of this mode and improving the service. According to (*11*), the research on carsharing has been following three main axes: optimization, time horizon and methodologies. The optimization has mainly focused on three pillars: business service, infrastructure, and fleet management. The time horizon describes the decision-making range of actions that can be taken at a strategic, planning, or day-to-day decision level. Finally, the commonly applied methodologies concern simulation, combinatorial or stochastic optimization, and statistical analysis. Even though carsharing has been around for quite some time, models able to fully assess its functionalities are not yet fully developed. That is why, considering that the research introduced so far has not yet sufficiently covered the aspects concerning business profitability, in the first place, and the equity of this mode of transport, we have identified these two themes as the gap that will be filled by this dissertation.

This dissertation aims to develop a DSS for carsharing business (Figure 4). This system will adopt and extend an agent-based simulator focusing on the supply and the impact that different strategies will generate on the demand.

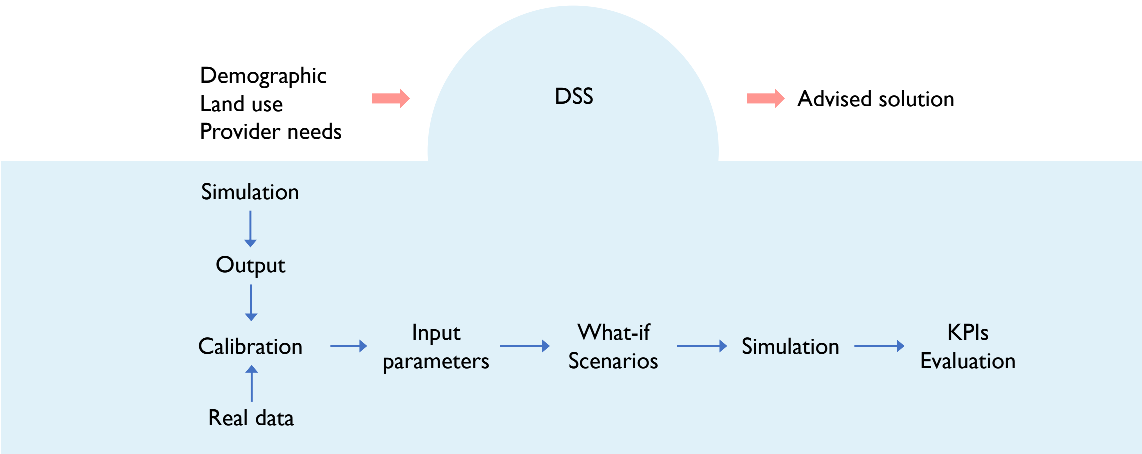

Figure 4. Decision Support System Diagram

The development of this system will mainly revolve around the implementation of different types of dynamic prices aimed at maximizing profit and the use of company resources (i.e., carsharing vehicles). At the same time, the impacts generated on the population where the carsharing service is introduced, will be based on equity measures deriving from the purchasing power of the users of the service. Easy-to-deploy vehicle reallocation strategies based on the simulation of carsharing scenarios will be applied with the aim of maximizing utilization and utility for the end customer. The time horizon used in this thesis will focus both on the tactical planning of the service and on day-to-day operations.

To pursue this goal, we have formulated several research questions (RQ).

RQ 1: Given a certain territory and population, is it possible to identify a carsharing business model that is optimal looking at both users' and the service provider's objectives?

Creating a DSS allows us to identify ways to increase user utility while optimizing supply resources. The method chosen for a trip depends on a multiplicity of factors: The reason one has for carrying out a certain movement, the activity that must be carried out, etc. It is clear, then, how travel is influenced by the socio-economic context. A certain context means that the people who live and travel in a certain area, could have different economic resources and different habits than others and, therefore, to favor different modes of transport. Certainly, the choice of one mode of transport rather than another is also influenced by the offer available in a specific area. Usually, supply and demand have diverging objectives. While the travelers representing the transport, demand aim at maximizing their utility, any company managing the supply will seek to maximize their own benefits derived from its service. To understand the different mechanics that lead carsharing users to opt for this service, and to understand the methods of carrying out the service that could lead to optimizing the offer, in this thesis we used two of the main German cities, Munich and Berlin, to evaluate how a fleet and a carsharing offer can be formulated in order to optimize the service, both for the population and for the company.

RQ 2: Is it possible to derive an analytical relation between supplier decisional variables and profit of carsharing operations through a simulation approach?

Despite simulation is a sound methodology for assessing pre-determined what-if scenarios, it is not suited for being employed in optimization problems due to its computational complexity. Hence, deriving a simpler model that allows to identify the optimal value of the decisional variables, and in particular the hourly price of the offer, is of great relevance. In this dissertation we show that it is possible to create a meta-model aiming at profit maximization based on the supply available at a certain moment in time. In the specific, this research question focuses on the financial model involving cost and benefits of a carsharing service employing a two-way model. The price can be, and is used also as, a method of managing the service (*16*). Given that car sharing providers are, more often than not, private actors, creating a profit for the company is one of the main goals. As for the interaction between company and customer, one of the most direct ways to increase profit is to have an offer with an optimal price. Starting from the assumption that the law determining the interaction between supply and demand relates the quantity demanded and the quantity offered of an economic good with the variations in its price, the method chosen to answer this question is to find the price to offer that will maximize profit once the demand and the state of the fleet is known. The idea behind this method is to create a simulation approach that allows to find, by changing the price and the offer, a profit, price, supply surface that grants to identify, as these quantities vary, the maximum profit given the state of the network.

RQ 3: How can a dynamic pricing strategy be developed to increase the profit of the company and, at the same time, improve the utilization of the fleet?

Pricing based on demand (whether it is a fixed price based on surveys placed at potential members of the service or prices based on the times the resources are used) can be constructed without a deep knowledge of the network and be used for planned and spontaneous booking models. Supply based dynamic pricing such as prices function of the resources available, need a thorough knowledge of the demand and the supply state and are more suited to spontaneous bookings. Various types of dynamic prices have been applied in car sharing with different objectives, starting from the dynamic price used in the one-way to encourage the reallocation of vehicles by taking advantage of offers to customers (*24*), to the dynamic price for on-demand ridesharing (*25*). Inspired by pricing techniques developed in the airport (*26*) and hotel sector (*27*) we develop different pricing strategies with the aim of increasing profit and improving the service in terms of vehicle use. First, the methodologies used by carsharing companies to increase their profits cannot be applied in the same way in different situations. Second, by extension, the methods cited above and that are applied in other sectors are not directly extendable to this specific mode of transport but need a translation based on the properties of the service, on its place of introduction and on the company's knowledge of its service. Basically, the amount of data held by the company can lead to different ways of deploying resources. In the fifth part of this dissertation, we define how, given the amount of information that the carsharing company has, which is the approach that generates, in terms of profit and use, the best outcome.

RQ4: Is it possible to assess the quality of a business model in a multi-criteria and multi-actor analysis framework?

Following the previous research question, we have defined strategies with the aim of exploiting the heterogeneity of the market and induce an improvement in the efficiency of the service. Once these strategies are defined, it is necessary to develop a systematic assessment method of the impact that will measure and evaluate the changes of the offer on the user base. In addition, these impacts must be made not only measurable, but also comparable. Regarding the impact that a specific offer has on the pool of users of the service, in the second and third part of this thesis, we have developed a multi-criteria approach to estimate how user behavior is modified. First of all, in the second part we show how it is possible to analyze both the outcome of a price strategy variation for the company and how, always this same price variation, brings a change in the modal choice habits of users and how specific chains of activities are more or less favored. The systematic assessment method shown aims to evaluate multiple conflicting criteria in decision making, where decision making means the implementation of different pricing strategies. Secondly, in the third part of this dissertation, by explicitly focusing on the income diversity of the members of the carsharing service, we developed indicators that allow, more in the specific, not only to understand the impact of the service on its users but also to understand its influence on different income brackets.

1.4 Contribution and Outline of the Thesis

This thesis consists of five parts. This first part introduces the research (context, motivation, and objectives). The second and third part are dedicated to the study of the demand for carsharing, respectively how the users of the service react to different types of business models (one-way and two-way), and how, through simulation, different pricing strategies impact different customer groups defined by different spending power or wages. The third part discusses the impacts generated by the introduction in the territory of a two-way car sharing service and the possible and different benefits brought to different groups of the population. Following, the fourth part describes the development and introduction of a novel pricing mode seeking maximum profit using real service data. Finally, the fifth part concludes the thesis. The overall structure of the thesis is presented in Figure 5.

Part I: Introduction

Background and state of the art

Chapter 1
Introduction and state of the art of sharing mobility and carsharing.

Part II: Carsharing Models Analysis

Assessing different business models

Chapter 2
Assessment of two different business models and how they differ in their impact on the demand. Equity considerations related to the interaction with these two different models

Part III: Dynamic Pricing I, Berlin Case Study

Availability-based and time-based dynamic pricing. Introducing the value of time

Chapter 3
Explorative analysis using Berlin as a test case for the introduction of an availability-based dynamic pricing variating in function of the supply. Introduction of the value of time in the simulation.

Chapter 4
An experimental design employing homogenous distribution of the value of time.

Chapter 5
Introduction of the time-based dynamic pricing together with different homogenous distribution of the value of time

Part IV: Two-Way Analysis

Methods to assess the equity of a new introduced carsharing system

Chapter 6
Introducing the case study of the city of Munich. Description of the impact following the introduction of a two-way carsharing system.

Part V: Dynamic Pricing II, Munich Case Study

Method for calibrating a carhsaring scenario. Creation of the maximum profit price

Chapter 7
Development of calibration method for carsharing scenario in agent-based simulation. Development of the maximum profit price.

Chapter 8
Techniques for profit and utility optimization using different dynamic prices. Hybridization of different prices with the goal of increase service acceptance and profit.

Part VI: Conclusions

Chapter 9
Conclusions and future research directions

Figure 5. Thesis Structure

1.4.1 Practical Contributions

Development of a practical decision support system

Carsharing is a system mainly driven by private companies. Approaches regarding the improvement of business models have been developed to make this system more competitive. This research further develops this framework by implementing a system that evaluates the quality of certain strategies through a simulation approach. Through the extension of a state-of-the-art agent-based simulator we introduce a new method to evaluate the impact of policies that, without a simulation approach, could lead to a huge use of resources that many companies could not afford. This decision support system makes it possible to evaluate the introduction of different types of prices, different business models and the introduction of a service from scratch considering the characteristics of the territory and of the population.

Development of a maximum profit pricing strategy

Carsharing is a business with very small profit margins. The introduction of fixed prices, even if easier for users to interpret, rarely leads to an increase in profit. This thesis describes an approach that, by defining a dynamic price, leads to profit maximization regardless of the area in which this service is introduced. The way in which this price is developed is also generalizable and adaptable to multiple contexts without distorting its effectiveness.

Estimation of the impact of introducing dynamic prices

Dynamic pricing has already been developed in carsharing with different goals. Usually, the various studies that have addressed this issue tend to turn more to the supply through techniques to reduce the costs of reallocating the fleet or by increasing the use of resources. In this thesis, we evaluate not only the impact generated by these dynamic pricing strategies on the supply, but we analyze and describe the effect that they have on the population affected by this service, and how different segments of the population undergo the introduction of this offer. Finally, we develop new ways to build this type of prices by describing which are the most efficient through a simulation approach.

Business models development

A dynamic pricing strategy is basically a price that, instead of being fixed and independent of any event (i.e., static price), varies as another quantity changes. This price dependence can be structured in different ways and is a core component of the corporate business model. In this dissertation we have created several dynamic pricing strategies that update the price offered as two specific quantities vary: time and fleet. Thus, dividing these types of prices into these two large families, we first introduced a price that depended on the consumption of resources in each single station. Different functional forms describing the dependence of the price on the number of available resources were proposed and the impact on the population and on the carsharing system is analyzed. These functional forms are essentially hyperbolic or exponential in nature. At the same time, we also focused our attention on pricing strategies of a temporal nature, which therefore varied according to the booking time. The development of different multipliers - multipliers that allow a more or less strong price variation - and therefore of different price profiles has made the impact of more or less aggressive offers in the simulation stage more direct and easier to interpret. This allows us to recreate the business model that best suits the company's purposes during the decision-making process.

Introduction of new ways to develop and assess realistic scenarios

Carsharing is a local service that contributes approximately to the 0.5% of the modal split in urban areas. Compared to other modes of transport, carsharing has a very low number of regular users and is mostly used for non-recurring activities. This makes it difficult to identify emerging trends or aggregate behavioral areas that identify the use of this specific service. The fact that the choice of this mode of transport is non-recurring and, above all, that it is aimed at satisfying leisure, shopping, or non-commuting activities, makes the analysis of this system very complex. In addition, the system in which it is inserted is a complex system, made up of different stakeholders who, when trying to represent them in their entirety, bring a high complexity and heterogeneity. Put simply, the more realistic the scenario, the more complex it tends to be. In this dissertation we have developed complex and heterogeneous scenarios and conceived methods (see the second part of this thesis) that allow to reduce the complexities to obtain a better understanding of the relational functions present between demand, supply and price.

1.4.2 Scientific Contributions

Introduction of the income in the utility model

The utility (or scoring) is defined as "the actual performance of the plan in the synthetic reality"(*19*). This scoring is a measure that describes the goodness of a chain of actions and activities performed during a given day. The higher this score, the more the consumer's preferences are fulfilled. Since we are talking about consumers, we imply the fact that these preferences are specific to each person. This means that, inevitably, the habits and behaviors of each person reflect their socio-economic situation. Since we are talking about consumers, we imply the fact that these preferences are specific to each person. This means that, inevitably, the habits and behaviors of each person reflect their socio-economic situation. All other conditions being equal, a specific cost impacts members of different economic groups differently. To better simulate this axiom, we have implemented in the simulator, and more specifically in the utility function, a component relating to the spending power of each user. The introduction of this variable in the scenario influences the simulation by characterizing the agents individually. The result is that we will not have a homogeneous system in which users are described only by their daily movements - which in turn are a result of the allocation of a choice - but a heterogeneous system where every customer is described by a variable that carries an information that actively influence mobility choices: the income. This introduction implicitly carries with it part of the rational component that describes how a specific mode of transport will be used (in this case the carsharing), and as it will be accepted by each individual user.

Calibration of an agent-based simulator for car sharing

Methods of calibrating an agent-based car sharing simulator are quite rare. This is mainly caused by the difficulty of finding the data and by the rarity of simulators that allow to replicate this specific service. Using data from a car sharing company operating in Munich, we have developed an innovative method to calibrate a simulator using the revenue and the number of hours of rental per day. This method allows for a more realistic assessment of the possible impacts of introducing a carsharing service as well as the impacts of specific strategies. This calibration model is independent of the type of car sharing and independent of the user base of the service. Through the introduction of this new calibration method, we have presented the possibility of adjusting the simulation environment not only for a carsharing service, but for all those innovative modes of transport that base their business model on indicators that directly depend on the consumption of resources by the users. This method can in fact be used to calibrate simulations regarding MaaS or other sharing mobility services (e.g., bikesharing, scootersharing).

Profit maximization method

The profit generated by a given service can depend on multiple factors, both exogenous and endogenous. In this thesis we develop a procedure that allows us to arrive at a mathematical formulation of the price that has as its objective the maximization of profit. In this model, only the state of the fleet is used as an explicit variable, also defined as the number of car-hours that the service can offer. By simulating various price and supply conditions, therefore considering all those variables deriving from the population as implicit, this metamodel thus created allows, through a process of maximization, to obtain a continuous function that links three fundamental variables such as profit, price, and the supply.

Methodological contribution valid for other mobility services

The methodology described in this thesis and its use in the simulation field as a decision support system is not specifically linked to the two-way car sharing service only. The methodological approach reported here can be used and extended first of all to all the different types of carsharing (i.e., one-way, free floating and mixed service), it can be introduced for other types of shared mobility (e.g., bikesharing, scootersharing), it can be applied independently of the technology used by these systems (i.e., for autonomous vehicles) and can finally be extended for mobility studies based on MaaS.

II. Carsharing Models Analysis

In this part we discuss how two car sharing systems, one-way and two-way, are accepted using an identical user base. This first step leads us to evaluate what types of behaviors users tend to adopt when choosing one type of carsharing over another. Furthermore, we introduce the Berlin case study by differentiating each user by their value of time. This will allow us to make considerations not only regarding their behavior in choosing the service, but also regarding the performance of their daily activities which will therefore be based on their economic possibilities.

This case study allows us to understand how users who use one of the two business models rather than another for their movements, have different chains of activities and, above all, adopt a specific behavior different from the users of the other carsharing model.

This part is based on the work published in:

Giorgione Giulio, Luca Bolzani, and Francesco Viti. "Assessing Two-Way and One-Way Carsharing: An Agent-Based Simulation Approach." Transportation Research Procedia 52 (2021): 541–48. https://doi.org/10.1016/j.trpro.2021.01.064.

2 ASSESSING TWO-WAY AND ONE-WAY CARSHARING: AN AGENT-BASED SIMULATION APPROACH 19

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2
Assessing Two-way and One-way Carsharing: an Agent-Based Simulation Approach

Carsharing companies can customize their service by adopting different pricing schemes and offers with the aim of increasing fleet use and profits. Different business models have been developed such as round-trip and one-way. Is it clear that, even though many aspects of the business model and operations are the same, the different way in which these services are supplied leads to a diverse response from the users. In this work, we analyze how a fixed pricing scheme affects the behavior of the members of two different carsharing systems: two-way and one-way, explicitly considering their different income distributions to analyze social equity aspects. The dynamic pricing policy is simulated in MATSim, an agent-based simulator able to generate realistic mode choices based on individual activity-travel behavior. Scenarios with a synthetic population of carsharing members for the city of Berlin are analyzed. We aim to provide an experimental analysis that addresses the different behavior of different demand sectors, categorized by income, in function of the supply distributed on the territory. Simulation results show that the two services are not in competition between each other: the two-way service is used as a substitute for private cars while the one-way system is preferred from agents who choose to use multiple types of modes during the day. The response from the different income classes tends to be similar for both services since all the users within the same purchase power have the same degree of acceptance for both systems.

2.1 Introduction

To tackle sustainability and traffic congestion issues, companies and public institutions are showing a growing interest in new mobility solutions, in particular sharing services (car sharing, carpooling, park sharing), on-demand ride-hailing services (Call-a-bus, Uber, etc.) and mobility-as-a-service (e.g., Whim). Coordinated efforts are being made to match mobility needs with sustainable mobility services in order to fight car dependence. Indeed, carsharing vehicles contribute to the creation of more sustainable cities given their better fuel efficiency if compared to private cars (Martin and Shaheen, 2011).

Traditionally, carsharing services are differentiate between one-way (station-based and free-floating) and two-way system. On one hand, these two systems share a lot of similarities in reducing externalities such as emissions and car ownership (Martin and Shaheen, 2011) while, on the other hand, the way they are used by the users can be different. This gives rise to different streams of research that, most of the time, treat these two services independently. In a study conducted by Ferrero et al. (2018) it is shown how the most studied stream of research for the one-way is the fleet-management while for the two-way the focus is more on the infrastructure design related to the parking location strategies.

Works regarding simulation comparing both systems at the same time are rare. Lempert et al. (2019) and Namazu and Dowlatabadi (2018) focus their work on a survey based approach in order to define, respectively, the impact on car ownership and the reasons leading users to choose for a carsharing membership for both two-way and one-way systems. Cisterna et al. (2019) adopted a combined simulation and discrete analysis approach to study the membership choice of two carsharing systems, two-way and one-way free-floating. In order to get an insight into the relationship between fleet size and demand, Orbe et al. (2015) evaluate the effect of variable user demand on a two-way and one-way (both station-based and free-floating) carsharing fleet in Zurich using agent-based simulation.

As already mentioned, one of the expected long-term benefits of carsharing is the reduction of vehicle ownership bringing to their members new ways of moving in their cities, but it is not clear yet if these benefits can be considered equally distributed. Studies reported that vehicles cluster in areas that are densely populated by young residents with high levels of education Tyndall (2017), making the service more available to those segments of the population that are already socially advantaged. From a policy point of view Shaheen, et al. (2017) describe how sharing mobility may provide spatial and temporal resolutions to bridge the transportation gaps by providing a first-and-last-mile connection to the traditional public transportation network, by reducing waiting time and by increasing travel-time reliability.

Even though, to the best of authors' knowledge, studies that address the equity in carsharing through a simulation approach, are very uncommon, approaches to study equity with an agent-based simulator are more popular in the literature. Concerning road-pricing, Grether et al. (2008) look at the effect of an afternoon toll on a synthetic population and how the change in price affects their consumption patterns. Using road pricing, Lucas Meyer de Freitas et al. (2016), analyze winners and losers of a congestion pricing scheme for the city of Zurich.

In order to bridge the different gaps described in this section, the goal of this work is to introduce a comparative analysis between a two-way and one-way carsharing services using financial and operational key performance indicators (KPIs) to assess the systems' behavior from the supply perspective, and equity- and travel-related KPIs to determine the response of the demand using economic-sensitive variables collected through an agent-based simulation.

2.2 Methodology

Regarding both two-way (TW) and one-way (OW) carsharing systems, it becomes clear that a trip-based model is not employable to assess important KPIs such as service availability at a precise point in space and time (Ciari et al., 2014). Additionally, disaggregated methods are necessary to describe the behavior of the individuals and the activities executed at different locations and at different times. That is why, in order to assess single user's behavior, an agent-based modeling approach is used. In this work we adopt agent-based simulation to analyze a TW and a OW carsharing system on the Berlin network, following a well-established stream of research in the field, which adopts a similar methodological approach (Lopes et al., 2014; Laarabi et al., 2017). The agent-based simulator chosen to perform this assessment is MATSim. "MATSim is an activity-based, extendable, multi-agent simulation framework implemented in Java. The framework is designed for large-scale scenarios […] and based on the co-evolutionary principle" for optimizing the agents' activity schedule (Horni et al., 2016). The open-source nature and the presence of an ad-hoc carsharing contribution for the software made it the most suited software to be used for our analysis. The scenario used for the simulation is derived from Ziemke D. and Nagel K. (2017). It consists of a synthetic population representing 10% of the inhabitants in the region of Berlin and Brandenburg, Germany. Using QGIS, a free and open-source cross-platform desktop geographic information system, we exported the synthetic population for the sole city of Berlin, roughly 280000 agents.

2.2.1 Introduction of the Value of Time

Using the Berlin micro census data (Amt für Statistik, 2017) we distributed the income on the synthetic population following the income distribution per neighborhood. Using only the income as sensitive variable would not be sufficient. What could make one choose for a mode of transport instead of another is the value of time saved by doing that choice. For this reason, the value of time (VOT) is chosen as parameter and it is applied to the population following the procedure illustrated in Giorgione et al. (2019) based on the values retrieved from (*42*). We obtain the sysnthetic population in Figure 1. Carsharing stations were located randomly within the Berlin central area as shown, in yellow, in the same figure. The reason behind this choice was to place stations where density is the highest and, evaluate whether people living far from the stations used the service and keep the same number of stations used in the previous work (*41*).

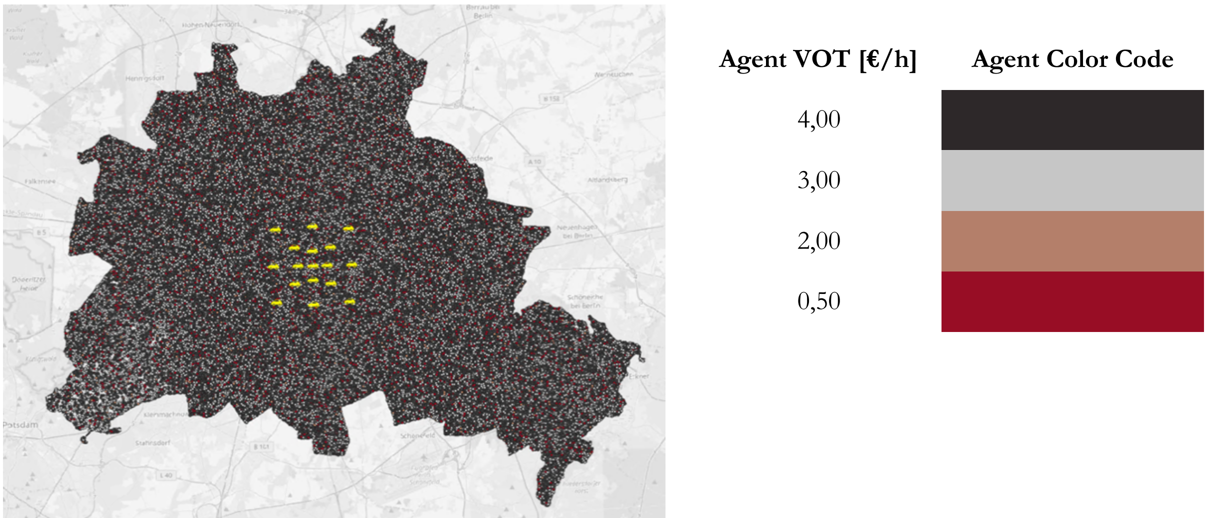

Figure 1. (a) first picture; (b) VOT and color code.

The information regarding the VOT was introduced in the *plans* file. This file - generated from census data - consists of the complete list of agents 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). Every user is described by its personal activity schedule with attributes such as activity type, coordinates of the location where the activity takes place, temporal duration of the activity and mode of transport used to reach a determined facility.

As already observed, to determine the economic effects of two distinct services on different income classes, it is important to include a variable sensitive to this transformation. To incorporate this variable in MATSim we introduce the VOT in the scoring function:

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

With N as the number of activities. Trip q is the trip that follows activity q (*19*). The scoring is a measure of the utility a user gets to perform a specific activity at the desired time using a precise mode of transport. In equation (1) this is defined by the score of a plan (the ensemble of all the daily activities executed by an agent), which is the sum of $S_{act,q}$, the score generated doing an activity and $S_{trav,mode(q)}$, that is, the disutility of travelling. For every agent, the first term has the same form as in the next equation:

$$S_{act,q} = S_{dur,q} + S_{wait,q} + S_{late,ar,q} + S_{early,dp,q} + S_{short,dur,q} \tag{2}$$

where the five contributions to the scoring consist of the utility of performing an activity, the waiting time spent before starting an activity, the late arrival penalty, the cost for not staying long enough and a penalty from a 'too short' activity (*19*), respectively. The VOT is applied in the first addend:

$$S_{dur} = (\beta_{dur,q} * t_{typ,q}) * (\alpha_{VOT} * VOT) * ln\,(t_{dur,q}/t_{0,q}), \tag{3}$$

Where $t_{dur,q}$ is the performed activity duration, $\beta_{dur,q}$ is the marginal utility of activity duration and and $t_{0,q}$ is the duration since the utility starts to be positive (*19*). In equation (3) we introduce the VOT and α_{VOT} as a scale factor for the VOT. Since the VOT is evaluated *ex-ante*, we are introducing the concept that an activity will produce more value if the person doing that activity gains a higher value from it, this value is, as explained before, directly linked to the income.

2.2.2 Carsharing

In this analysis we aim to assess the response of a set of users of two different types of carsharing services. Concerning the ability to use both carsharing services, the 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., they 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.

While the concept at the base is the same, the two systems differ on how the service is provided, the pricing model and the fleet composition. We created 17 stations for both services and placed them in the same geographical location.

As described in Münzel et al. (2018), the TW service tends to have fewer cars. That is why we allocated two cars per station. The pricing model consist of a fixed price rate of 6 euros per hour and unlimited kilometers. As the price is paid by the hour, we introduced a grace period of 5 minutes. The hour is charged as a whole if the booking time exceeds this grace period. OW services have a larger fleet (*43*), this is why in this case we allocated 8 cars per station. The pricing model consist of a fixed price rate of 0,25 euros per minute while moving and of 0,10 euros per minute in case of a stop without dropping the car.

2.3 Results

The following results are divided in two sections describing the response of the demand from an equity and individual perspective and the response of the supply system from an operational point of view.

2.3.1 Demand Response Analysis

With equity we refer to fair and balanced distribution of resources among the population. Hence, we evaluate to what extent both services are accepted by the population when the latter is subdivided by VOT.

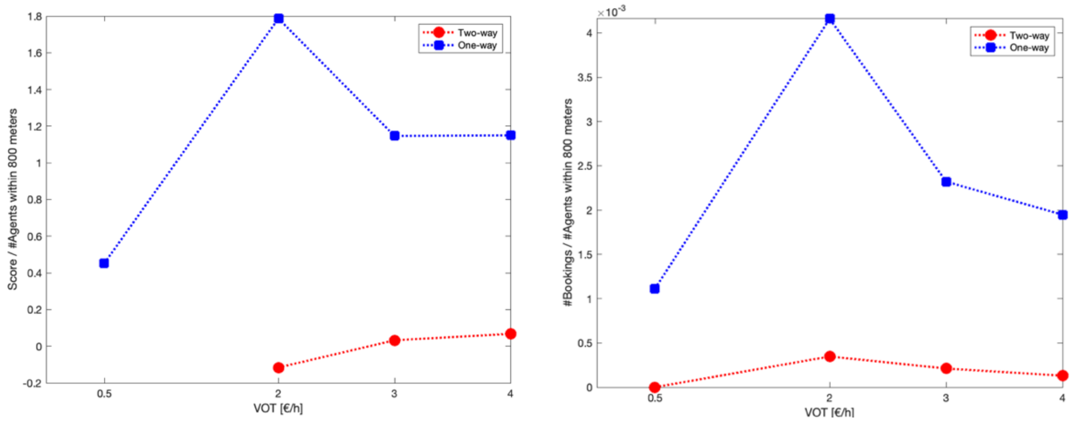

Figure 2. Average (a) score and (b) bookings per VOT class

Figure 2a shows the average score over the number of agents located at walking distance from the carsharing station and clustered by VOT. A first observation is that no agents with a VOT of 0.5 (lowest income in the simulated population) opted for the two-way service. Similarly, Figure 2b shows the number of bookings on the number of agents at walking distance from the carsharing station clustered by VOT. The response of the demand appears to be fairly similar for both services, i.e., low VOT classes tend to benefit less if compared to other classes, resulting in an ascending trend. The higher value of scores and bookings for the VOT of 2 €/h is due to the relatively higher pay off the agents in this class have in using the carsharing and, possibly, to the significantly smaller number of agents living around the stations.

Table 1. Number of agents living within 800 meters from a carsharing station

VOT [€/h]	# Agents
0.5	3392
2	885
3	14222
4	15403

Concerning the number of bookings for both services, Figure 2a shows how agents with the same VOT have a similar behavior when using the TW and the OW systems meaning that one service is not more equitable than the other. To assess the bookings distribution during the day, we show the demand profile of the users in Figure 3a.

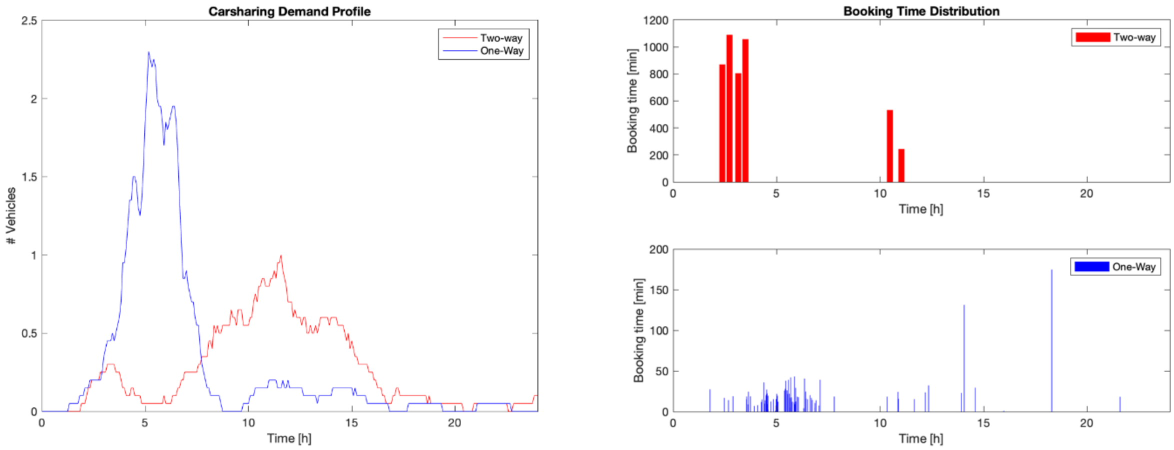

Figure 3. (a) Demand Profile; (b) Booking Time distribution

This profile indicates clearly distinct mobility patterns: whilst OW users tend to book a car mainly before and during the morning peak period, TW users reveal a peak in the demand after the peak period. This suggests that OW users book the car, in the morning, for commuting trip purposes, whereas TW users adopt the service for other activities than going to work. This is to be expected, since work is a high-value and long-duration activity and arriving on time is more desirable compared to other activities. As described in Figure 3b, TW users book the car in the morning using it throughout the day (with an average booking time of 15 hours for bookings happening in the early morning until 8 a.m.) while OW users opt for the carsharing service both for commuting (with an average booking time of 20 minutes for bookings starting in the early morning until 8 a.m.) and other activities. The chance of using the OW carsharing system allows agents to go to work and to leave the car in order not to pay a parked vehicle during their working hour; moreover, other cheaper types of transportation can be used to execute other activities characterized by lighter penalties for late arrival. The TW system is more used in the middle of the day, usually for activities far from the city center. Indeed, in Figure 4a we show that the use of a TW carsharing service is not dedicated to a specific activity.

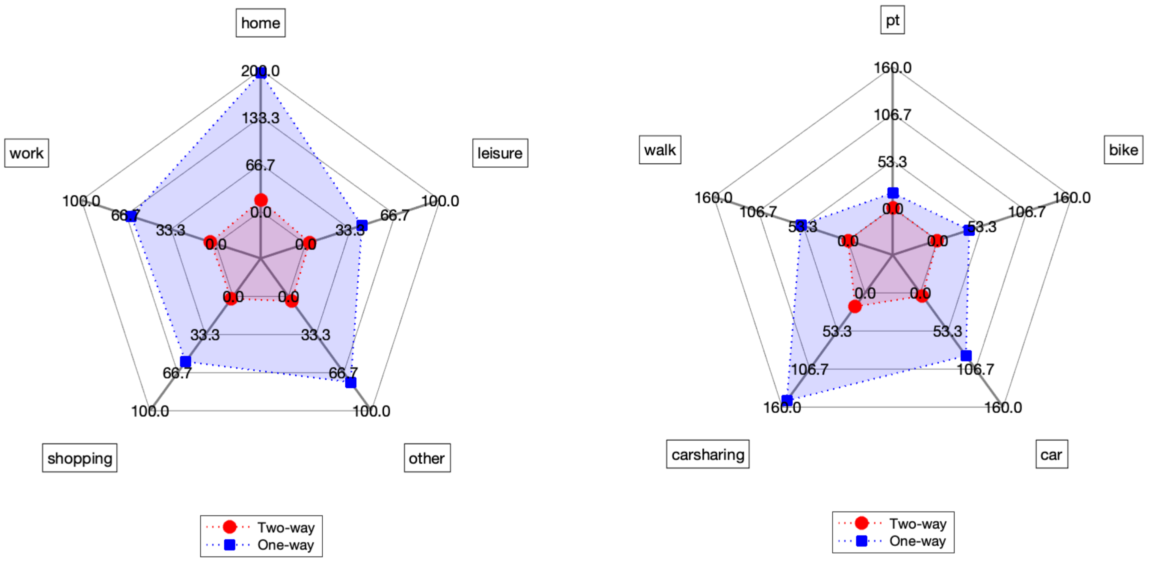

Figure 4. Number of (a) activities executed; (b) mode used

Figure 4 shows the behavior of the agents who used the carsharing at least once during their daily schedule. Figure 4a shows an axis-by-axis comparison of the mode used. Concerning the one-way carsharing, we can see how this mode is not used to execute any activity in the specific. More insights come from Figure4b where the nature of these two services is shown: the TW system is used as substitute for all the other modes while the OW integrates with other means of transportation. In general, agents, tend to prefer the OW system. The average score for the TW and OW system is, respectively, 195.26 and 513.76 with a variance of 300.86 and 476.18. The OW service has a higher mean which suggest a greater utility for the agents using this system.

In Figure 5 we show the booking distribution on the territory. This shows where people using the services live.

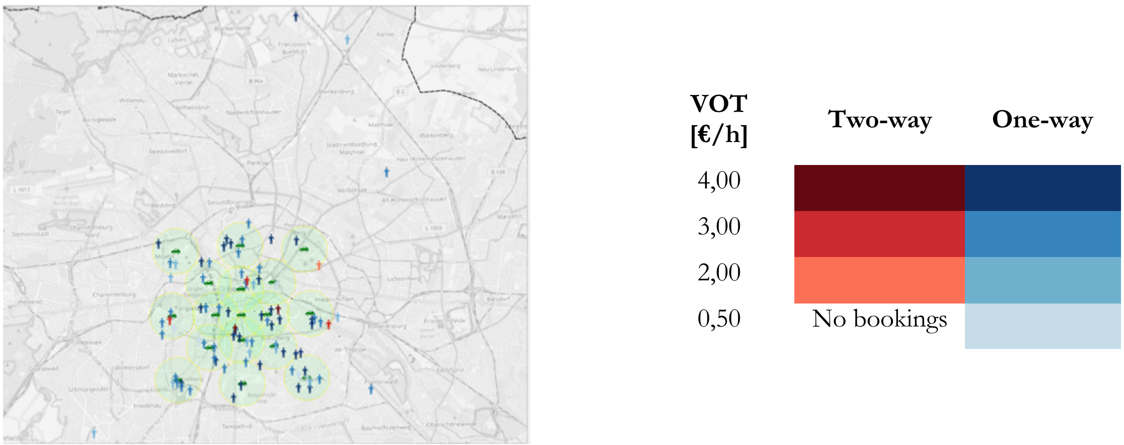

Figure 5. Territorial distribution of booking per VOT and carsharing service

The OW service is used even from people living far from the stations, this reinforces what is shown in Figure 4b: OW carsharing can be used inside a multi-modal journey while the TW service is used only by people living nearby a carsharing station.

Even though all evidences produce a more favorable results for the OW service from a user's perspective, analyzing the results of the simulation from the provider standpoint can lead to a wider understanding of the phenomena created by the implementation of these two services.

2.3.2 Analysis of Carsharing Operations

As a service provider, companies' main KPIs can be broken down into fleet management indicators such as number of bookings, distance, booking times and economic indicator like revenue, kilometric and hourly gains. In Figure 6 we show the overall KPIs for both carsharing services.

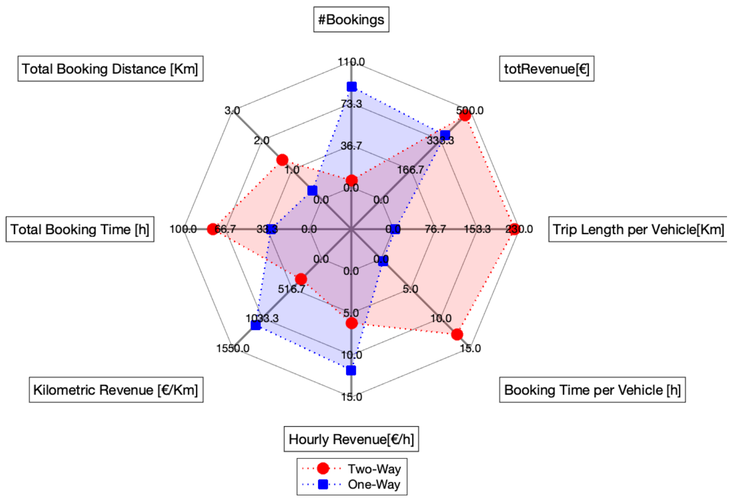

Figure 6. Provider's KPIs.

The disparity in number of bookings is more evident in this last figure. 88 vehicles were booked on the OW service against only 6 in the TW. This resulted in higher kilometric and hourly revenues for the former, especially considering that booking times and distances are way lower than the latter service. Even though the number of bookings is significantly higher, the OW system cannot reach the same total revenue as the TW service, the average trip length (around 3 kilometers and half for the OW and 220 kilometers for the TW) and the average rental times (20 minutes for the OW and almost 13 hours for the TW), bring a higher revenue even though the number of vehicles offered by the service is significantly lower. The TW system provides vehicles that are booked for longer times and that time is paid by the final user.

For a further assessment of the competition among the two system we have run two other simulations making one service available at the time for the same carsharing members.

Table 2. Number of agents booking for different Scenarios

Scenario Code	Scenario	Two-way Bookings	One-way Bookings
1	Two-way + One-way	6	88
2	Two-way only	7	-
3	One-way only	-	78

The difference between the main scenario (two-way + one-way) and the "two-way only" one is negligible. For the "one-way only" the difference is higher, but the number of users is not increasing. Moreover, in any case no agent is going to use both service in any of the simulation. In the end, 40 % of the agents using the OW service in the scenario 1 are using it again in scenario 3 while none of the agents using the TW service in the scenario 1 are using the service again scenario 2.

2.4 Conclusions

Assessing TW and OW carsharing system in the area of Berlin leads to a diversified response from the users' community that does not appear to be based on their purchase power. Users with similar VOT have the same behavior in terms of number of bookings made when using both services with a similar scoring trend, meaning that their VOT classes have the same group response in term of utility.

The services are substantially different, they are used for different reasons, and they are not in competition in terms of customer profiles. The TW system is used mainly as substitute of a private car and, considering the number of bookings, is a niche service for the transportation system. Overall, the price of 6 euros per hour appears too high when compared to other alternatives; this effect is even intensified by the time frame of the MATSim simulation: it simulates one day of activities and does not have the ability to take into account long term mobility decision.

TW users' behavior shows how the implementation of this service can reduce car ownership but, in terms of sustainability, the only contribution can come from a more efficient car fleet (newer vehicles are less polluting) or from using electric vehicles. Differently, The OW system is seen as an integration to the modal offer available in the area. Indeed, this service is more sustainable and can alleviate congestion by increasing the number of trips made with different type of modes.

On one hand, the OW can be considered as a greener sharing service but, on the other hand, it is clear how the low distance travelled, revenue and booking time led to smaller income on the operator side which, without a good system of subsides, could hardly generate profit.

III. Berlin Dynamic Pricing

In this part, the first Berlin case study on two-way car sharing is introduced. The main purpose of this part concerns the introduction of methods to evaluate the quality of the service in terms of user satisfaction. Here, we explain the introduction of the value of time in the scoring function of the agent-based simulator and how this value is used to differentiate the behaviors of multiple users.

Subsequently, different distributions of the value of time are proposed, first heterogeneous and then homogeneous, used with the aim of reducing the complexity of the system and therefore finding behavioral patterns. In addition, different station placements are used to evaluate their different usage. Finally, several dynamic pricing strategies are introduced (i.e., availability-based dynamic pricing and time-based dynamic pricing) and their impact on the different population groups is also assessed.

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3

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

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 con sists 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 increase 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.

3.1 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 paying a usage fee (*44*). 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 (*45*). In North-America This flexibility contributed to an increasing car utilization rate in favor of the carsharing service (*46*) whereas daily usage of cars is only about 10% (*47*); 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 (*48*).

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 (*49*), (*50*). 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 (*51*). 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 (*48*). 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 (*52*).

Different pricing strategies were also applied in free-floating carsharing (*53*). 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 (*53*).

Even though carsharing is a quite an established concept (*54*), 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 (*55*). 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 (*19*). 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 (*55*).

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 (*56*). 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.

3.2 Methodology

In the practice, the most typical model used to represent travel demand is still the classic four-step model (*57*). 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 (*58*). 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 (*59*)(*60*)(*61*).

Multiple agent-based simulators were examined before choosing which simulation approach was more suited to our work. SimMobility (*62*), 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 (*63*) 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 (*64*) 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.

3.2.1 Scenario Setup

MATSim is an open-source software, written in Java, for implementing large-scale agent-based transport simulations (*19*). 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 (*19*). The three basic inputs 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 (*65*). 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 Figure 1.

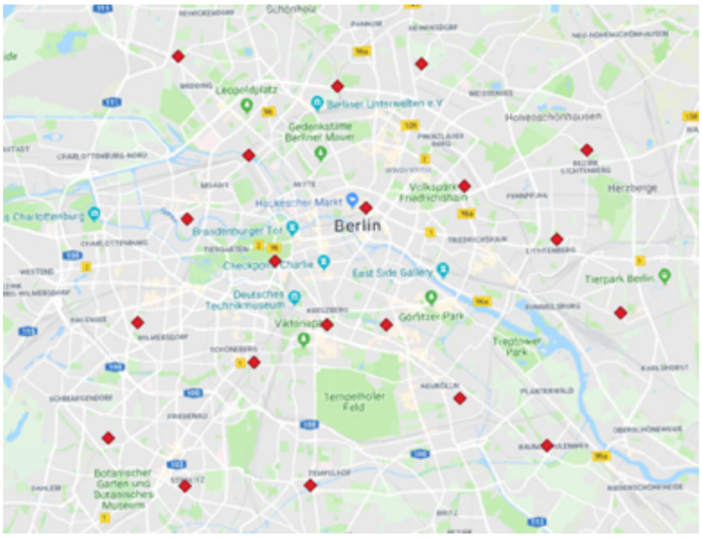


Figure 1. Carsharing station distribution.

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 (*39*), 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 (*66*); 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 (*56*), 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.

3.2.2 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).

3.2.3 Value of Time

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 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 Figure 2.

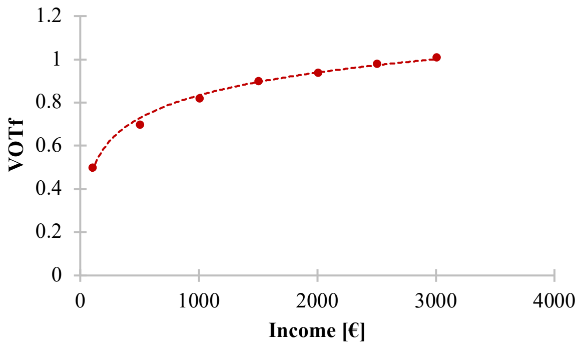


Figure 2. Income Dependence from VOTf

The function (4) obtained this way is:

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

3.2.4 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.

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

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.

3.3 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 on 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

3.3.1 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 Figure 3.

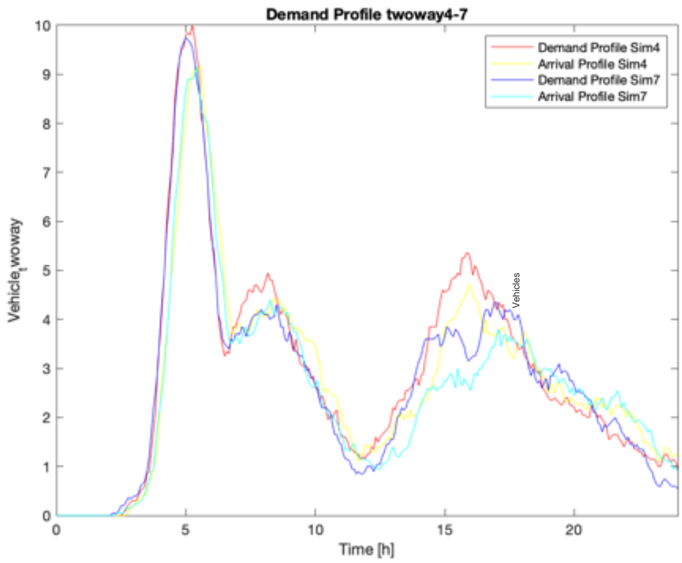


Figure 3. Demand and Arrival profile Sim4-Sim7.

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 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.

3.3.2 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 Figure4. People with the lowest VOT tend to abandon the carsharing mode in favor of other modes of transportation (Figure 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 (Figure 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.

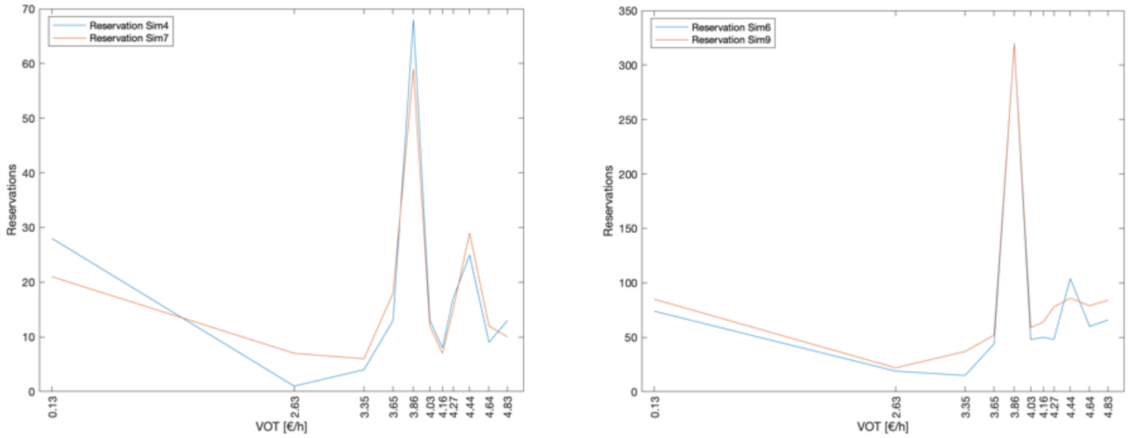


Figure 4. (a) Shift in Reservation Sim4-Sim7; (b) Shift in Reservation Sim6-Sim9.

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 Figure 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.

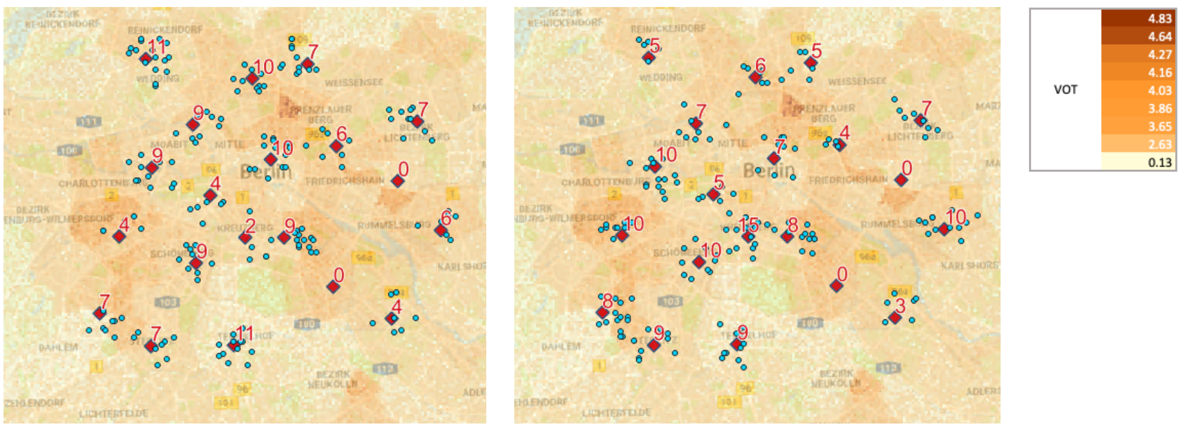


Figure 5. (a)VOT Heatmap Sim4; (b) VOT Heatmap Sim7; (c) Heatmap Scale

3.4 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.

4

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

Carsharing companies can customize their service by adopting different pricing schemes and offers with the goal of increasing fleet usage and profits. 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 develop an experimental design for conducting an explorative analysis of how an availability-based dynamic pricing scheme impacts demand and supply performances. 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 the city of Berlin and its surrounding region, in which an availability-based dynamic pricing whose price depends on vehicles availability in booking stations is applied. Results confirm 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. Overall, the policy here applied appears not to be fair since it is not equally welcome from all the population classes and, furthermore, hinders low-income groups from using the carsharing service.

4.1 Introduction

The idea behind carsharing services is straightforward: individuals can get access to a lease car, without the burden of owning it, through membership to a carsharing program. Vehicles are available on demand for a short-term rental by paying a usage fee (*70*). The widespread diffusion of mobile applications helped carsharing to become a mainstream service since they are often used to book carsharing services on the fly. That allows fast payment, personalized experience for users and also implies continuous supervision and usage data collection and analysis for companies (*71*). Offering flexible access to a car is arguably also one of the features which contributed the most to its success (*72*) and, at the same time, allows having cars being used over 10% of the time over a day, which is considerably higher than the average for private cars (*47*). This evidence makes clear the effect of a paradigm shift toward shared mobility. Users tend to avoid the burden and the expense of ownership but benefits of the flexibility and the accessibility of a car. During the last two decades, carsharing attracted more and more attention in a variety of research fields, as witnessed by works on market analysis, pricing, location, travel behavior, and sustainability (*73*, *74*). Given the private management nature of the carsharing, some studies had a strong focus on managing the fleet while, at the same time, increasing companies' profit (*75*)(*76*). The goal of this study is assessing the impact of a dynamic pricing policy on carsharing usage of a round-trip program members. In fact, pricing policies on carsharing systems still tends to be a fairly unexplored topic. That is explained by situations of 'local monopoly', regions where an operator did not have any competitor, being the norm (*77*). Some of the few works on the topic, are shortly reviewed here after.

Concerning the dynamic nature of a pricing strategy in one-way systems, a simulation using Vienna taxi data proved a dynamic incentive scheme to be effective in equilibrating the fleet at the stations (*78*). Furthermore, with the aim of maximizing company profits, dynamic pricing was applied on the one-way system in a theoretical case study on the city of Lisbon. Results showed that pricing can be used to increase profit thanks to achieving a more balanced system (*79*). Influence of vehicle distribution on 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 (*80*).

Free-floating carsharing has also been analyzed with different pricing strategies, e.g. in (*77*). 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. Conclusions found the spatio-temporal profile of carsharing demand to be sensitive to pricing structures.

Even though carsharing is quite an established concept (*81*), models able to assess its functionality have not been fully developed yet. This situation makes it hard to assess real cases and to plan in normal conditions of use. Traditional four-step models tend to use data that is too aggregated to allow researchers to grasp the peculiarity of a carsharing services. 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 (*55*). The simulation of innovative transport modes with agent-based models has been proven useful because of their microscopic nature. That is, regarding the carsharing, the peculiarity of the services offered can be estimated in a realistic way and can capture car availability at a given location at a given time. Among the various agent-based simulation platforms, MATSim (Multi-Agent Transport Simulation), while acting on large-scale scenarios, is capable of providing a completely disaggregated representation of carsharing operations and use (i.e. single vehicle and single user level (*19*)). Regarding pricing schemes, different active pricing strategies were already tested in MATSim, particularly road tolls. 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 borders (*55*).

Focusing on the application of dynamic pricing policies on round-trip carsharing supply systems, this paper develops a comprehensive experimental design created for the implementation of an availability-based dynamic pricing (ABDP) strategy, combining the two streams of work with MATSim mentioned above. To the best of the authors' knowledge, this bridges the current gap on assessing a pricing policy for carsharing with a variable depending on the socio-economic attribute. Given the need to model the behavior of carsharing users with those kinds of attributes, in order to investigate on which supply attributes impact the demand and how, an explorative analysis has been conducted introducing a dynamic pricing policy on a population with a diverse income distribution based on the people living in the Berlin Area. The introduction of the value of time (VOT) influenced the users' response to price schemes helping to better simulate the behavior of different groups of users. Furthermore, was found that carsharing users with an average VOT tends to take resources from users with a lower VOT. Motivated by the need to have a better understanding of the trends shown in (*41*), a new geographical distribution for the (VOT) is arranged and a new distribution of the stations is planned. This removes some degrees of freedom, simplifies the complexity of the phenomena, and estimates the influence of the ABDP on the demand more systematically and quantitatively. The goal of the analysis of this strategy is, first of all, to assess the fairness of the system and, secondly, to evaluate the impact on the supply characteristics like car utilization (reservation duration and utilization rate) and fleet utilization (geographical distribution of the reservations and number of reservation) (Figure 1).

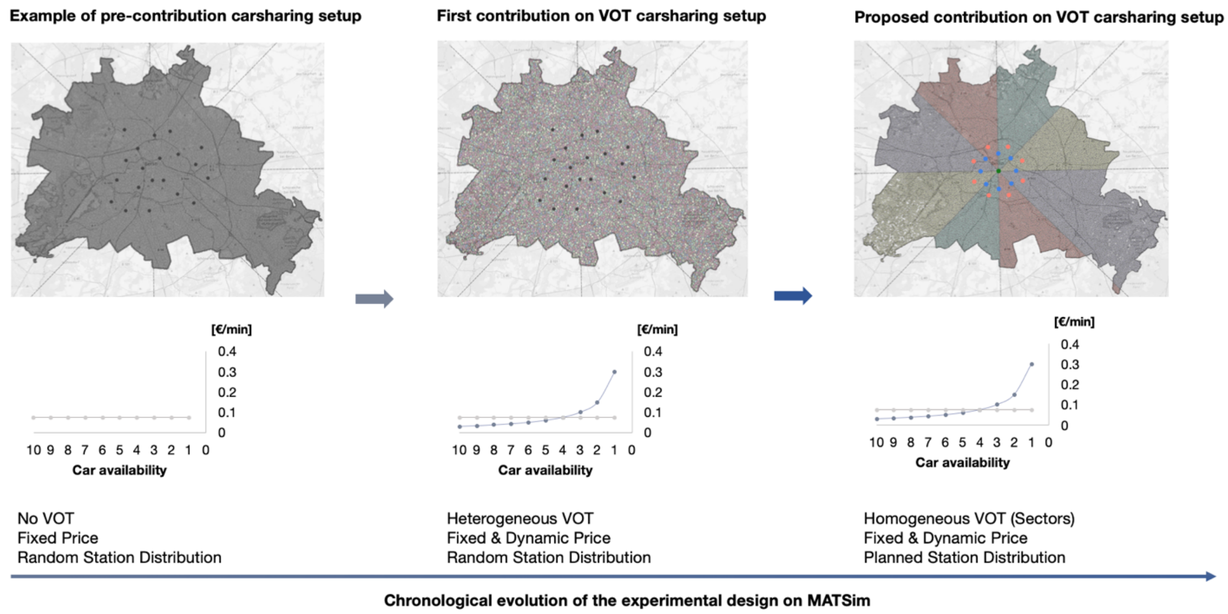


Figure 1 Evolution of the MATSim contribution on carsharing regarding VOT and pricing

One of the challenges of the previous study was to handle the high complexity of controlling the results given the large number of degrees of freedom in a real case study. That is why, for this work, we came up with a more controllable way of varying the supply and demand characteristics such as homogeneous VOT and a planned stations distribution.

On one hand, it is expected that having a dynamic pricing offer should lead to a more homogeneous rental performance in terms of space since the members will look in their neighborhood for the cheapest car: the utility of renting a vehicle in a station with high availability becomes higher than renting a vehicle in a station with low availability, considering that the user can take advantage of cheaper fees. However, on the other hand, the utility increment due to a lower price should lead to a trade-off because of the creation of a disutility due to the shifted activity schedule. Finally, a variable use of the carsharing for the same offer is expected since the spending power varies from user to user (*82*).

4.2 Methodology

For what concerns the practice, the classical four-step modeling is still the approach most widely used in the practice to represent travel demand (*57*). Forecasts are made considering one area as a whole and flows are commonly measured in vehicles/hour in an aggregated way. It is evident, regarding round-trip carsharing, an aggregated trip-based model cannot be able to assess important KPIs such as the availability at a precise point in space and time (*36*). Temporal and spatial resolution becomes of paramount importance when assessing the capabilities of a carsharing service. Disaggregated methods are necessary to describe the behavioral component of a single user and the activities executed by people at different locations and at different times. The most natural way to apply this criterion is through agent-based modeling. In this work we adopt an agent-based simulation to analyze a round-trip carsharing system on the Berlin network, following a well-established stream of research in the field, which adopts a similar methodological approach (*59*)(*37*)(*38*).

Different agent-based simulators available in the literature were considered before resorting to MATSim. Among others, SimMobility (*62*) is an integrated simulation platform designed to be activity based, multi-modal, multi- scale and fully modular. Currently, however, a module able to fully simulate carsharing is still missing. PTV MaaS Accelerator Program (*63*) is on the other hand capable of simulating ride-sharing and multimodality. The closed-source essence of the software and the poor literature on it became an essential issue for its use in this study. Mezzo (*83*) simulates road traffic at the level of individual, even though it shares a similar modular structure as MATSim where someone could create specific packages to implement new functionalities, the absence of the carsharing mode was also a hurdle for our scope. 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 platforms to simulate carsharing scenarios through an agent-based model.

4.2.1 Scenario Setup

MATSim is an open-source software, written in java, used to implement large-scale agent-based transport simulations (*19*). Trips are derived from individual activity chains which represent people's behavior. Individuals are defined by several attributes (e.g., age, gender, driving license ownership, employment situation, …) whereas the synthetic population is generated and calibrated based on empirical data. The simulation consists of a typical day in which every agent performs its daily tasks (a plan), generating the daily travel demand. In each iteration agents evaluate the fitness of their own plan with a score, and, on the next iterations, strategies are applied in order to try to improve their utility. By adopting this approach an equilibrium is reached, subject to constraints, where agents cannot further improve their plans unilaterally (*19*). The basic input files used by MATSim are the following:

Network

The network is obtained importing the OSM (Open Street Map) map of Berlin into JOSM (Java Open Street Map) which is an extensible editor for OSM and for Java (*65*). Once the desired map is loaded, a plugin developed ad-hoc for MATSim converts the needed graph in a network readable by the software with basic attributes for nodes and links. The study area in this work is the Berlin region (Figure 2).

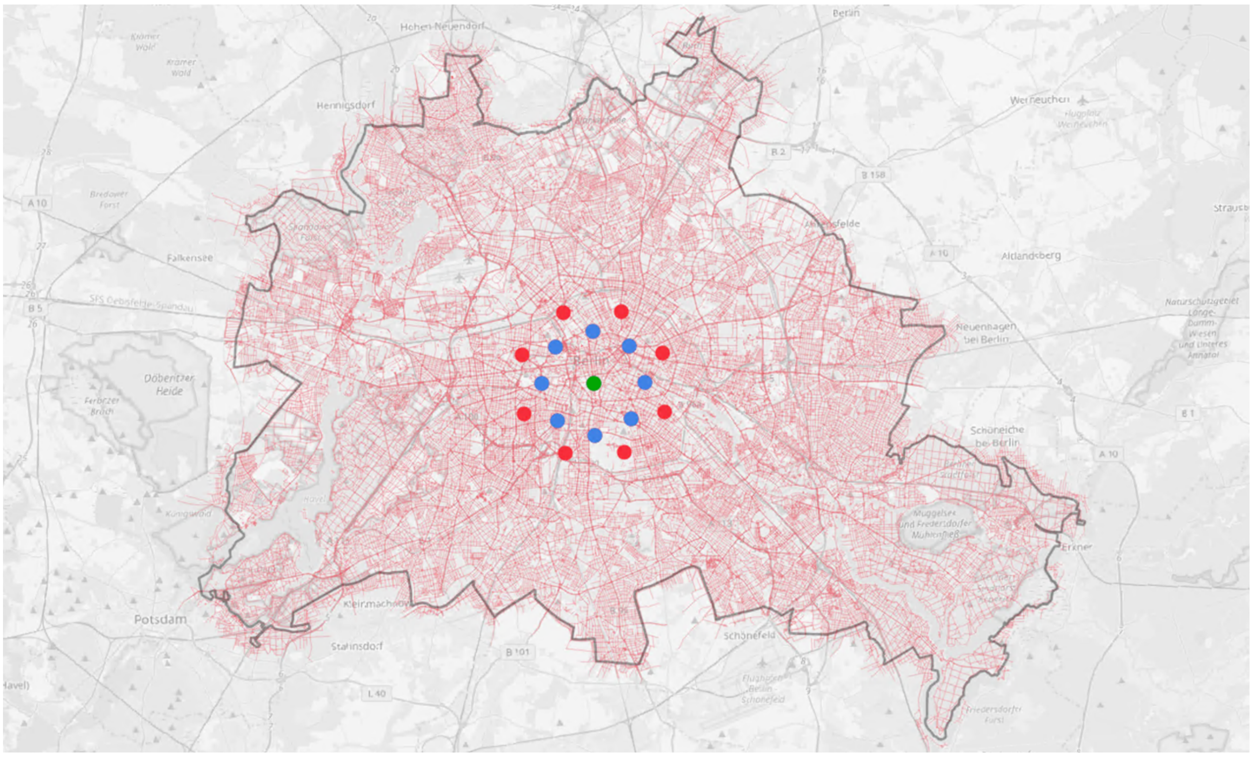


Figure 2 Study Area and Station Distribution

CSStations

A *CSStations* file consists of a list of all the stations and the vehicles available at the beginning of the simulation day. One of the main focuses of the experimental design is the station distribution (Figure 2). The main issue observed in (*41*) was that trends were not easily recognizable. To simplify the complexity of the scenario we designed a new and more homogeneous location distribution for 17 stations in order to serve specific areas in the Berlin region. The assumption behind this decision is that users are willing to walk up to 800 meters (i.e., 12 minutes of walk on average) to reach a carsharing car. The assumption is justified since, in MATSim, even though is possible to reach a carsharing station using all the modes available (i.e., bike, public transportation, …) the share of the users reaching the service walking is over 97% of the total. First of all, we designed 3 types of station with the following differences:

- Central station (green): serves 8 different sectors,
- Radial stations (blue): located on the main 4 axes, they can serve 2 sectors at time,
- Area stations (red): located on the median of every sector, they serve the same sector they are placed in.

The beeline distance between any pair of stations is of at least 2 kilometers so they cannot normally serve the same users. This should remove one degree of freedom since road users in MATSim can only decide to use or not carsharing as their mode of transport but cannot choose which station to use. Every station has 10 available cars following the same pricing scheme and conditions.

Plans

A *plans* file (or *population* file) consists of a synthetic population mimicking the one living in the study area, usually generated from census data. In this file the simulator finds the complete agents list with their relative activity chain. Attributes such as person ID, gender, age, license, car availability, employment status, etc., describe every agent that is part of the simulation. The plans file used in this work is based on the one used in (*39*) and consists of a 10% sample of the state of Berlin 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, duration of the activity and mode of transport used to reach a specific facility. Since this population was lacking of some of the essential attributes described above, additional information was gathered from another population file described in (*66*); here a 1% sample of the federal state of Berlin and the federal state of Brandenburg population is used to export the aforementioned attributes for every agent. 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 (QGIS), 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. The same approach is used to link the income to every agent using the distribution of the income for every neighborhood (*84*).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 (*82*), was needed. VOT is directly linked to income and other characteristics of the population heterogeneity, its study, together with the supply utilization, can be used to analyze the fairness of the system.

Car Sharing Membership

A *CSMembership* contains a list of all the agents authorized to use the service. As a matter of fact, carsharing is a membership program, that means individuals can become members and therefore use the service only if they meet some specific requirements (e.g., hold a driving license, have a credit card, etc.). In this study every agent holding a driving license is allowed to use the carsharing as an additional mode of transportation (i.e., is a member of the service) 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, belonging to different groups referring to different modules or functionalities of the software, are set up 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.

4.2.2 Carsharing Model

The work made by Ciari to integrate this service in MATSim started in the 2009 and is still ongoing and maintained by Balac (*59*),(*85*). The score used in MATSim for the evaluation of agents' plan considers both the undertaken activities and the performed trips Equation 1.

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

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 traveling with a given mode. The second component of this relationship is specific to each mode of transport supported by MATSim. In (*69*), 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 consists of 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 duration of the reservation and the distance traveled, 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 model, 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).

4.2.3 Value of Time

The other main focus of this work is to create a homogeneous distribution of the VOT to have a better insight into of the user behavior when facing events that bring a monetary cost. That is, we create a controlled simulation scenario where the population is sharply clustered in VOT-based sectors. 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 sensitive parameter. We separated the population into four different VOT groups. Every income group appears in two sectors opposite to each other (Figure 3). There are two basic ways to create sectors on geographic map once given center: using a coaxial clustering in order to create a monocentric city or using a radial clustering dividing the entire area in slices. Even though the coaxial method would follow the logic of a monocentric city where more expensive neighborhoods are located in the center, we choose the latter design since it increases the contact points of different VOT. In (Figure 4) is possible to see how every cluster is always in contact with at least other 2 sectors, this ensure that all radial stations can attract two different type of users and the central one can actually offer its service to every agent. This specific kind of clustering is created to evaluate the evolution of the rentals once the ABDP policy is applied assessing the shifting of the renters' VOT. Differently to the first contribution, only four VOT classes have been selected compared to the eleven of the previous work; this choice helps understanding better the overall trends without losing information given the proximity of the VOT values. All the users are then represented on the map as a small dot and colored in function of its VOT.

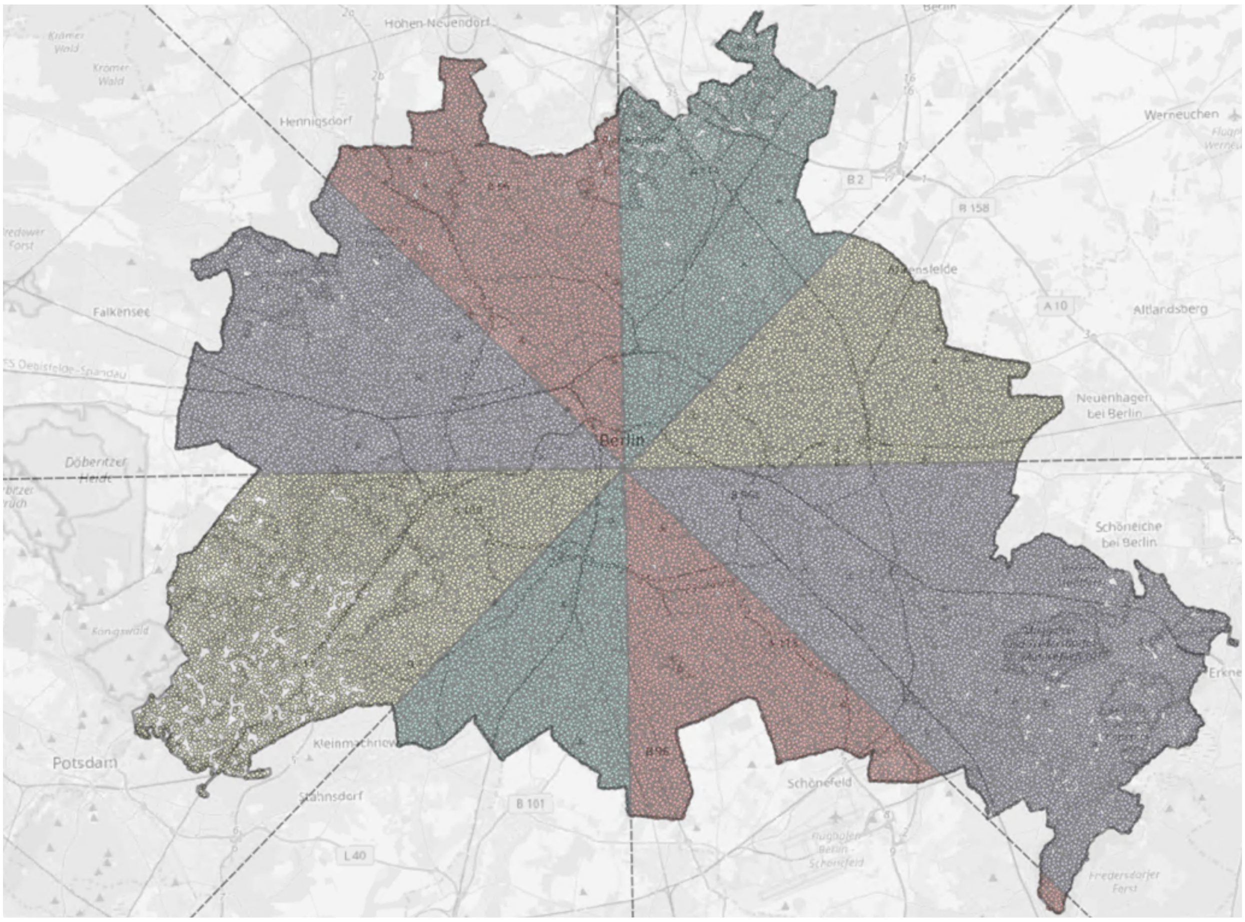


Figure 3 VOT Distribution

The VOT is derived from (*42*): first of all, a marginal value ($VOT_{marginal}$ = 4,83[€/h]) is taken which is link to the income by the Equation 1 where VOT_f is the VOT factor. Based on the consideration made in (*41*), the VOT is then classified in 4 different values to simulate the different spending power of every agent (Table 1).

Table 1 VOT values

Sector Name	**VOT [€/h]**
Green Sectors	4.00
Yellow Sectors	3.00
Purple Sectors	2.00
Red Sectors	0.50

The VOT is then implemented in MATSim in the scoring function, working as a purchase power utility function in order to characterize every user by their budget.

4.2.4 Dynamic Pricing

A scenario is built in which the carsharing price varies depending on the car availability: the trip becomes more expensive as fewer cars are available at the station at booking time. This strategy seeks for a more uniform distribution of cars and vehicle usage in time and space and is only indirectly dependent on the actual demand. The demand itself, on the other hand, can be sensitive to pricing only 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 (Equation 2) in order to make the general scoring function (Equation 1) and agents' choices sensible to different VOTs:

$$S_{trav,q,cs} = \alpha_{cs} + \beta_{c,cs}\left[\frac{c_t(t) * t_r}{a^j} + (c_d * d) + (\ \beta_{VOT} * VOT_{cs}^i)\right] + \beta_{t,w}(t_a + t_e) + \beta_{t,cs} * t_{trav} \qquad (3)$$

(Equation 3) is obtained introducing $\beta_{VOT} * VOT_{cs}^i$ 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. The dynamic pricing is introduced as a hyperbolic function using the number of cars available as the denominator in order to simulate a higher price when the number of cars is low. The hyperbolic function allows a smoother increase of the price. The final score for travelling will be then affected by a function having a shape like drawn in (Figure 5), where it is also illustrated the shift from a fixed pricing to an ABDP. Both the ABDP and the fixed pricing amounts are chosen pairing the size of the areas underneath the curve in order to reach the same revenue for a hypothetical company when all the vehicles in the station are booked. Pricing setup is the following:

ABDP: 0.3 $\left[\frac{€}{min}\right]$. Price of the last vehicle available at the station,

Fixed pricing = 0.075 $\left[\frac{€}{min}\right]$.

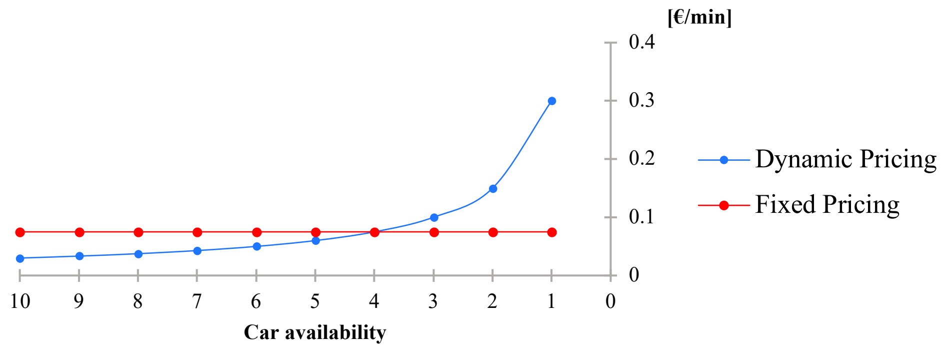


Figure 4 Hyperbolic form of the ABDP compared to the fixed pricing

Since the goal of this paper is to analyze how an ABDP scheme impacts the demand and the supply performance of a carsharing service while some demographic attributes are homogeneous, the VOT has been implemented only in the carsharing score. Future studies will examine the impact of the VOT when implemented even for other modes.

4.3 Results

While scenario 1 is created to check if the introduction of the VOT has an impact on the simulation, scenarios 2 and 3 are divided between the "base" case (2), where the fixed price rate is applied, and those where the ABDP is activated (3).

Scenarios are the following:

- Sim1: where VOT and ABDP are not enabled,
- Sim2: where VOT is enabled and ABDP is not enabled,
- Sim3: where VOT and ABDP are enabled.

4.3.1 Temporal Effect on Demand

In order to evaluate the effect of dynamic pricing on the demand, the most important observations derive from the comparison of scenarios 2 and 3. First of all, the impact of the ABDP on the temporal distribution of the demand is addressed. Once the ABDP is applied, we observe a slight difference in the reservation timing (Figure 5a).

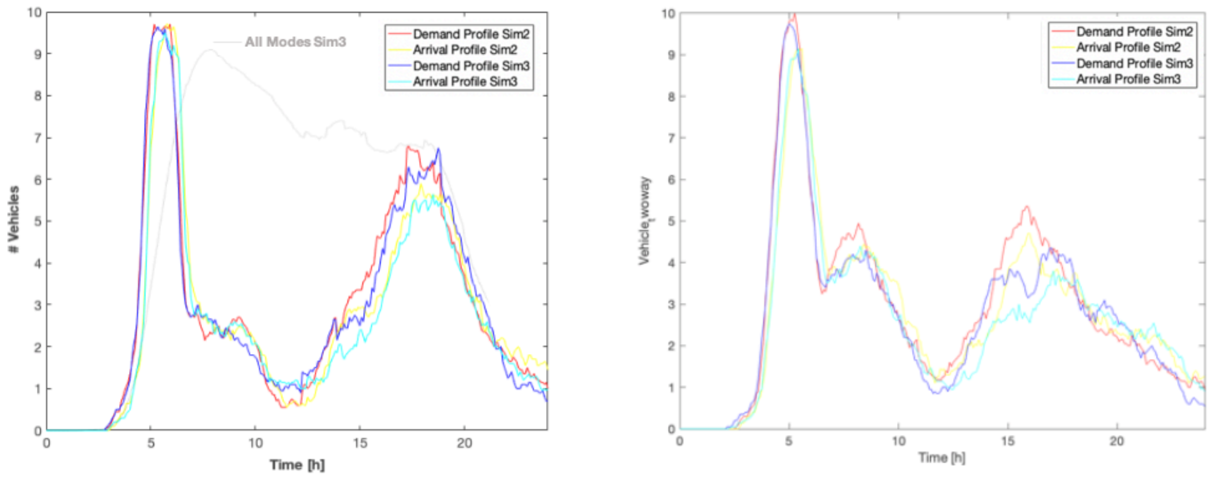


Figure 5 a) Current Contribution Demand Profile, b) First Contribution Demand Profile

Even though it is not in this work goals, it can be noticed how the carsharing demand profile (in colors) tend to have an anticipated morning peak if compared to the demand profile for all the modes combined (in grey). The general demand profile is drawn, in scale, behind the carsharing demand profile in order to give an idea of its trend. Generally, this is due to the fact that people who need to leave early in the morning cannot usually rely on the public transportation and, for them, carsharing represents an additional mode of transportation to the private car. Naturally a dynamic pricing policy like the one in exam could hardly induce people to shift towards a later booking since, given the nature of the strategy, the reservation could be more expensive. Either way, the main focus of this work is on the relative shift of the demand once the pricing policy is applied. The blue demand profile, which corresponds to the implementation of dynamic pricing, does not follow the same profile as the red one (Sim2). While compared to the fixed pricing the number of bookings suffers in the morning and in the afternoon peak. The periods of the day with a lower peak (late morning and evening) are slightly more attractive in case of dynamic pricing. We can see that when the arrival profile (cyan curve) reaches a peak, the blue curve tends to take over the red one. This correlation implies that the adjustment is due mainly to monetary reason. A similar trend (Figure 5b) was found on the previous contribution (*41*), The demand profile goes from 3 peaks (red) to 4 peaks (blue) due to the return of the carsharing vehicles to the station, lowering the price, while in (Figure 5a) there is still one peak but it is clear how the demand profile of Sim3 tends to have a more gentle slope and, indeed, all peaks have a lower maximum and are spread over a longer period. In order to see how this shift in the demand is correlated to individual attributes of the agents, we also analyze the economic effect.

4.3.2 Economical Effect on Demand

The following section describes how much the VOT affects the number of reservations but also the duration of the reservations. The shift in reservation number in the scenario with VOT activated (Sim2) and with both VOT and ABDP activated (Sim3) are shown in (Figure 6a).

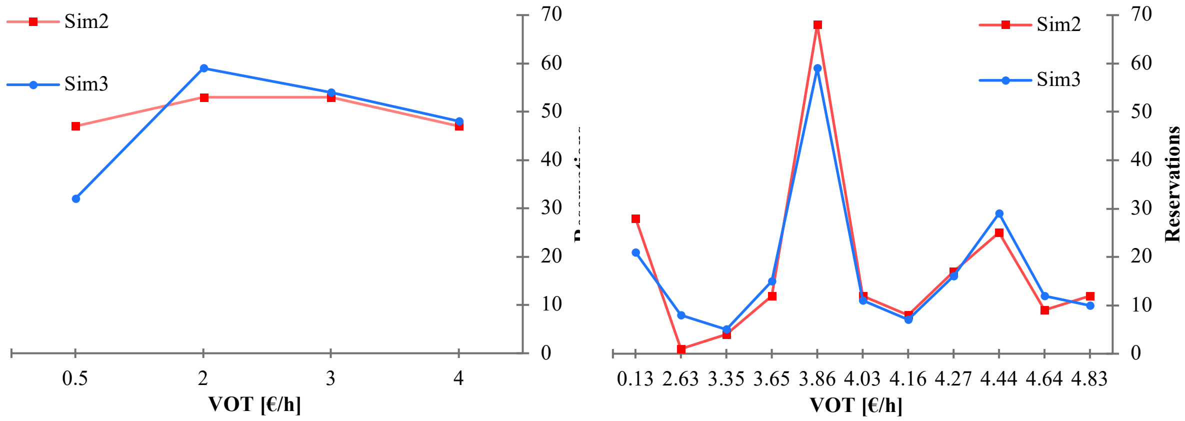


Figure 6 a) Current Contribution Reservations, b) Previous Contribution Reservations

Because of the design of the experiment, we can assume that, overall, the only difference among these four categories of the population is their willingness to pay. Still, Sim2 already shows different behavioral responses depending on the VOT characteristics. That is to say, the introduction of VOT shows a reduction of usage for the low VOT group (0.5 €/h) as well as a light increase of usage for the highest VOT category (3 €/h and 4 €/h). Therefore, in Sim2 and Sim3 carsharing resources tend to be exploited mostly by people with a medium VOT (2 [€/h]) but the introduction of the dynamic pricing amplified that difference. A similar trend (Figure 6b) was found in the previous contribution (*41*).

The strongest outcome is that people with the lowest VOT tend to abandon the carsharing mode in favor of other modes of transportation such as public transport or bike. Resources are quite equitably spread across the other categories even though population with a high VOT (≥3 [€/h]) tend to be affected less by the ABDP (Table 2).

Table 2 Shift in Reservation

Sector Name	# Bookings Sim1	# Bookings Sim2	# Bookings Sim3	Deviation Sim2 and Sim3	VOT [€/h]
Green Sector	54	47	48	2.08%	4
Yellow Sector	44	53	54	1.85%	3
Purple Sector	53	53	59	10.17%	2
Red Sector	38	47	32	-46.88%	0,5

In addition to the difference in number of reservations, an explanatory indicator we can use to gain additional insights into the effect of dynamic pricing is the duration of the booking. In contrast to the number of reservations, the same trend is kept between the different groups before and after the introduction of ABDP. Globally, all reservations are shorter (Figure 7) after the introduction of a new pricing policy and while their number of booking increases, the population with a medium VOT (purple sector) appears to have the strongest reduction in booking times reaching the same level as the lowest VOT category.

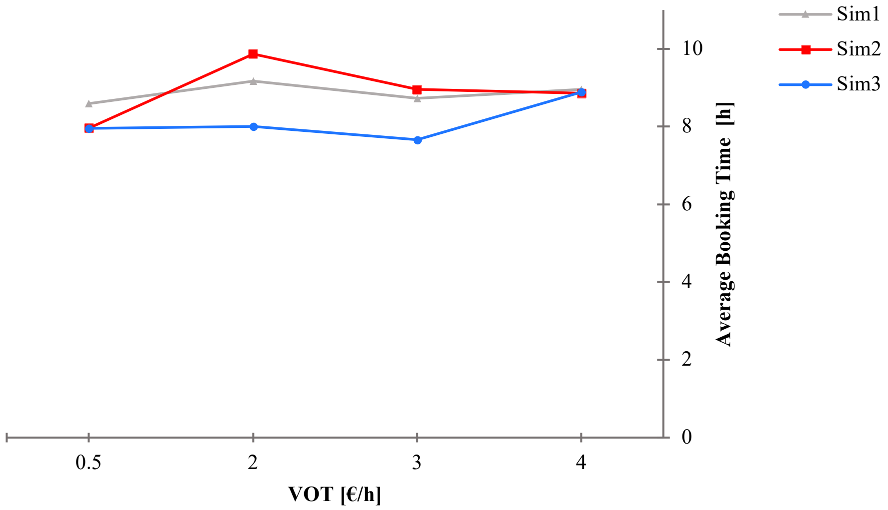


Figure 7 Shift in Booking Time

Overall, (Figure 8) shows that the ABPD seems to impact the behavior of all users in a way that they will trade long bookings for a higher number of bookings and vice versa. Apart from the highest VOT group which undergoes a strong reduction, there is a symmetry between the two indicators.

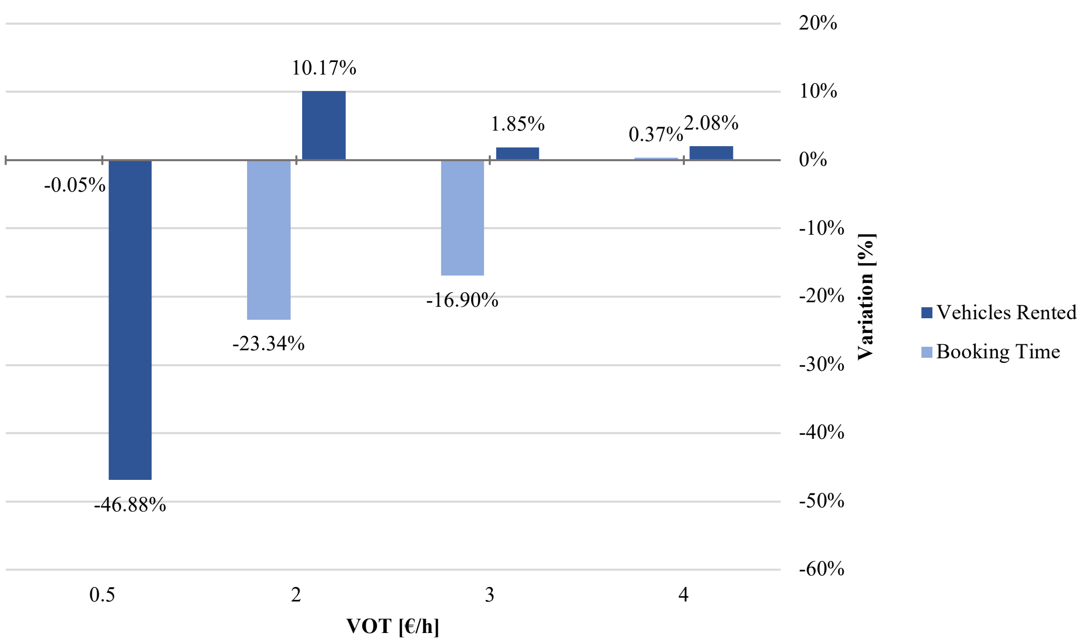


Figure 8 Variation of Vehicles Booked and Booking Time from Sim2 to Sim3

4.4 Discussion

The observed data tend to show an impact of dynamic pricing on carsharing users' behavior. Once the ABDP policy is applied, people with a low VOT will decrease their carsharing usage, people with a medium-high and high VOT will not experience a consistent change in their booking behavior and people with a medium VOT are going to book more. The policy here applied, as it is, doesn't appear to be fair since it is not equally welcome from all the population classes. Results show that people suffering the most from the implementation of the proposed ABDP have the lowest VOT. This question the fairness of the procedure because people who already have an easy access to other means of transportation (having a higher income) are those who still take resources from such a service. We expect and it is reasonable to aim at building a service that can substitute car ownership especially for people who cannot afford it. In order to balance this, modifying other aspect of the offer can be an option for balancing the impact of this dynamic pricing. Different criteria could be included in a "tailor-made" service for car sharing, such as more complex pricing schemes involving the membership for example or station-based costs.

Based on the previous results, we can argue that, in order to keep a cheap rental fare, medium and medium-high VOT groups reduce the booking duration. Instead, people with low VOT values, have a softer decrease in booking time, possibly because of the high importance of performing their activity, but a stronger decrease in number of reservations, meaning that if it is not a crucial activity, people with a low VOT tends to choose another mode over the carsharing. This trade-off could also explain why some groups are less affected by the ABDP and why the indicators do not follow a linear evolution with respect to the VOT. Yet, in general dynamic pricing has a negative impact on the usage of the service. An analysis on supplier's indicators will enable to draw conclusions on the rentability of such a policy.

Table 3 Distance Travelled and Number of Bookings

	Total Reservation Time [h]	**Total Distance Travelled [Km]**	**# Bookings**	**Avg distance Travelled per Vehicle [Km]**
Sim2	1722.46	6578.82	200	32.89
Sim3	1531.52	6893.93	193	36.19
% Difference	-11.1%	4.8%	-3.5%	10%

Cars are reserved for a shorter time but used to cover longer distances. These can lead to a faster degradation of the fleet given that the average kilometers travel his greater in Sim3. In general, car availability is higher when an ABDP strategy is applied while the number of booking is, nonetheless, lower, meaning that even though vehicles stay in a station for a longer time, they don't become desirable for other users.

4.5 Conclusions

The work presented in this paper 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 experimental design consisted in a homogenization of the VOT classes in similar sectors and on a symmetric stations planning made to reduce the degrees of freedom of a previous contribution which results proved of difficult interpretation. Once the design was complete an ABDP strategy has been applied and compared to a fixed pricing strategy. The experimental design here proposed has identified the same trends found in a previous study (*41*). Hence, since the results of the previous study are confirmed, it is possible to assume that the agents took their decision considering their willingness to pay. The stability of the outcome in various scenarios reinforces the correlation between users' behavior and VOT category. The fact that the *modus operandi* of experimental design, concerning the demand, was to only bring changes in VOT and not in the user activity chains leads to a mode choice mostly function of the spending power of each agent and not of their activities. Finally, the presented work raises some consideration for its future development. in the moment this policy is applied in a network served by a good high-density public transportation service, people with a low VOT might use the carsharing as a last mile service given the reduced price of this kind of carsharing usage. If, on the other hand, this carsharing policy is applied in a network that is not very well served by public transport, people with low VOT cannot access both modes and be cut-off from every mode except the private one. From an operator point of view, this research raises new questions on if and how an ABDP strategy could be more or less beneficial. To help answer such questions, in the future work, this contribution will be expanded using real supply data from a carsharing company. More in general, the results of this research provide insight, and are therefore a useful building block, to answer a more general question: can dynamic pricing contribute to have carsharing programs which are more accessible and equitable and, at the same time, more profitable? Answering this question is the main goal of this research and will be addressed in the near future.

5
Dynamic Pricing on Round-Trip Carsharing Services: Travel Behavior and Equity Impact Analysis through an Agent-Based Simulation

Carsharing companies can customize their service by adopting different pricing schemes and offers with the goal of increasing service attractivity, fleet usage and profits. Dynamic pricing strategies can be designed to adjust and balance cars' availability temporally and spatially; they may pose some questions regarding customer equity, since such measures could impact their activities and mode choice. In this paper, we develop an experimental design for conducting an explorative analysis of how availability-based and time-based dynamic pricing schemes impact demand and supply performances. The strategy is simulated in the open-source agent-based software MATSim and compared to a fixed pricing policy scheme. Two spatial distributions of the value of time for the population of Berlin are applied (radially and coaxially) to systematically analyze agents' behavior response to these pricing policies. Results confirm that when dynamic pricing is applied people with low value of time tend to abandon the carsharing mode in favor of other modes of transportation. Overall, the strategy applied in this study appears to be unfair, since it hinders low-income groups from using the carsharing service.

5.1 Introduction

5.1.1 Literature Review

The idea behind carsharing services is straightforward: individuals can get access to a lease car without the burden of owning it, through membership of a carsharing program. Vehicles are available on demand for a short-term rental by paying a usage fee [1]. The widespread diffusion of mobile applications helped carsharing to become a mainstream service, since they are often used to book carsharing services on the fly, which allows for fast payment, provides users with a personalized experience, and implies a continuous supervision and usage data collection and analysis on the part of companies [2]. Offering flexible access to a car is arguably also one of the features which contributed the most to its success [3], allowing cars to be used up to 10% of the time over a day, which is considerably higher than the average for private cars [4]. A survey in the Netherlands showed that, among 363 carsharing users, 15% to 20% less kilometers were driven, resulting in 13% to 18% less CO2 emissions [5]. Carsharing has been demonstrated to help reduce greenhouse gas emissions—an average reduction of 0.58 t/year per household is observed in north America [6]. Furthermore, one carsharing vehicle has been shown to replace up to 13 privately owned vehicles, resulting in monthly household savings per US members of 154–435 $ [7]. This evidence makes the effect of a paradigm shift toward shared mobility clear. Users tend to avoid the burden and the expense of ownership but benefit from the flexibility and the accessibility of a car. During the last two decades, carsharing attracted more and more attention in a variety of research fields, as witnessed by works on market analysis, pricing, location, travel behavior, and sustainability [8,9]. Given the private management nature of carsharing, some studies had a strong focus on efficiently managing the fleet while, at the same time, increasing companies' profit [10,11]. The goal of this study is to assess the impact of two dynamic pricing policies on a round-trip carsharing program from both the members' and the operational perspective. In fact, pricing policies on carsharing systems are still a fairly unexplored topic.

Concerning dynamic pricing strategies in one-way systems, a simulation study using Vienna's taxi data proved that a dynamic incentive scheme is effective in equilibrating the fleet at the stations [12]. Furthermore, aiming at maximizing company profits, dynamic pricing was applied to a one-way system in a theoretical case study on the city of Lisbon. Results showed that pricing can be used to increase profit by achieving a more balanced system and hence reducing operational costs [13]. The influence of vehicle distribution on pricing computation was also addressed by the creation of a digitized decision support system. The support of an information system using dynamic pricing helped reduce the need for vehicle relocation, enhancing vehicle availability [14]. One-way free-floating carsharing has also been analyzed with different pricing strategies, e.g., in [15]. The problem of how free-floating demand varies with different pricing strategies was applied to a case study on the metropolitan area of Zurich, Switzerland. Conclusions found the spatio-temporal profile of carsharing demand to be sensitive to pricing structures.

Even though carsharing is quite an established concept [16], models able to systematically assess its functionality have not been fully developed yet. Traditional trip-based models tend to use data that is too aggregated to allow researchers to grasp the peculiarity of a carsharing service. 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 [17]. The simulation of innovative transport modes with agent-based models has proven useful because of their microscopic nature and high temporal resolution. That is, regarding carsharing, the peculiarity of the services offered can be estimated in a realistic way and can capture car availability at a given location and at a given time. Among the various agent-based simulation platforms, MATSim (Multi-Agent Transport Simulation), while suitable for large-scale scenarios, is capable of providing a completely disaggregated representation of carsharing operations and utilization (i.e., single vehicle and single user definition [18]). Regarding pricing schemes, different pricing strategies were already tested in MATSim, particularly road tolls. 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. Multi-agent simulation was found to be more thorough in modeling the reaction of single travelers due to time-dependent tolls [17]. The ability of this type of simulator to identify the distribution of benefits at the system level in a road pricing context is illustrated in [19]. The study points out how the condition to identify said benefits introduces a non-linearity in the system in order not to cancel out gains and losses. In the context of cordon-pricing, MATSim is applied in order to assess the gains and losses of such policy [20]. Results show that this framework is a suitable decision-making tool for this kind of pricing scheme. In a study about the modeling of different pricing schemes [15] it is stated how establishing more solid patterns of consumer preferences can improve the ability of the simulator to deliver reliable system-level forecasts. Price policies regarding parking have been explored as well, showing that free-floating vehicles are able to use parking spaces more efficiently than private vehicles [21].

Most of these articles identify the calibration phase as undoubtedly important, given the granularity of the simulator. The property of this framework to be used in a wide variety of situations implies that several types of data need to be available in order to model all the characteristics that contribute to the agents' behavior.

Studies related to dynamic pricing in carsharing have been conducted in order to maximize profit or vehicle utilization. Depending on the type of service, different strategies have been analyzed to improve the service. In the case of one-way station-based carsharing services, price variations based on the time of the day and pick-up zone help increase profits and balance carsharing vehicles' stock [13]. Using reinforcement learning, a similar problem is addressed regarding the balance in the distribution of the fleet. A dynamic pricing scheme is found to be effective in flattening the uneven distribution of the vehicles among the stations [22]. Other forms of shared mobility have been the object of research on dynamic pricing schemes. A negative price strategy was introduced in dock-less bike sharing [23]. The study addresses a relocation problem using a user-based approach. The dynamic pricing proposed was found to be effective in attracting customers and balancing bike repositioning. Since two-way carsharing does not suffer relocation issues, given the intrinsic nature of the system, studies related to round-trip carsharing are more limited than their one-way counterparts. Dynamic pricing (or dynamic price discrimination) is extensively studied in the airline industry literature. It is defined as the adjustment of "prices based on the option value of future sales, which varies with time and units available" [24]. Considering the commonalities and differences between air and car sharing systems, it can be beneficial to carsharing operators to apply effective dynamic pricing strategies. For example, concerning dynamic pricing strategies in airline operations, it is noticeable how the goal of such scheme is to address incomplete markets rather than to make customers pay more [24]. Two main branches exist in airline pricing: intertemporal price discrimination (to buy a product for future consumption needs) and dynamic adjustment to stochastic demand (price in function of the selling rate of a product). In [25] it is shown how these two complementing forces lead to significantly higher revenues if compared to more restrictive pricing strategies. Similar trends are found on the use of dynamic pricing strategies on hosting platforms such as Airbnb, where price changes in function of the day and the season [26]. Overall, carsharing differs greatly from these other services—for example, the number of cars at one station cannot be compared to the number of seats in a commercial flight and the booking time horizon, which for airline tickets varies from days to months. In carsharing, it varies from an instant to a few days in advance. That is why, given the specificity typical of a carsharing model, these dynamic pricing strategies cannot be directly applied to the service. In previous steps of this research, it was reported that carsharing users with an average and average-to-high value of time (VOT) tend to take resources from users with a lower VOT [27]. However, since the spatial distribution of users and their relative distance/access to stations is also an important factor determining usage patterns, and this, in turn, has impact on equity consideration, in this study we use an experimental design that allows us to highlight the analysis of pricing schemes from the strategic positioning of stations.

5.1.2 Research Gap

Focusing on the application of dynamic pricing policies to a round-trip carsharing supply system, this paper develops a comprehensive experimental design created for the impact analysis of an availability-based dynamic pricing (ABDP) and a time-based dynamic pricing (TBDP) strategy, simulating the two approaches with the MATSim agent-based simulation platform. This work bridges the current gap on carsharing pricing policy assessment, explicitly considering the heterogeneity in members' socio-economic attributes, in particular their income-related spending capabilities. The introduction of the VOT influences the users' response to pricing schemes, helping to better simulate the behavior of different groups of users. Given the need to model the behavior of carsharing users with those kinds of attributes, in order to investigate which feature of the supply impacts demand and how, an explorative analysis has been conducted, introducing two dynamic pricing strategies on a population living in the Berlin Area (Germany) with a diverse income distribution.

The "first contribution on VOT carsharing" [27] introduced a dynamic pricing strategy for the two-way carsharing mode on a population with a heterogeneous VOT. When the dynamic pricing was applied, a light increase in the number of bookings was noticeable, and people with low value of time tended to abandon the carsharing mode in favor of other modes of transportation. One of the challenges of the previous study was to handle the high complexity in checking and interpreting the results, given the large number of parameters given by the many degrees of freedom of the realistically simulated case study.

The remainder of the paper is organized in four sections. The next section, "Materials and Methods", provides the methodology, describing the setup of the scenario, how the value of time was evaluated and how the dynamic pricing strategies were implemented. Section 3, "Results", describes the results for both the scenarios from the demand and supply system point of view. Section 4, "Discussion", presents an examination of the results, summarizing and explaining their outcome. Finally, Section 5, "Conclusions", proposes insights for future work.

5.2 Materials and Methods

Considering the high complexity of the problem, given by the high number of plans to be executed and the entanglement of the various variables of the simulation, we came up with a more controllable way of varying the supply and demand characteristics, such as a homogeneous VOT and a planned station distribution.

On the one hand, it is expected that having a dynamic pricing offer should lead to a more homogeneous rental performance in terms of space, since the members will look in their neighborhood for the cheapest car: the utility of renting a vehicle in a station with high availability becomes higher than renting a vehicle in a station with low availability, considering that the user can take advantage of cheaper fees. However, on the other hand, the utility increment due to a lower price should lead to a trade-off because of the creation of a disutility due to the shifted activity schedule or longer access times to the service. Finally, a diversified use of carsharing among the members, for the same offer, is expected, since the spending power varies from user to user [28].

Trip-based approaches using analytical or simulation models, like the classic four-step modeling approach, are still the most widely used in practice to represent travel demand [29], in particular in planning and assessing applications of large-scale networks. Forecasts are made considering one area as a whole, and flows are commonly measured in vehicles per hour in an aggregated way. It is evident that to assess round-trip carsharing, an aggregated trip-based model cannot be able to reliably assess important key performance indicators (KPIs) such as service availability at a precise point in space and time [30], users' cost savings by chaining trips and activities, and service profitability and usage during a typical day of operations. Additionally, the relatively limited number of vehicles in a neighborhood suggests adopting a mesoscopic approach, which is considered a more suited modeling scale in order to capture emerging system-wide trends from individuals' activity-travel behavior. Temporal and spatial resolution becomes of paramount importance when assessing the capabilities of a carsharing service. Disaggregated methods (e.g., activity-based models) are necessary to describe the behavioral component of a single user and the activities executed by people at different locations and at different times. The most natural way to apply this criterion is through agent-based modeling. In this work, we adopt an agent-based simulation approach to analyze a round-trip carsharing system on the Berlin network, following a well-established stream of research in the field, which adopts a similar methodological approach [31–33].

Different agent-based simulators available in the literature were considered before resorting to the open-source simulation platform MATSim. Among others, SimMobility [34] is an integrated simulation platform designed to be activity-based, multi-modal, multi-scale and fully modular. At the time of deciding which model to adopt, however, a module able to fully simulate carsharing was missing. The PTV MaaS Accelerator Program [35], on the other hand, is capable of simulating ridesharing and multimodality. The closed-source nature of the software and the lack of scientific literature adopting it became essential issues for its use in this study. Mezzo [36] simulates road traffic at the level of individuals. Even though it has a modular structure similar to the one in MATSim, where one can create specific packages to implement new functionalities, the absence of the carsharing mode was also a hurdle for our study. Netlogo [37] is another established multi-agent programmable modeling environment used in transportation. Its general purpose allows it to be employed in various applications, such as stakeholder's policy acceptability [38]. We selected MATSim since up to today, it is one of the few tools that allows for the simulation of carsharing services interacting with other transportation modes, hence allowing for the explicit consideration of the elasticity of car sharing demand toward other modes of transport. Since its deployment, the carsharing contribution to MATSim has been one of the most widely used platforms to simulate carsharing scenarios through an agent-based model.

5.2.1 Scenario Setup

MATSim is an open-source software, programmed in Java, used to implement large-scale agent-based transport simulations [18]. Trips are derived from individual activity chains, which represent people's activity-travel behavior. Individuals can be defined by several attributes (e.g., age, gender, driving license ownership, employment situation, …) and, altogether, they make up the synthetic population, which is generated and calibrated based on empirical data. The simulation consists of iterations of a typical day in which every agent performs its daily tasks (a plan), generating the daily travel demand. In each iteration agents evaluate the fitness of their own plan with a score, and, on the following iterations, strategies are applied in order to try to improve their utility. By adopting this approach an equilibrium is reached, subject to constraints, where agents cannot further improve their plans unilaterally [18]. The basic input files used by MATSim are the following:

Network

The network is obtained importing the OSM (Open Street Map) map of Berlin into JOSM (Java Open Street Map), which is an extensible editor for OSM and for Java [39]. Once the desired map is loaded, a plugin developed ad hoc for MATSim converts the needed graph to a network readable by the software with basic attributes for nodes and links. The reason behind choosing Berlin as our case study is given by the fact that an already generated synthetic population and network is available [40], thus simplifying the population generation phase. Furthermore, given that this study addresses an urban carsharing system, the city zone of Berlin was taken as study area (Figure 1).

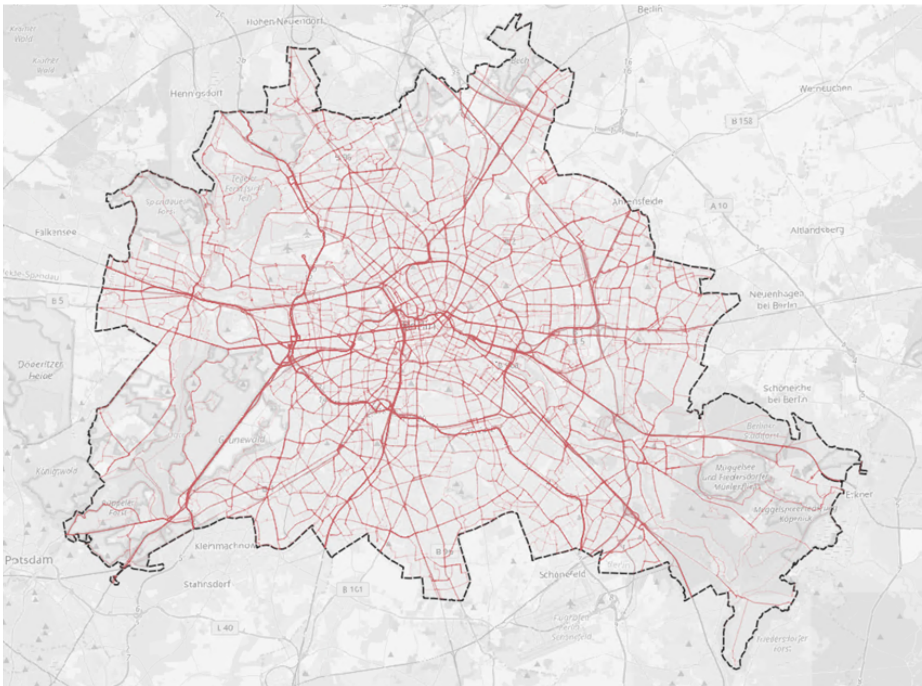


Figure 1. Study Area.

Carsharing Membership

The CSMembership file contains a list of all the agents authorized to use the carsharing service. As a matter of fact, carsharing is a membership program, which means individuals can become members and therefore use the service only if they meet some specific requirements (e.g., holding a driver's license, possessing a credit card, etc.). In this study every agent holding a driver's license is allowed to use the carsharing as an additional mode of transportation (i.e., they are considered to be a member of the service) and, moreover, this mode can be used for a subtour or for the complete trip chain. This means that the membership is stochastically applied to agents that can drive a vehicle.

Configuration

A config file is the connection between the user and MATSim. A list of parameters, belonging to different groups referring to different modules or functionalities of the software, 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 to modify their plans.

Plans

A plans file (or population file) consists of a synthetic population mimicking profiles living in the study area, usually generated from census data. In this file the simulator finds the complete agents list with their assigned activity chain. Attributes such as person ID, gender, age, license, car availability, employment status, etc., describe every agent that is part of the simulation. The plans file used in this work is based on the one used in [40] and consists of an 8% sample of the state of Berlin's 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, duration of the activity, and mode of transport used to reach a specific facility. Since this population lacks some of the essential attributes described above (i.e., license and car availability), additional information was gathered from another population file described in [41]; here, a 1% sample of the federal state of Berlin and the federal state of Brandenburg's population is used to export the aforementioned attributes for every agent. This data is univocally linked to a set of GPS coordinates. Having obtained the distribution for every attribute given the district, using a GIS software (QGIS), we linked the agents' GPS coordinates with the districts' shapefile. That resulted in the assignment of every attribute to a specific agent in the 8% population sample. The same approach was used to link the individual income to every agent using the distribution of the income for every neighborhood [42]. Since the main intention of this paper is to evaluate the users' behavioral change after the introduction of dynamic pricing, a variable like the value of time (VOT), which is sensible to travel price [28], was needed. Since VOT is directly linked to income and other characteristics of the population heterogeneity, its study, together with the supply utilization, can be used to analyze the fairness of the system.

5.2.2 Scoring and Value of Time

The score used in MATSim for the evaluation of the 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 the number of activities and q the trip that is induced by the activity. The first term, *Sact,q*, represents the positive component of the utility (in MATSim this is called scoring) related to executing the set of activities; the second one, *Strav,mode(q)*, represents the disutility of traveling with a given sequence of modes. The second component of this equation is specific to each mode of transport supported by MATSim. The first term has the same form for all the agents and is defined as in Equation (2) [18].

$$S_{act,q} = S_{dur,q} + S_{wait,q} + S_{late,ar,q} + S_{early,dp,q} + S_{short,dur,q} \tag{2}$$

where the five contributions to the scoring consist of: *Sdur,q*, utility of performing an activity related to its duration; *Swait,q*, waiting time spent before starting an activity; *Slate,ar,q*, late arrival penalty; *Searly,dp,q*, the cost of early arrivals; and *Sshort,dur,q*, a penalty from a "too short" duration [18].

In this work, an ad hoc distribution of the VOT was applied in order to have better insight into the users' behavior when facing events that involve a monetary cost. That is, we created a controlled simulation scenario where the population is sharply clustered in VOT-based sectors. In order to determine which effects can be evaluated by changing specific pricing policies, it is important to include a variable sensitive to these variations. Using only the income as sensitive variable would not be sufficient since it lacks a specific time component. What could make one choose, for example, a mode of transport instead of another is the value of the time saved by making that choice, considering the trip's purpose and its related utility determinants (scheduling time, duration, location choice). For this reason, the VOT is chosen as sensitive parameter, since it can be assigned ex ante using the marginal value obtained from [43] and directly introduced in the scoring function of MATSim. We therefore introduced the VOT in the utility of performing an activity q as described in the following equation:

$$S_{dur} = (\beta_{dur,q} \times t_{typ,q}) \times (\alpha_{VOT} \times VOT) \times ln\,(t_{dur,q}/t_{0,q}) \tag{3}$$

where t_{dur} is the performed activity duration, $\beta_{dur,q}$ is the marginal utility of the activity duration, α_{VOT} is the scale factor for the VOT, and $t_{0,q}$ is the duration since the utility starts to be positive. The VOT is fetched directly from the plans file used as input from MATSim. Applying the VOT in the section of the scoring related to the duration of the activity has a specific meaning: if the duration of the activity changes, this change is measured as the difference between the desired duration of the activity (input of the system) and the actual duration (output of the simulation), it means that the impact on the scoring has a multiplied factor equal to the VOT. At the same time, the fact that an activity is performed leads to an increment of the score that is multiplied by a factor equal to the VOT. This means that higher VOT classes tend to lose more in terms of scoring when the activity does not have the desired duration and gain more when the activity is closer to the desired duration.

Differently from the previous contribution, that used the heterogeneous distribution of eleven classes of VOT [27], only four VOT classes have been selected in this study. The reason behind this choice was to aggregate similar behavior for similar VOT and to keep at the same time a similar range (i.e., from 0.13€/h to 4.83 €/h). Moreover, its spatial distribution is more uniform than in our previous study [16]. This choice helps to understand the overall trends, by removing some degrees of freedom given by the randomness of the VOT distribution. An abundance of users with a specific VOT next to a station could skew the conclusions (that is, too many bookings from that income class), making the results less clear and less interpretable. There are two basic ways to create sectors on a geographic map once the center is given: using a coaxial clustering in order to create a monocentric city or using a radial clustering dividing the entire area in slices. While the coaxial method would follow the logic of a monocentric city where more expensive neighborhoods are located in the center, the radial design increases the contact points of different VOTs and could reveal specific behaviors in stations that are at the border between two VOT regions (e.g., adjacent quarters with different population characteristics and income levels). It should also be observed that the radial combination gives room to more station combinations among different VOT levels, while the coaxial distribution allows for contact only between two contiguous VOT classes. On the one hand, in the radial scenario, we expect stations on the border to be more used than the others, serving only one VOT; on the other hand, in the coaxial configuration, we expect that the longer the distance from the center, the smaller the number of bookings. All the users are represented on the map as a small dot and colored in function of their VOT (Figure 2).

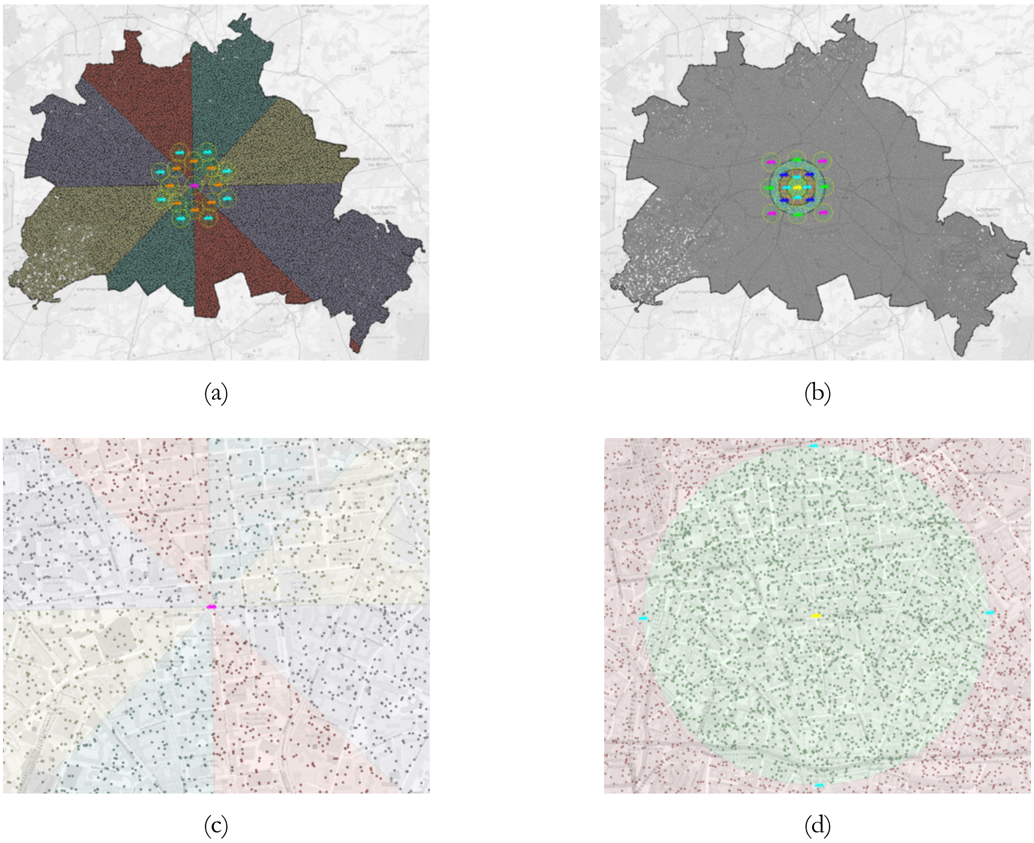


Figure 2. Distribution of the value of time (VOT) and carsharing stations: (a) radial; (b) coaxial; and their relative close-up: (c) radial ; (d) coaxial.

For every station, a yellow dashed circle is drawn. This circle represents the catchment area. This is an area of 800 meters radius; this length is considered the access distance threshold users are generally willing to travel (mainly walking or seldomly using the bike or the public transport) in order to access a carsharing service [44,45]. Anyway, users residing out of the buffer zone could perform a spontaneous booking if a subtour happens in said area.

Concerning the radial distribution, the stations are placed according to three classes, function of the VOT distribution in Table 1. The stations are placed both in the center and on the sectors' border in order to assess if stations serving one or two VOT classes have specific emerging behaviors.

Table 1. VOT values and station distributions for radial configuration.

Sector Name	**VOT [€/h]**	**Stations Name**	**Color code**
Green	4.00	Central	Magenta
Yellow	3.00	Border	Orange
Purple	2.00	Inner	Cyan
Red	0.50		

Regarding the coaxial distribution, the stations are placed both at the border between two VOT clusters and immerged in one cluster, as in Table 2. In order to reach the same number of stations as in the radial distribution, four stations were assigned to every sector plus the central one.

Table 2. VOT values and station distributions for coaxial configuration.

Table 2. VOT values and station distributions for coaxial configuration.

Sector Name	VOT [€/h]	Stations Name	Color Code
Green	4.00	Zone 4	Yellow
Red	3.00	Zone 4–3	Green
Cyan	2.00	Zone 3–2	Blue
Grey	0.50	Zone 2–0.5	Cyan
		Zone 0.5	Magenta

5.2.3 Dynamic Pricing

Two scenarios assessing different pricing strategies were created. These are: an availability-based pricing scheme, where the trip becomes more expensive as fewer cars are available at a station at the time of booking and a time-dependent pricing scheme, whose pricing value depends on the time of day when a car is booked, independently of car availability.

Availability-Based Dynamic Pricing (ABDP)

This strategy seeks a more uniform distribution of cars and vehicle usage in time and space and is only indirectly dependent on the actual demand. The demand itself, on the other hand, can be sensitive to pricing only if demand elasticity is explicitly considered. This concept is integrated in MATSim by updating the carsharing scoring function:

$$S_{trav,q,cs} = \alpha_{cs} + \beta_{c,cs}\left[\frac{(c_t(t) \times t_r) + (c_d \times d)}{a^y{}_j}\right] + \beta_{t,w}(t_a + t_e) + \beta_{t,cs} \times t_{trav} \qquad (3)$$

The equation is obtained introducing $a^y{}_j$ where a is the number of cars available at the station j at the moment of booking and y is the steepness of the pricing curve, $\alpha_{cs(q)}$ is the carsharing-specific constant, $\beta_{c,cs}$ is the marginal utility of the time spent traveling by carsharing, c_t and c_d are respectively the marginal monetary cost of time and distance, t_r is the total reservation time, d the distance traveled, $\beta_{t,w}$ the marginal utility of an additional unit of time spent walking, t_a and t_e are respectively the access and egress time, $\beta_{t,cs}$ represents the marginal utility of an additional unit of time spent traveling with carsharing, and t_{trav} is the actual (in vehicle) travel time.

In their simplest form, ABDP strategies depend only on the supply available at the moment of booking (i.e., the number of vehicles). These strategies result in three different main price profiles: linear, concave, or convex. When the linear form is used, bookings tend to be strongly underpriced when the supply availability is high [27]. In order to avoid this behavior, and inspired by airline dynamic pricing strategies, this pricing scheme follows a hyperbolic function approach, as already applied in [25]. The final score for traveling will then be affected by a function having a shape like the one drawn in Figure 3, where the shift from a fixed pricing (FP) to an ABDP is also illustrated.

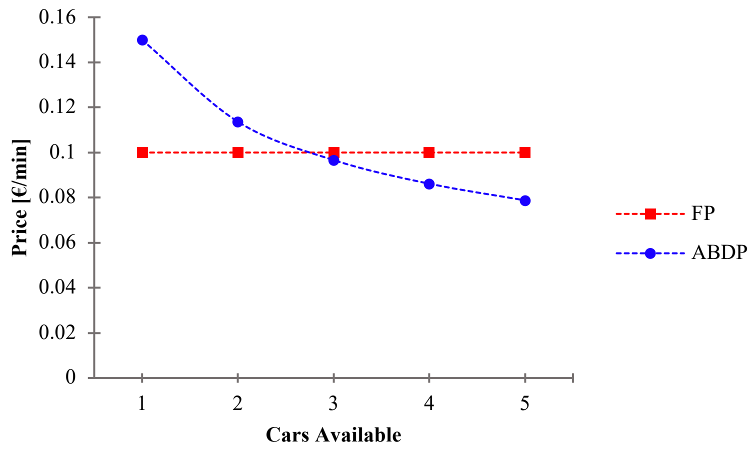


Figure 3. Hyperbolic form of availability-based dynamic pricing (ABDP) compared to fixed pricing (FP).

Both ABDP and FP amounts are chosen balancing areas below the curve in order, for a hypothetical company, to reach the same revenue when all vehicles in the station are booked. Pricing setup is the following:

- ABDP: 0.15 $\left[\frac{€}{min}\right]$. price of the last vehicle available at the station
- Fixed pricing = 0.1 $\left[\frac{€}{min}\right]$

The ABDP policy is a demand-responsive strategy. Since the price offered to the client is not fixed a priori, this strategy could be difficult to implement in practice for companies that apply a business model based on planned bookings. On the contrary, it could more easily be employed in case of spontaneous bookings.

Time-Based Dynamic Pricing (TBDP)

The TBDP scenario simulates a pricing scheme dependent on the time of day at which a car is used regardless of the situation at the station where the rental happens. It is designed as in Figure 4.

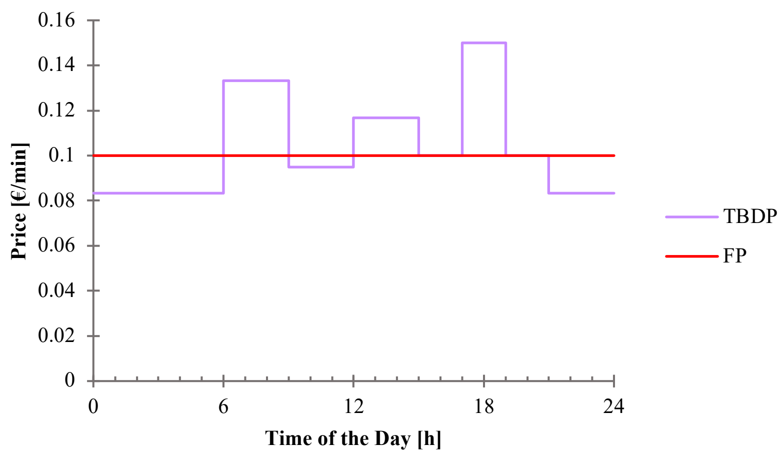


Figure 4. Price design for time-based dynamic pricing TBDP compared to FP.

The idea behind this strategy is to make cars more expensive during peak hour time, on the one hand, to generate higher revenues for the company during the most demanded times of the day, and, on the other hand, to move the demand away from the peak period. To obtain the pricing curve, a simulation with FP was run, and the carsharing demand was used to design the price profile. The demand profile obtained is consistent with the 2019 revealed traffic data for the city of Berlin [46]. The final curve was achieved setting the area under the purple curve equal to the area underneath the red one.

This policy is a passive strategy. Prices are already known by the system for every booking, and thus it is easier to apply the strategy to companies that prefer planned bookings as their business model. Of course, the TBDP strategy can be implemented without great effort even in business models contemplating spontaneous bookings.

5.3 Results

The studied region is the Berlin city area, which has been created by importing data from an open street map [47] in QGIS [48], a geographic information system. The area consists of a synthetic population of 280,113 agents, i.e., 8% of the actual population of Berlin [49]. All the agents are members of the carsharing service, and the number of users less than 800 meters away from a station is shown in Table 3.

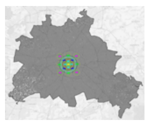
Table 3. Users within 800 meters from a station according to VOT.

VOT [€/h]	Radial	Coaxial
4.00	9959	2739
3.00	9987	4106
2.00	10,990	7310
0.50	8820	14,181

Only round-trip carsharing is available, with an offer of 85 vehicles divided into 5 vehicles per station for a total of 17 stations for both scenarios. The number of vehicles per station is chosen according to an average fleet size of a round-trip carsharing service in Berlin. All scenarios were run for 600 iterations with a computation time of approximately 30 hours each, running on an HPC [50] with 8 cores (at 2.4 GHz) using 70 GB of RAM. During simulations, each agent was allowed to change his transportation mode, route, and departure time. More information about the code run can be found in Appendix A.

In the following, we report results of the simulation for the radial configuration and the coaxial configuration of the VOT using the scenario definitions as shown in Table 4.

Table 4. Scenario definition.

Scenario Code	Name	Pricing Strategies	Color Code	
		Fixed		
1	Radial configuration	Availability-based		
		Time-based		
		Fixed		
2	Coaxial configuration	Availability-based		
		Time-based		

5.3.1 Effects on Carsharing Operations for Radial Configuration

Carsharing service providers' main KPIs can be divided into economic indicators (e.g., revenue) and fleet management indicators (e.g., number of bookings, distance, booking times). The overall KPIs for the radial configuration are reported in Figure 5.

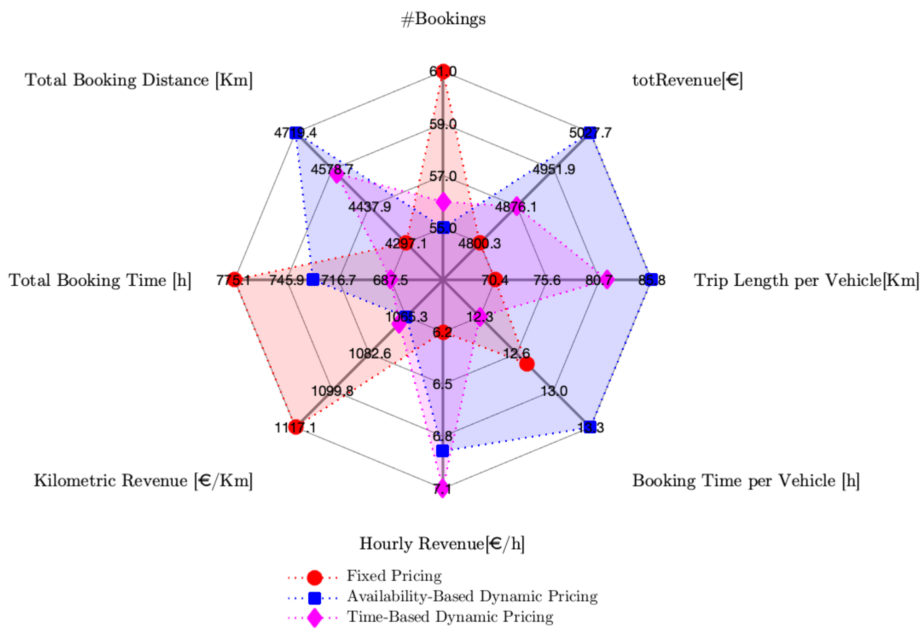


Figure 5. Provider's key performance indicators (KPIs).

Each axis reports the value of a specific KPI for the three pricing schemes and ranges between the minimum value (lower limit) and the maximum value (upper limit) amongst the three strategies. For every pricing configuration, the following KPIs are defined:

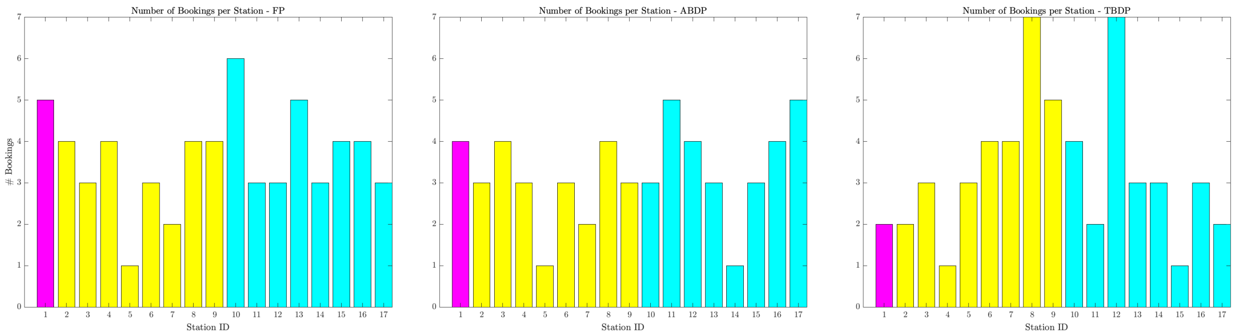
- #Bookings: total amount of bookings for the whole day
- Tot revenue: sum of all the revenue generated during the single rents
- Trip length per vehicle: average distance traveled
- Booking time per vehicle: average booking time
- Hourly revenue: average revenue generated in one hour of booking
- Kilometric revenue: average revenue generated for every kilometer traveled
- Total booking time: sum of all the booking times
- Total booking distance: sum of all the distance traveled

Once a dynamic pricing strategy is introduced, we observe that the total revenue increases, in particular in the case of an ABDP. Furthermore, it must be considered that the revenue calculation does not explicitly include accessory costs such as maintenance costs and cleaning efforts, that account for one third of carsharing service costs [51]. However, these are directly linked to the number of kilometers traveled and usage rates of a car. For this reason, it is important to consider the life expectancy of a carsharing car and note that the ABDP strategy leads to a higher total booking distance if compared to the FP strategy.

A TBDP encourages people to book for shorter times. This can lead to a loss of revenues because cars are sitting unused on the road for most of the time.

Even though the fixed pricing leads to higher total booking times, it does not bring an increase of revenue to the company. It becomes a negative factor since the company gives away resources for a lower price (low hourly revenue).

The number of bookings can be further analyzed in terms of number of bookings per station, in order to optimize operations, as shown in Figure 6. The color code here follows the one illustrated in Figure 2a and described in Table 1 for the station distribution.



(a) (b) (c)

Figure 6 Number of bookings per station. (a) FP strategy; (b) ABDP strategy; (c) TBDP strategy.

The ABDP tends to homogenize the station's utilization, reducing the range between the most used and underused stations (from four vehicles to three). The TBDP has the opposite effect and tends to concentrate the activity on a limited number of stations; here the range passes from four vehicles in the FP to a deviation of six vehicles. There are more underused stations when dynamic pricing is applied.

5.3.2 Effects on Demand for Radial Configuration

On the demand pattern side, indicators are different compared to the ones previously described and focus on the modes chosen, activities done, and score.

People using carsharing in the FP scenario are not necessarily going to use the service again when the dynamic pricing strategy is applied. To assess their choices, we monitored the behavior of this group of people after the introduction of dynamic pricing. To do that, we call:

- FP-ABDP to the indicators retrieved in the ABDP simulation for the users that took the carsharing when a FP strategy was in place; and
- FP-TBDP to the indicators retrieved in the TBDP simulation for the users that took the carsharing when a FP strategy was in place.

Figure 7 shows the score distribution over carsharing users for the three different scenarios, as well as for these two additional groups. We observe that changing the strategy from fixed to dynamic pricing leads to a higher mean of the score distribution for agents using carsharing. FP brings a higher variance but most of it is on the negative side of the graph. Overall, agents abandoning the carsharing service in TBDP increase their score, while the same does not happen in ABDP.

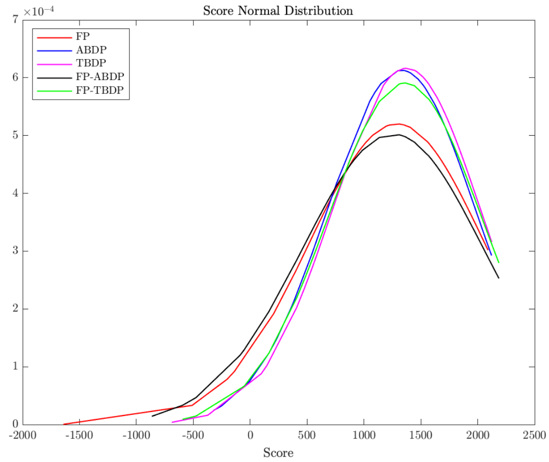
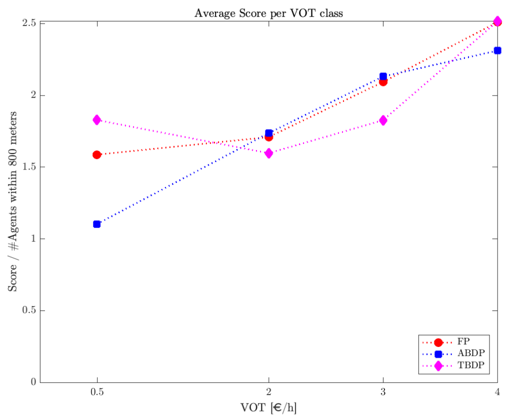
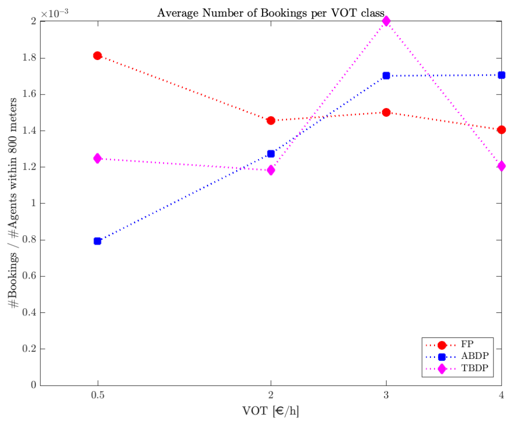


Figure 7. Normal distribution of the score.

To have a better assessment of what happens to every VOT class in terms of average score, we refer to Figure 8. The number of VOT agents refers to the amount of people of a certain VOT who have access to the service (i.e., who live within an 800 m radius from a station). On Figure 8a, we can see that the score grows according to the increasing VOT, meaning that high VOT classes obtain a greater utility when using carsharing. At the same time, when the ABDP is applied, the most affected class is the lowest VOT one. The same method applied to the number of bookings (Figure 8b) shows, on the one hand, a stronger loss for low VOT agents who book less if compared to the FP scenario. On the other hand, high VOT groups tend to execute more bookings.



(a)



(b)

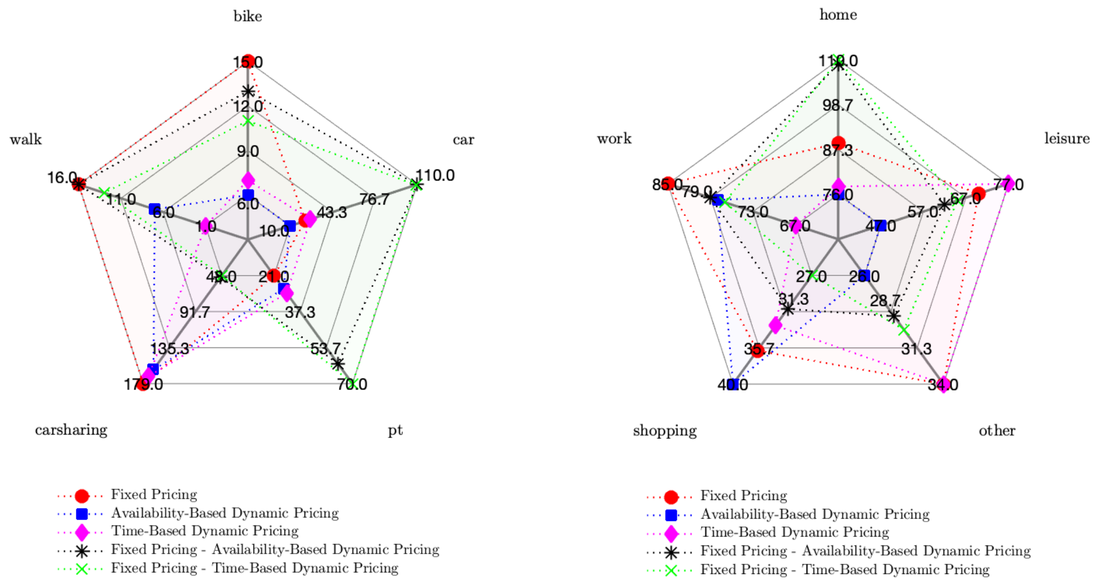
Figure 8. Average (a) score; (b) bookings per VOT class.

It is possible to notice that for the highest VOT in the TBDP scenario we do not have the same behavior as in the ABDP. There are two reasons why this can happen: one endogenous and one behavioral. First of all, as we stated before in Subsection 2.2., the VOT is introduced in the scoring function related to the duration of the activity, and it multiplies $\beta_{dur,q}$ the marginal utility of activity duration. For activities related to work, this marginal utility is the highest; however, at the same time, the working hours are when the price is the highest. This combination impacts more people with high value of time. Secondly, we must consider that people with high value of time—which in this study comes from the income—are people that can usually take advantage of a large number of modes. This results in their ability to switch to more convenient modes if carsharing is not convenient (i.e., they receive a low score using it) and keep using carsharing if it is convenient anyway. This explanation is illustrated by Figure 8a, in which it is shown that, even though there are fewer bookings, the score is the highest among all the scenarios and VOT classes.

To better understand these dynamics, related to different pricing scenarios, we assessed the impact of the dynamic pricing on both aspects of the score: mode and activity choice.

Figure 9a shows two different trends: modes that are used in combination with carsharing (red, blue, and magenta) and the modes with which former carsharing users replace the service when dynamic pricing is applied (black and green). Even though customers opt for all kinds of modes, it is the car that mainly replaces carsharing, as its numbers are higher than for other modes. Those who choose carsharing opt for the service for the most part of their daily trip chain.

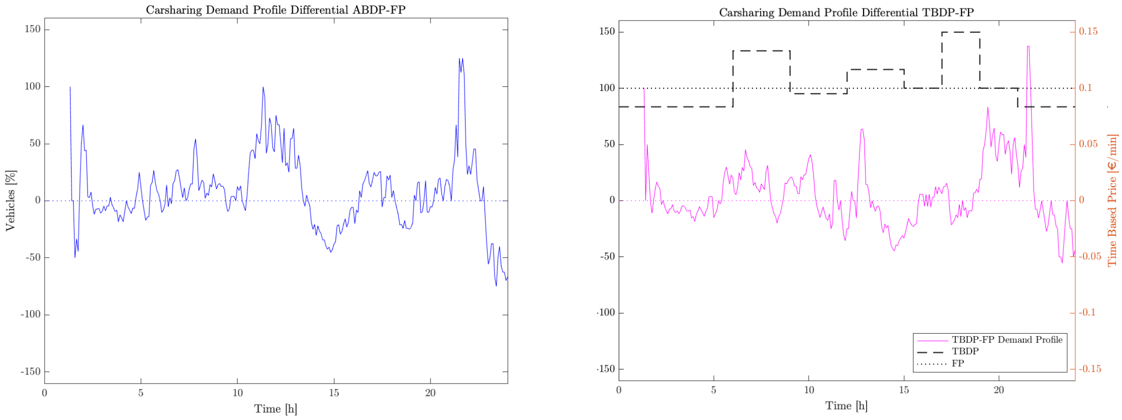
Figure 9b shows the activities performed during the day. When FP is applied, car-sharing agents' main activity is working, while for the ABDP and the TBDP the service respectively attracts users who travel for shopping and leisure. Finally, users that have more home activities during the day (i.e., they go back home more often before proceeding to the next activity) are the users who used carsharing only when the FP strategy was active.



(a) (b)

Figure 9. Distribution of (a) modes; (b) activities.

To show that the user groups have a different behavior if a dynamic pricing strategy is applied, we show (Figure 10) the difference in percentage of the booking profile when dynamic pricing strategies were offered against the fixed pricing strategy. When the line is above zero the number of bookings happening at a specific time is higher in the dynamic pricing than in the fixed price scenario. Vice-versa, if the line goes under zero, the FP strategy scenario shows more bookings.



(a) (b)

Figure 10. Carsharing demand profile for (a) FP and ABDP; (b) FP and TBDP.

In Figure 10a, we see how the morning peak is not much affected by the dynamic pricing. This is due to the fact that the penalty in arriving late at work is higher than for other activities. The typical effect of this kind of pricing can be seen during the late morning since a peak is followed by a loss in bookings. This effect is due to the price increment linked to the reservations made in the previous hours. The same behavior can be seen in the afternoon and in the evening.

In Figure 10b, we can see the same behavior in the early morning, while in the afternoon peaks tend to follow the pricing scheme with some delay. In the first part of the morning (from 6:00 to 7:00) the high price does not lower the demand; the reason is similar to the one given in the previous paragraph for the ABDP strategy: the utility generated at work is higher than the one generated in other activities. Around 8:30, the price weights more, but from 9:00 the lower price increases the number of bookings. In the afternoon and in the evening the booking behavior follows more the dynamic pricing strategy, except for the late-night period, where it is not possible, given the pricing strategy, to attract more demand.

5.3.3 Effects on Carsharing Operations for Coaxial Configuration

The subdivision of the companies' main KPIs is the same as in the previous paragraph: economic indicators (e.g., revenue) and fleet (e.g., number of bookings, distance, booking times). The overall KPIs for the coaxial configuration are reported in Figure 11.

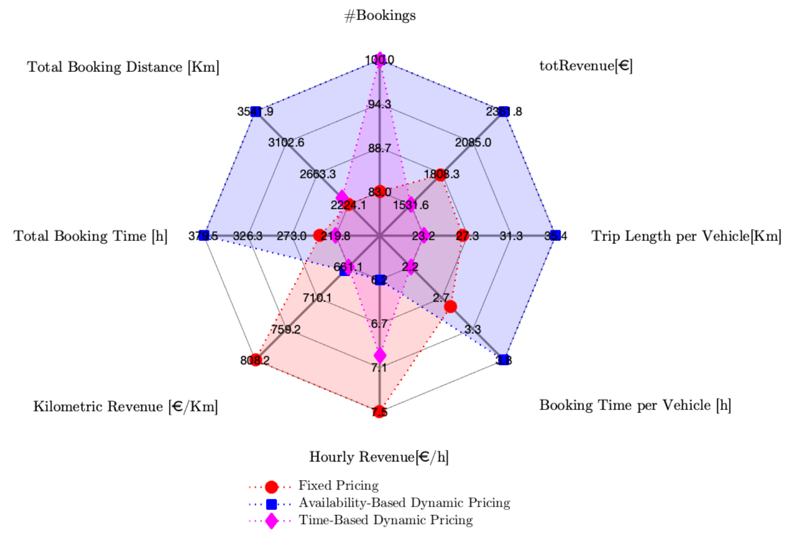
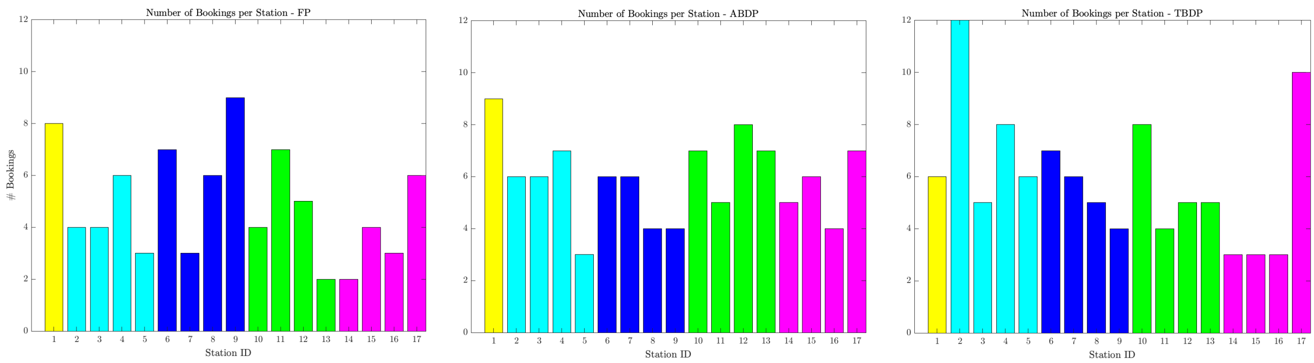


Figure 11. Provider's KPIs.

The KPIs tend to be similar to the ones reported in the radial configuration, meaning that service providers' indicators do not significantly vary in function of the distribution of the purchase power in the city. With this configuration, the TBDP strategy collects the highest amount of booking, but the ABDP is still the one that guarantees the highest revenue to the operator among the three schemes. As for the previous case, it has to be considered that the revenue calculation does not include accessory costs such as maintenance costs, as these are directly linked to the number of kilometers traveled and usage rates of a car. For this reason, it is important to take into account the life expectancy of a carsharing car and note that the ABDP strategy leads to a higher total booking distance if compared to the FP or ABDP strategy. That is, taking into account the life cycle, part of the advantage could be eroded by the need to change cars more often.

Even in this occasion, the TBDP encourages people to book for shorter times. This can lead to a loss of revenue because cars are left unused on the road for most of the time.

The number of bookings can be further analyzed in number of bookings per station, in order to optimize operations, as shown in Figure 12. The color code here follows the one illustrated in Figure 3b and described in Table 2 for the station distribution.



(a) (b) (c)

Figure 12. Number of bookings per station (a) FP strategy; (b) ABDP strategy; (c) TBDP strategy.

Here, the ABDP tends to not homogenize the station's use even though it reduces the range between the most used and underused stations. The TBDP tends to concentrate the activity on a limited number of stations, resulting in high amounts of underused stations, similarly to what happens in Figure 12a.

5.3.4 Effects on Demand for Coaxial Configuration

On the demand side, the indicators focus again on modes, activities, and score.

In this scenario, we found the same behavior from carsharing users as in the previous configuration. Agents using carsharing in the FP scenario are not necessarily going to use the service when the dynamic pricing strategy is applied; that is why we monitored the behavior of this group of people after the introduction of the dynamic pricing (FP-ABDP for the introduction of the ABDP strategy and FP-TBDP for the introduction of the TBDP strategy).

In Figure 13 we show the distribution of the score over carsharing users for the three different scenarios as well as these two additional groups.

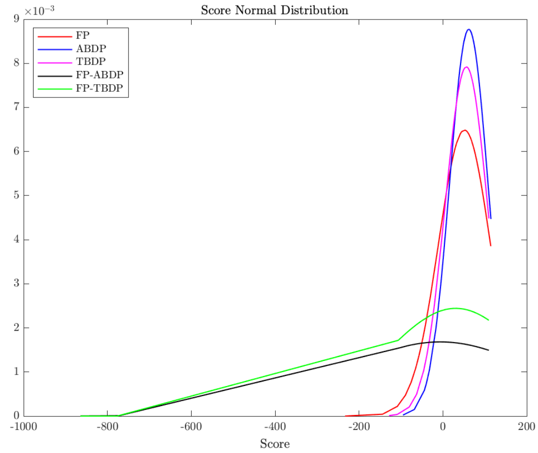


Figure 13. Normal distribution of the score.

Even on this occasion, switching to a dynamic pricing strategy leads to a higher average score for agents using carsharing.

To have a better assessment of what happens to every VOT class in terms of average score, we refer to Figure 14.

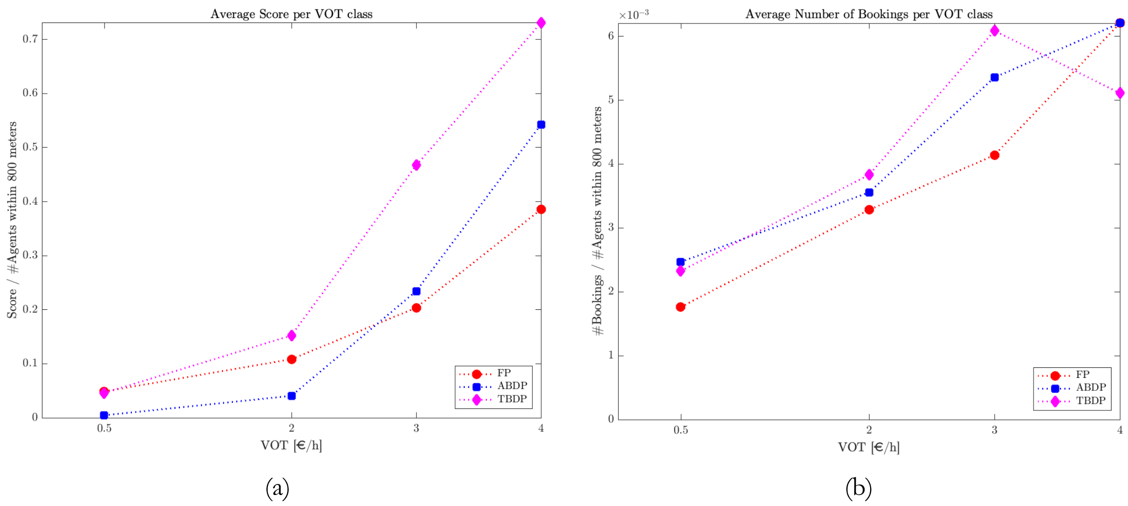
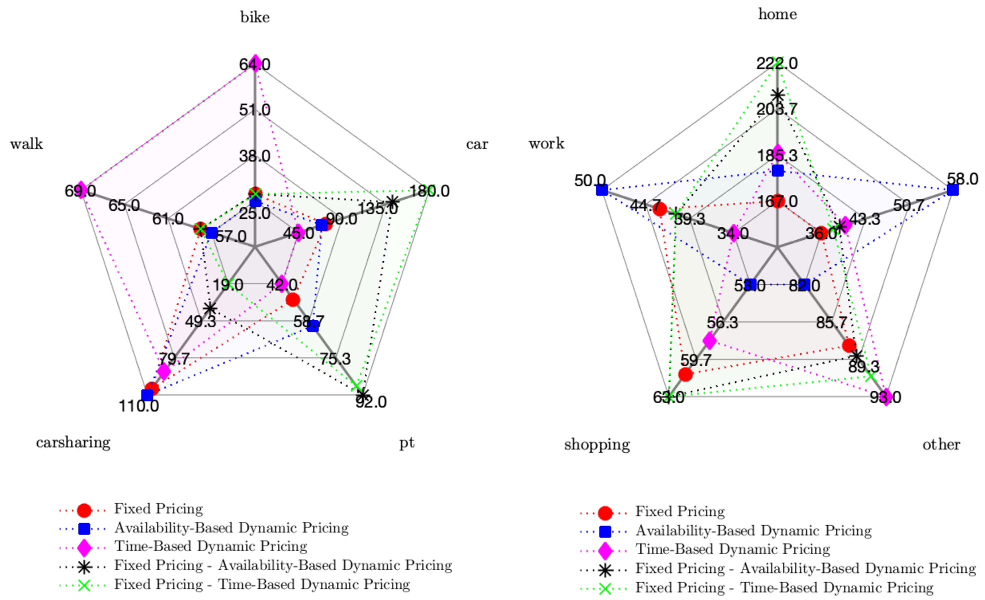


Figure 14. Ratio on number of agents per VOT for (a) score; (b) bookings.

On Figure 14a we can see that the score grows together with the VOT, meaning that high VOT classes have greater utility using carsharing. The ABDP strategy affects lower VOT groups negatively, making them gain a lower utility if compared to other scenarios. In this configuration, once the TBDP strategy is applied, lower VOT groups achieve a better score than when the FP strategy is active. The same method applied to the number of bookings (Figure 14b) shows that it is possible to obtain more bookings when a dynamic pricing strategy is applied. However, the groups with high VOT are the ones who systematically gain the most with this policy. In Figure 14b we can notice a similar trend as in Figure 8b. The reason is similar to the one given above, in Section 3.2, with the addition that, for the coaxial configuration, people with high VOT live in the city center, where the public transportation offer is stronger. This results in a higher score in Figure 14a than the one obtained in Figure 8a, since the agents that use carsharing are the ones that strongly benefit from it.

In order to better understand these dynamics between different pricing scenarios, in Figure 15 we assessed the impact of the dynamic pricing on both aspects of the score: mode and activity choice.

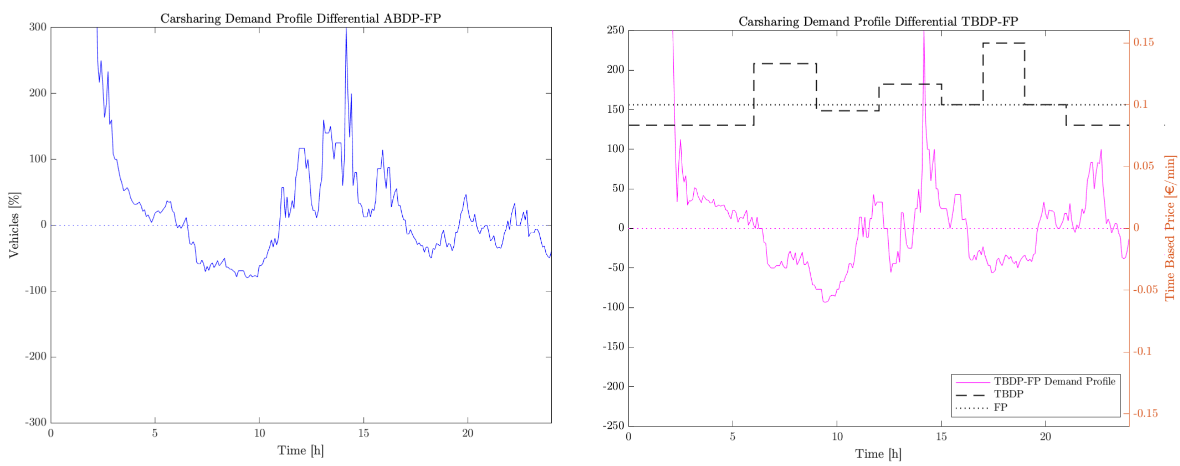


(a) (b)

Figure 15. Distribution of (a) modes; (b) activities.

Figure 15a shows two different trends: the modes that are used in combination with carsharing and those with which former carsharing users replace the service once dynamic pricing is applied. Customers tend to opt for all modes, but the car is the main replacement for carsharing when we switch from an FP to an ABDP strategy, and public transport is the main replacement for carsharing when we switch from an FP to a TBDP strategy. Those who choose carsharing in the dynamic strategy opt for the service for most of their daily trip chain. Figure 15b shows the activities performed during the day. When FP is applied, agents' main activity is shopping, while for the ABDP and the TBDP, the service respectively attracts users who travel for work and leisure (the former) or shopping and other activities (the latter). Finally, users that have more home activities during the day (i.e., who go back home more often before proceeding to the next activity) are the users who used carsharing only when the FP strategy was active.

To show that the user group has different a behavior if a dynamic pricing strategy is applied, we show (Figure 16) the difference in percentage of the booking profile when dynamic pricing strategies were offered against the fixed pricing strategy.



(a) (b)

Figure 16 Carsharing demand profile for (a) FP and ABDP; (b) FP and TBDP.

In Figure 16a, we see how the morning peak is affected by the dynamic pricing. People have lower fares early in the morning, and this leads to a lower number of departures once the morning peak is over. For the same reason, lower peaks alternate with higher peaks, since users that can wait for cars to be returned at the station take advantage of better prices. Figure 16a is more "extreme" when compared to Figure 10a. The increase after 10:00 and the following decrease (this time after 15:00) is similar to the one experienced in the radial scenario. In Figure 16b, we can see the same behavior in the morning, this time justified by a lower price, and even in the evening, as peaks tend to follow the pricing scheme.

5.4 Discussion

The observed data shows an impact of dynamic pricing on carsharing users' behavior. Once the dynamic pricing strategies are applied, people with a low VOT will see the utility of using carsharing decrease. The implemented policy, as it is, does not appear to guarantee equity, since it does not have the same impact for all population classes. Either way, both strategies have different impacts whether carried out in cities with a more radial configuration or with a coaxial distribution of the purchase power.

Concerning the radial scenario, we obtained a light homogenization in terms of bookings per station. This could be beneficial for companies looking for a better distribution of their fleet, and results could be improved with a different configuration, with closer stations (i.e., increasing the number of stations the agents can access by walking for distances lower than 1600 meters). Overall, the average score is higher for both strategies but, as different agents start to use the service, the utility is distributed differently, benefitting people with an average and average-to-high VOT, in case of an ABDP strategy. This is because the policy, as it is conceived, favors users that are able to spend more when the vehicles' price rises. Trends for the TBDP have a specular movement that follows the FP strategy. Moreover, the TBDP can achieve a better daily spatial distribution of the demand concerning the afternoon peak. Morning trends are similar, since most of the activities executed in the morning are about work, an activity with high penalties for late arrival—penalties that are stronger than the benefits that a change of departure time can produce. On a future perspective, if the carsharing trend continues to grow, such a strategy can be attractive to public regulators, since it leads to specific benefits in actively reducing or increasing carsharing flows in specific times of the day. The morning behavior is similar even in the ABDP strategy. The morning demand profile is not strongly affected by the policy, while the afternoon period leads to a homogenization of the profile: the lower peak rises, and the high peak is more contained. While even this strategy can attract regulators, because of its inherent ability to smooth the demand peaks, it is harder to manage, since the demand profile is a function of the price that is itself modified by the demand elasticity. On the supply side, the ABDP strategy is the one that increases the revenue the most. At the same time, it reduces the amount of booking, allowing for a smaller fleet that, considering the trip length and booking time per vehicle—that is higher if compared to the other strategies—leads to a faster wear of the vehicles. This has to be taken into account for further analyses on longer time frames where maintenance costs are considered, to check if the increment in revenue brings an increase in profits.

Regarding the coaxial distribution, the difference between stations with the highest and the lowest number of daily bookings is reduced. This could be beneficial for companies, even though further analyses with closer stations should be done to prove its effectiveness. The average score is higher when a dynamic pricing strategy is applied, favoring agents who live in the city center. The ABDP strategy brings a loss of utility to the lower VOT classes while enhancing the score for the users with a stronger purchase power. This is because this kind of customers are less affected by the higher prices and are able to book a vehicle at any time of the day without being affected by the strategy. Overall, both strategies attract more bookings, independently of the income class, resulting in higher rental numbers. This is linked to the great benefits in score that these strategies create if applied to coaxial configuration. In this scenario, generally, we see the same benefits in terms of demand profile. Even the morning peek is affected by the introduction of these two strategies, because, considering that different users use the service, in the ABDP strategy more people find carsharing convenient to go to work, and in the TBDP strategy the lower price attracts people that need the car at that time. On the supply side, both strategies are able to increase the number of bookings, while only the ABDP brings a higher revenue for the company. The TBDP is more attractive only when the carsharing price is lower and does not level off the lower price with the number of bookings made when the service costs more. Although it reduces the kilometers traveled, lowering the cars' usage, it cannot produce higher revenues per vehicle booked.

5.5 Conclusions

In this paper we have conducted an explorative analysis of how availability-based and time-based dynamic pricing schemes impact demand and supply performances. When dynamic pricing is applied, people with low value of time tend to abandon the carsharing mode in favor of other modes of transportation. Depending on the pricing strategy offered, a carsharing company is able to raise its revenue or the number of cars booked per day. As was shown, dynamic pricing strategies can be forged to increase operators' revenue but, at the same time, it is not known yet if this can automatically generate higher profits. For example, a cost-benefit analysis could help carsharing companies to better understand the possible implications of choosing this kind of dynamic strategies.

Both pricing strategies here simulated appear to have different impacts for people belonging to different VOT classes, except for the TBDP with radial VOT distribution. This means that, in case a company should switch to a dynamic pricing strategy, a major involvement with a public and private partnership should be foreseen in order to control and mitigate the negative impacts such policy could have on the population. While end-users can take advantage of lower prices depending on the time of day or the state of the supply in the station where they pick up a vehicle, these same benefits can be distributed unequally. This distribution can be linked to the daily activity plans and to the income of the user. The user base used in this study is completely stochastic, and it is not based on an existing carsharing population. This means that considerations about equity can only be taken as a general conclusion. Further research could use a thoroughly defined member base and more realistic fleet in order to produce better insights on real case scenarios.

The ABDP strategy brings more benefits to companies in both scenarios, leading to an increase in revenue, while the TBDP strategy is beneficial when compared to an FP policy, if the income distribution resembles more the radial one. On the one hand, the ABDP's main limitation is its demand-responsive nature, since an instantaneous change in demand leads to an instantaneous change of the price which, as shown, results in a revenue increment. On the other hand, these strategies are hard to control for carsharing operators, making the fleet management difficult and introducing issues regarding planned bookings. TBDP strategies, as implemented here, are not demand-responsive and can be used to plan the pricing offers in advance.

The approach described in this work helped reduce the complexity of the problem and to understand the inner workings of these strategies. It would be preferable, in any case, to switch back to an individual VOT in order to assess more realistic scenarios, making use of the outcome of this work.

The kind of approach used in this paper to simulate dynamic pricing in carsharing can be adapted to other streams of research, for example to the trend of upcoming connected and autonomous vehicles. Considering this new mode, the study we proposed could be extended to all the agents who do not have a driver's license. The extension could even be done with MATSim, since an autonomous vehicle contribution has already been implemented.

Further research will focus on building a hybrid pricing (HP) policy that could mix the benefits of the two strategies here analyzed, reducing, at the same time, the disadvantages. An HP strategy based initially on the ABDP policy could lead to a desired demand profile that could be implemented through a TBDP strategy in order to be, at the same time, demand- and time-responsive, allowing for planned booking and increasing the revenue toward values that a sole TBDP price cannot achieve.

5.6 Appendix A

The version of MATSim employed to execute this experiment can be found at the following address: https://github.com/ggiorgione/streams, while the data used can be found at this address: https://github.com/ggiorgione/DynamicPricing.

IV. Two-Way Analysis

In this part we introduce the Munich case study using business data directly derived from Oply, a car sharing company operating in that area. Here, we evaluate the introduction of two-way car sharing in a place where this type of service was not present before. Subsequently, we will evaluate the impact of the introduction of this mode of transport on the different segments of the population using no longer the value of time but their income. Furthermore, an evaluation will be carried out based on the satisfaction that users of the service get using this newly introduced mode of transport.

This part is based on the work accepted for publication in:

Giorgione, Giulio, and Francesco Viti. "Assessing Equity in Carsharing Systems: The Case of Munich, Germany." Transportation Research Procedia, 2021, 8.

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6
Assessing Equity in Carsharing Systems: the case of Munich, Germany

This paper shows an application of a multi-agent transport simulation to evaluate equity effects of the introduction of a carsharing system. Using vehicles, members, and planning data of Oply, a carsharing service that operated in Munich until March 2020, we analyze the evolution of the distribution of costs and benefits among the inhabitants of this city. By explicitly introducing the income as an active part of the utility calculation we evaluate how offering a new mode of transport impacts the score of the agents. Two scenarios are employed to assess equity in economic terms and accessibility terms. Two different outcomes are expected: firstly, as a high pricing service, carsharing will favor high-income agents, thus skewing benefits towards them; secondly, we show that the granularity of this agent-based simulator makes it a handy tool when conducting policy evaluations on the introduction of a carsharing system.

6.1 Introduction

During the last decades new transportation modes and emerging mobility services have become a stable presence in everyday life. The blossom of new service models created a change in the way private companies and public institutions faced mobility issues leading to a paradigm shift in the transportation planning and management. Private-led services such as carsharing fostered competition among companies while governmental institutions faced new challenges in regulating emerging markets and frame them in the context of multimodality and sustainable mobility. Carsharing is a service composed by individuals who have access to a lease car through a membership program. Vehicles are rented for a short time by paying a usage fee and are booked on demand (*70*). Carsharing operations are essentially a private service, that is why some studies found their main focus on fleet management efficiency while increasing company profit (*1*; *1*). A potential benefit in the reallocation of vehicles can also be exploited through incentives that offer affordable prices to the user who, by making their trips, will help the carpooling company to balance its fleet (*86*). Given the increasing number of services, competition among operators make carsharing pricing one of the most important topics regarding business sustainability. There is a link between carsharing prices and journey-purpose profiles of the carsharing users, this influences who is using carsharing, when and where (*53*). Of course, pricing policies don't affect different users in the same way. In fact, to evaluate these types of impacts, an analysis of equity is carried out. Equity in this paper follows the definition by (*87*) as "the distribution of impacts (benefits and costs), and the degree to which this distribution is considered fair and appropriate"(*87*). Equity can be divided into two main categories: horizontal equity, which concerns the distribution of impacts among individuals who can be considered equal; vertical equity, which concerns the distribution of these impacts among unequal individuals (i.e., different economic resources, accessibility, mobility needs and skills). In this paper we will specifically deal with vertical equity with regard to income, also defined as social justice or social inclusion. For instance, when dynamic price is offered, carsharing users with an average and average-to-high value of time (VOT) tend to take resources away from users with a lower spending power (*88*). It is not trivial to foresee carsharing impacts, both on the population and on businesses, given the complex mobility patterns emerging from carsharing users, and the different parameters and decisional variables involved in the planning and operations. Testing new strategies, especially brand-new strategies, could be a difficult and resource-intensive task. For example, to set up pricing experiments in a real-world setting could require substantial disruption of carsharing operations. At the same time, the implementation of the wrong business model (i.e., a model that it is not suited to the nearby population) could lead to significant losses in a carsharing service. Considering that we are looking for emerging trends for a complex system driven by many variables and intermixing behavioral processes the use of a simulator is a valuable asset to get insights and can produce advanced screening of operational strategies. In this case, the simulation of innovative transport modes with agent-based models has been proven useful because of their microscopic nature (*89*). That is, regarding the carsharing, the peculiarity of the services offered can be estimated in a realistic way and can capture car availability at a given location at a given time. In this work we evaluate the impact of a carsharing service on a group of agents differentiated by their income. Employing an agent-based simulator, MATSim, and using the score (i.e., the utility generated by executing the desired activity plan) as main key performance indicator (KPI). We assess the eventual distribution of costs and benefits among the population. Essentially, this work aims at answering two questions:

- Will the carsharing mode exacerbate the differences among diverse income groups?
- Is this intensification local (i.e., around carsharing stations) or is spread over the city?

6.2 Method

Table 1. Notation

N	Number of activities
S	Score/Utility
q	performed activity
β_{dur}	Marginal utility of activity duration
t_{dur}	Performed activity duration
t_0	Duration when utility starts to be positive
α_I	Scale factor for the Income
I_u	Income of user u

When in need to determine the economic impact of the introduction of a new mode of transport on a given population, it is important to have an economic-sensitive variable ascribed to said population. In this work we are going to differentiate agents for their economic (i.e., income) and spatial (i.e., spatial location) attributes. Income is obtained from the German micro census (*90*)and, together with other demographic data, it is used as input within the land-use model SILO (*91*). Finally, we employ this model to generate a synthetic population for MATSim, updated to the year of our choice (2020) with income and spatial location assigned to every agent. This population is used to run simulations within MATSim. MATSim is an activity-based, extendable, multi-agent simulation framework implemented in Java (*19*). The carsharing data is extracted from the Munich dataset of Oply, a B2C carsharing company operating with a round-trip mixed system. Oply offered a two-way service using small areas instead of punctual stations. Using an Iterative Linking Algorithm (ILA) we link the agent's attributes assigned during the synthetic population generation to the closest Oply member. To do this we proceeded to apply the ILA based on the Euclidean distance within an agent created in the previous step from the micro census and Oply's members. The ILA allocates one agent (drawn from the whole population set) properties to the closest member and, once done so, it deletes the agent leaving only the member with all the desired attributes. By doing so we obtain a pool of around 15000 agents with a specific income, location, and daily activity chain. Two different simulations are run: one without and one with the carsharing service available to all the carsharing members. In order to assess the impact on the agents we evaluate the scoring as described in (*84*).

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

This is the score to evaluate the agent's plan (i.e., the daily activity chain), with N the number of activities and q the trip that is induced by the activity. The first term represents the positive component of the utility (in MATSim this is called scoring) related to executing the set of activities, the second one represents the disutility of travelling with a given sequence of modes. The second component of this equation is specific to each mode of transport supported in this case by MATSim (i.e., walk, bike, car, public transport and carsharing). The scores of different income groups are assessed and compared. This means that we need to introduce the income in MATSim in a way that it can impact the score. What could make one choose for one mode of transport or another is the value of time saved by doing that choice. Of course, this choice is dependent on the trip purpose and its utility determinants (time, duration, location). For this reason, the Income is chosen as input parameter since it is a propriety of the demand, and it can be introduced before the simulation. The Income is introduced in equation 2, in the part of the scoring evaluating the utility of doing a specific activity ($S_{act,q}$). In this work we consider $\alpha_I = 1$.

$$S_{dur} = \left(\beta_{dur,q} * t_{typ,q}\right) * (\alpha_I * I_u) * \ln\left(t_{dur,q}/t_{0,q}\right) \tag{2}$$

This implementation therefore imposes a difference not on the cost of travel time, which remains the same for the different groups, but on the impact that the completion of the work activity generates on the score. Following the introduction of the income, we pass to the simulation setup describing the case study used to assess the KPI explained in the previous section.

6.3 Case Study

In Figure 1 we show the network, the distribution of the carsharing members together with their hourly income and the distribution of the stations. While free-floating services tend to intercept customers willing to walk around 300 or 500 meters to reach a vehicle (*92*), round-trip members tend to walk longer distances to reach the station of departure. Around 80% of the City CarShare users walk at most half a mile (800 meters) to reach a carsharing station (*93*). Therefore, to consider a realistic area of influence of every station, a round buffer zone with a radius of 800 meters with the station as center is created. This is done to check if the phenomena induced by the introduction of the carsharing are local or distributed on the whole city.

Figure 1. Munich Network.

The Carsharing offer consists of 79 stations in which are distributed 186 cars. The location of the stations and the allocation of the cars follows the actual Oply distribution. Only the two-way service is offered.

Regarding the population we used the actual members pool of Oply. 14747 Agents are introduced and characterized by their position, hourly income (see Figure 1) and daily activities. In Figure 2a we show the frequency of the Income in the population together with the number of bookings per income group.

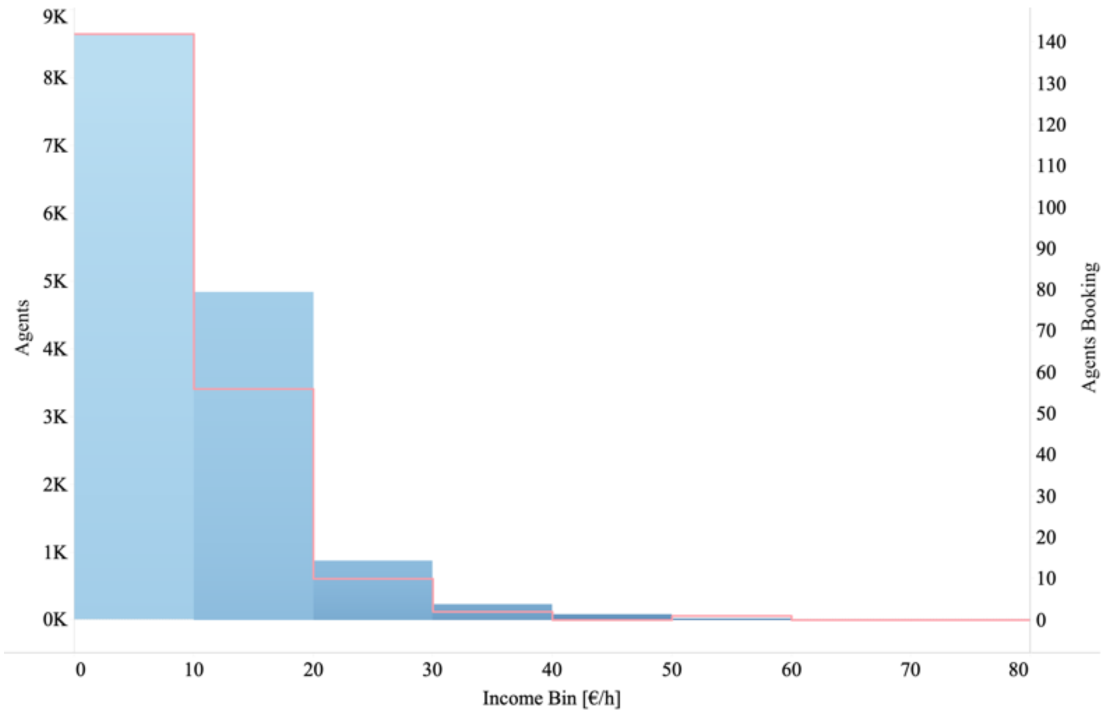

Figure 2 Hourly Income Frequency

We identify two different scenarios, one in which the carsharing mode is not active and one in which it is. This allows to analyze the emerging impact of introducing the car sharing as additional option to the mode alternatives offered to the car sharing members.

Table 1. Scenarios Identification

Scenario Name	Total Population	Carsharing Mode	Color Code
No Carsharing	14747	✕ **Not** Active	
Carsharing	14747	✓ Active	

These two scenarios are simulated in MATSim using a fixed price offer of 6€/h, which reflects the pricing policy applied by the company. The price is paid by the hour and no fractionable is considered except for the grace period. The grace period is defined as a time of five minutes in which, any booking closed within this time is not subject to the full hour payment (e.g., a booking that lasts 64 minutes will cost to the user 6€ while a booking that lasts 66 minutes will have a total cost of 12€). The main parameter used in evaluating the scoring (i.e., the carsharing constant) amounts to 19.30. This specific value allows the Carsharing scenario to reach a usage of the carsharing similar to an average day for Oply operations.

6.4 Results

Once the scenarios are set up, we run two different simulations on a PC with an Intel(R) Core (TM) i7-8700 CPU @ 3.20GHz, 3192 Mhz, 6 Core(s), 12 Logical Processor(s) and 64 Gigabytes of ram. The elapsed time for the simulation is 24 hours. Data is then processed using MATLAB and Python and edited in Tableau and QGIS for the graphical visualization.
As pointed out in the methodology section, the main KPI we are going to assess is the score (or otherwise defined, the utility). Focusing exclusively on the agents that booked the carsharing service in the Carsharing scenario, we calculate their scoring in both simulations and see how the

score has changed, hence, obtaining the delta score (DS) as shown in the following equation for an agent *u*.

$$\Delta S^u = S^u{}_{Carsharing} - S^u{}_{No\ Carsharing} \tag{3}$$

In order to find an answer to the first question "Will the carsharing mode exacerbate the differences among diverse income groups?", we define different income groups in order to formerly identify the score reached by agents with different purchase power.

Table 2. Income Groups

Group Name	Hourly Income [€/h]	Annual Income [€/h]
0	0 - 10	0 - 19200
10	10 - 20	19201 - 38400
20	20 - 30	38401 - 57600
30	Above 30	Above 57601

First of all, we take a look at the cumulative scoring retrieved for the different income groups in Figure 3.

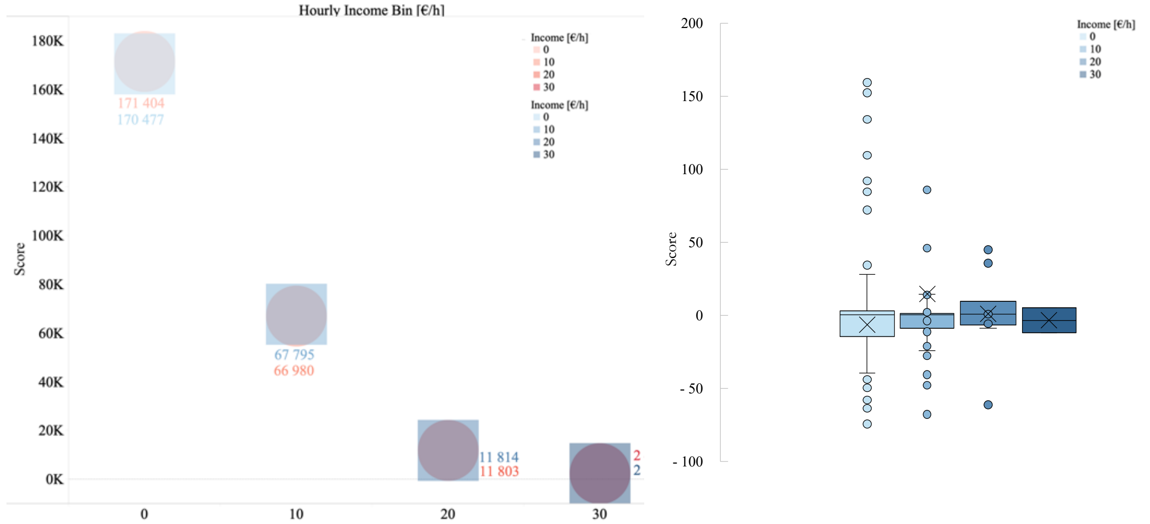

Figure 3 (a) Cumulative Score per Income Bin; (b) Extract of a daily activity chain.

Figure 3a shows that, once the carsharing service is offered, the utility of the agents that use the service declines if their income is low. The difference is lightly pronounced. We assess a loss of 0.5% on the cumulative score for incomes lower than 10 €/h, a small increment of 1.2 % for incomes between 10 and 20 €/h and, for all the other income groups, a rather unchanged outcome.

To understand the distribution of the score we show Figure 3b, here we represent the difference between the scores obtained in the two scenarios by income group. First of all, it is possible to notice how the number of outliers decreases the higher the income gets; this is due to the higher number of agents in that Income group (see Figure 1a). When comparing the four means we see how the central income groups (10 – 20 [€/h] and 20 – 30 [€/h]) are the one that, on average, benefit from the carsharing. The first and the last income groups see a negative difference, more pronounced for the first group ($\overline{\Delta S_0} = -7$) and less for the last one ($\overline{\Delta S_{30}} = -4$). Either way,

the last group reveals a smaller variance compared to the first one, this means that the score of this income group tends to stay the same between the two simulations and it is not much affected by the price of the specific transportation mode.
Together with an aggregate analysis, we believe that even a disaggregate approach could lead to important insights. In Figure 4 we show the scatter of the scoring for every agent and their hourly income.

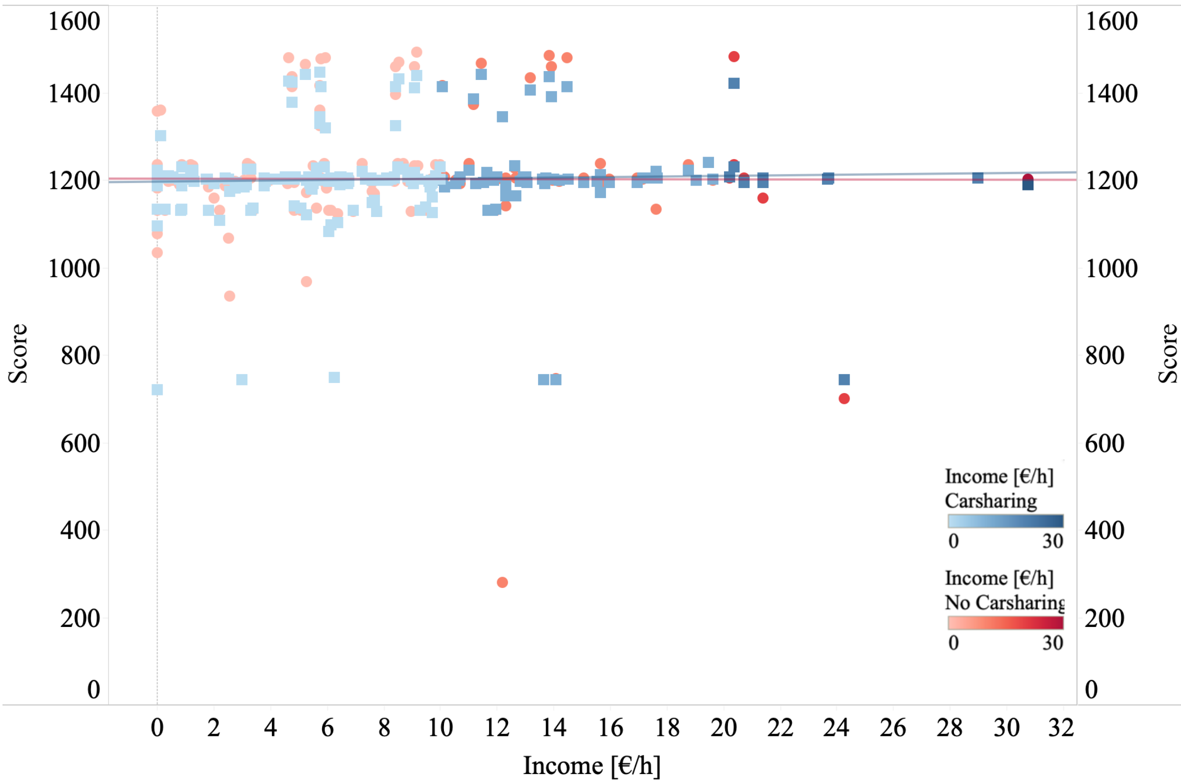

Figure 4. Score Between No Carsharing Scenario (Red) and Carsharing Scenario (Blue).

Represented as blue squares, as defined in Table 1, there are the agents that booked the carsharing in the Carsharing scenario, while, as red circles, there are the same agents that couldn't use this mode in the No Carsharing scenario because it was not present. The most important insight can be offered by the trend line. The interception of the red circles generates a horizontal line, this means that, overall, the different points balance each other returning a trend line that doesn't particularly favor lower or higher income groups. The moment the carsharing mode is available, the trend line generated by the interpolation of the new points, returns an ascending line. This effect is mainly given by the by the increment in score seen, for the central income groups, in Figure 3b.

Once we assessed that the score changes as the carsharing service is introduced, in Figure 5 we show whether the intensification of the change in the score happens around the carsharing stations, or it is more distributed along the city. In this figure we show the income level (in blue), the agents that used the carsharing mode, whether their score is negative or positive when compared to the first scenario, we represent their income as the size of the miniature and the carsharing stations by a yellow car.

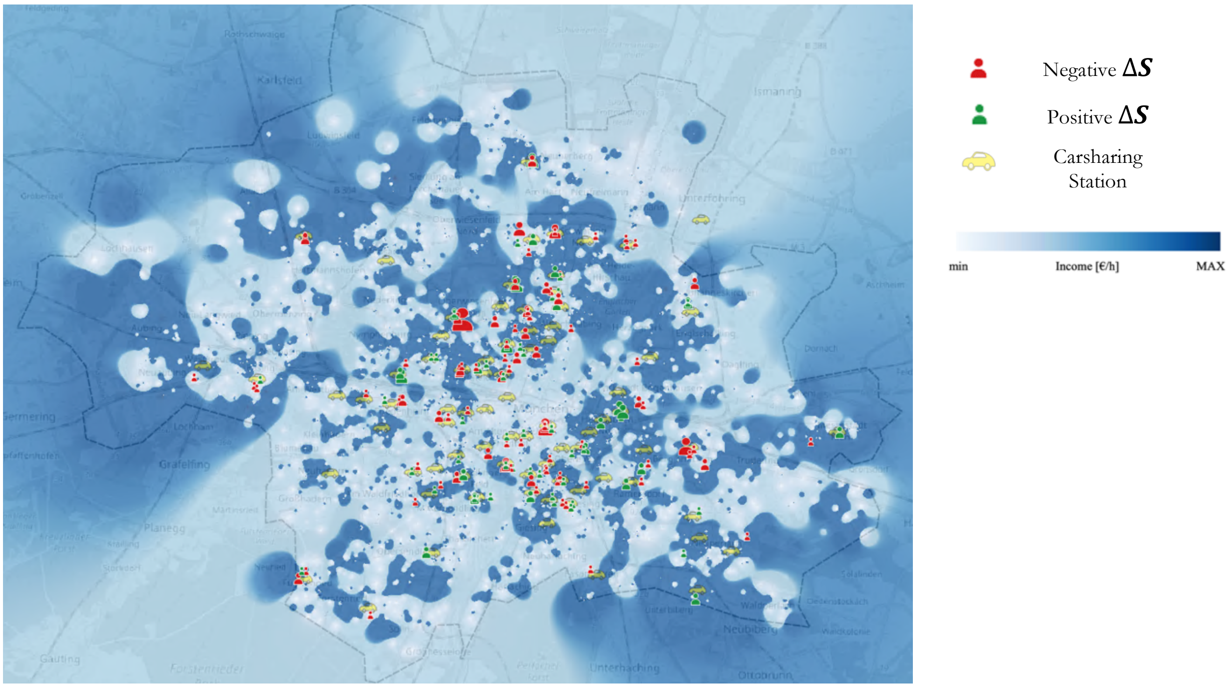

Figure 5. Booking Map

Given the nature of the service, only agents close to the stations would be supposed to use the carsharing mode. To check that, we show that the area of influence of a carsharing service tends to fade quickly once we get further from the station. As it can be seen from the map, only agents living or that happens to be around a carsharing station at the moment of the booking use the carsharing service. Defining the spatial equity as the distribution of the benefits (and, by logic, even of the disbenefits) on a specific area, we see that their distribution is not equally spread on the whole area but only around the stations. There are no agents from any specific income group booking cars and living (or happen to be) far from the station at the moment they need a carsharing car. This means that all the assessments made so far are localized in an area of influence that is close to the carsharing stations.

Furthermore, in Figure 6, we show the modal share in No Carsharing of the agents who will chose the carsharing in Carsharing scenario (Figure 6a), and the modal share of all the agents in No Carsharing (Figure 6b).

Figure 6 Modal Share of (a) carsharing users (in Carsharing Scenario) in the No Carsharing; (b) all users in No Carsharing

This shows how agents choosing the carsharing used to have a car usage higher when compared to the average of the whole population. This follows the findings of (*94*) that sees the round-trip carsharing as a substitute of the car mode, seldomly of public transportation and not a competitor of soft modes.

6.5 Discussions and Conclusions

The idea behind this work is that it is possible to use an agent-based simulator to evaluate the impact of the introduction of a carsharing service on the population of a given area. Once introduced the income as an active part of the utility calculation of the agents score, we assess the output of the simulation. This method employs data fetched from Oply, a Luxembourgish carsharing service operating in Germany. The results of this paper suggest that the introduction of a carsharing service brings an impact on the population. This impact is not evenly distributed neither in spatial nor in economic terms. The nature of the carsharing service, usually a service that is responsible for a tiny part of the modal share of a city, creates the condition for which only the agents leaving close-by a station are impacted. One of the shortcomings of this paper is that it doesn't link the distance from the station with a specific loss or improvement of the utility, but it restricts the analysis only to whether the service will impact or not the agents.

Furthermore, we showed how higher income groups benefit from the introduction of this service while lower income groups don't receive the same contribution in terms of utility. This conclusion finds support in the literature, for instance (*95*) shows through a survey that "While lower-income households are less likely to utilize carsharing when compared to higher-income households" but, he adds that "carsharing can enhance mobility for lower-income populations, primarily when interacting with a public transportation coverage variable.". to test the carsharing together with public transportation was not the goal of this paper but we will consider the second sentence as a good application of the software for future works.

What we demonstrate with this work is that, with an agent-based model like MATSim it is possible to simulate the introduction of a new mobility service. We show that the impact seen on the population follows what is expected in a real-world scenario and is dependent on the income of every agent.

Considering that in this paper we show that carsharing usage is sensible to people's income and that it is possible to show this behavior through an agent-based simulator, future works should address the quantification of the relationship carsharing and income more in-depth. A validation phase could be added in order to conclude what the assessments made until now (survey on carsharing members and the simulation approach described in this paper) stated. A next step could include a validation step. Even though the results of this paper come from a population based on national surveys and micro census and on a scenario calibrated on real carsharing operational data, a validation phase could be needed in order to step over the trends and reach the actual usability of this forecasts in day-to-day carsharing operations.

V. Munich Dynamic Pricing

In this part, after proposing and identifying the impact of two specific dynamic pricing strategies, we present a method of modeling a price that generates the maximum possible profit for a carsharing service in the city of Munich. In this phase we will evaluate the impact of these strategies not only on the population but also on the carsharing business by assessing, among the main indicators, the profit, the number of bookings and the rental time. One of the main highlights of this part is the innovative calibration method for carsharing regarding the agent-based simulator MATSim. Using data obtained directly from Oply, a car sharing business operating in Munich, we proceed to calibrate the simulation using revenue and time. Finally, techniques are described in order to optimize both the profit (from the business point of view) and the usefulness (from the end user point of view) of a carsharing system. This approach will lead to the definition of a hybrid pricing system that exploits the main components of the different dynamic pricing strategies.

Section 7.6 "Appendix" shows an application of the maximum profit price creation procedure for two of the seventy-nine stations in this study. The purpose of this chapter is to show the reader how the procedure is applicable at different scales.

This part is based on the work submitted and still under review in:

Giorgione Giulio, Dzmitry Kliazovich, Luca Bolzani, Francesco Ciari, and Francesco Viti. "Systematic Analysis and Modelling of Profit Maximization on Carsharing". Research in Transportation Business & Management.

Giorgione Giulio and Francesco Viti. "Profit and Utility Optimization Through Joint Dynamic Pricing and Vehicle Relocation in Carsharing Operations". Transportation Research Record.

And on the work presented at:

TRB Annual Meeting 25-29 January 2021. Giorgione Giulio, Dzmitry Kliazovich, Luca Bolzani, Francesco Ciari, and Francesco Viti. "Systematic Analysis and Modelling of Profit Maximization on Carsharing".

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7
Systematic Analysis and Modelling of Profit Maximization on Carsharing

The success of carsharing as a relatively new and more sustainable way of travelling is moving private car ownership towards a service use model. Competitivity is an essential aspect of this service and ways to increase profit while offering the most appealing service are still getting explored. Among others, dynamic pricing strategies can be designed to increase profit by attracting more users, selling more rental hours, or maximizing fleet utilization. In this paper, we propose an experimental method aimed at developing a model for maximizing service profit. Using agent-based modeling to generate realistic scenarios, we analyze pricing as a function of the potential demand (i.e., number of members) and supply (hours of booking supplied). The process of reaching the maximum profit consists of testing various combinations of pricing–demand and pricing–supply ranges in order to find the values that maximize the profit for every demand and supply level. Once the optimal prices are known, a polynomial fitting and an optimization method are used to generate a functional form linking all the maximal profit obtaining the advised price to offer for any specific supply levels. Results show how the profit only slightly depends on the variability of the potential demand, while it strongly depends on the amount of supply. It is then shown how it is possible to obtain a linear relation that maximizes the profit in function of the price offered once the supply is given.

7.1 Introduction

Carsharing users benefit from the access to a shared fleet of vehicles on a pay-per-use model. This cancels the burden of owning a car and the related cost connected to maintenance, fuel, and insurance. Carsharing vehicles are typically available for short-term rentals and paid by the minute or by the hour. Carsharing comes in different formats (Jorge and Correia, 2013; (*65*):

- Station-Based Round-Trip or Two-Way carsharing: customers can pick up a vehicle from any station, but it must be returned to the same station where the rent started.
- Station-Based One-way carsharing: customers can pick up a vehicle from any station and it can be returned to any available station.
- Free-floating carsharing: pick up and drop off can happen in a vast operation area designated by the carsharing provider without any predefined station.

One of the main features of a carsharing system is flexibility. This, together with the diffusion of mobile applications and internet helped carsharing services to become mainstream. The most straightforward use of this technology is to book vehicles on the fly. Moreover, an app allows fast payment, user-tailored experience for users and grants continuous supervision from operators together with massive opportunities for data collection and analysis (*71*). It is evident how the ability to offer a flexible interaction with vehicles is one of the features that contributed the most to the carsharing success (*72*) and, at the same time, makes daily utilization rates to soar above 10%, which is considerably higher than the average rates for private cars (*47*). The growth of this service in the frame of the sharing economy principles makes the effect of a paradigm shift towards sharing mobility clear (*96*). During the course of the last decades, the expansion of this service attracted research from a variety of fields ranging from market analysis, pricing, location and allocation strategies to travel behavior and sustainability (Degirmenci and Breitner, 2014; Perboli et al., 2018). With these services being usually managed by private actors, several studies had focused focus on how to efficiently manage the fleet and how to increase profit and revenues (Di Febbraro et al., 2012; (*10*). Great focus has been placed on carsharing operations, more specifically on carsharing relocation in one-way operations, but still, the research done so far tends to be too context-specific and therefore difficult to apply in different situations (*10*).

The increased number of operators, their expansion and competition phenomena make carsharing pricing important for business sustainability. Pricing schemes affect the spatial and journey-purpose profiles of the carsharing usage, influencing who is using carsharing, when and where (*77*). This shows how a well-conceived pricing scheme can make the difference between a successful company and a non-profitable business. Focusing on one-way systems, zone and time of day price variations have been proposed. With the goal of balancing the fleet distribution in the system a mixed integer non-linear programming model was applied in order to increase profit, showing that optimal prices are usually 23% higher than the base rate applied and, even though less demand is served, the enhanced performance of the system can boost earnings on the company side (*79*).

The relation between price, demand and supply is still not fully understood, given the high complexity of the problem due to the many interacting demand and supply state factors. Profit can depend from a multitude of variables: diverse characteristics of the demand such as its elasticity and its intrinsic features (e.g. age, income, way of living, type of trips made) (*30*), exogeneous conditions such as different policies applied in the area of service and specific incentives given to the company (*76*), supply characteristics such as fleet availability and competition (*97*), and its operational costs that depend on fleet usage and location. Therefore, coming up with a simple model to be used in profit optimization is not trivial.

In this paper, we take inspiration from dynamic pricing schemes developed in other businesses and disciplines, which have a long tradition in seeking profit maximization strategies, such as, for example, tourism management, transportation economy and logistic, airline business. Methods of dynamic price variability with revenue maximization goals have been applied in hotel management; findings suggested that a stronger price variability leads to higher revenues (*27*). Charging a distinct price for the same service is found to be one key for increasing revenues and similar behavior is also observed in airline management. Here, it is noticeable how the goal of such strategies is to exploit the heterogeneity in markets and not to make customers pay more (*98*). There are two main schemes adopted in airlines pricing: intertemporal price discrimination - to buy a product for future consumption needs - and dynamic adjustment to stochastic demand - price in function of the selling rate of a product. It is observed how the synergy of these two approaches leads to significantly higher revenues when compared to more restrictive pricing strategies (*26*). Dynamic pricing (or dynamic price discrimination) is indeed a well explored stream in the airline industry literature. It is defined as the adjustment of "prices based on the option value of future sales, which varies with time and units available" (*98*). Acquiring insights into this pricing strategy and capturing the analogies can be beneficial for carsharing operators in terms of profit maximization objectives.

Our recent works on carsharing pricing strategies suggested new ways to maximize companies' revenues. With the goal of assessing travel behavior and equity impacts, we studied two dynamic pricing strategies evaluating their impact on a carsharing company revenue. Findings show that prices based on availability help to increase revenue when compared to fixed pricing schemes (*41*). Taking advantage of one of its main peculiarities, one-way carsharing has been the target of a profit maximization strategy by means of user-based vehicle relocation. Exploiting this relocation strategy and avoiding the more conventional operator-based relocation, it was found how the operator's profit can be increased (*24*). Concerning both the two-way and one-way service, a way to optimize carsharing profits in the planning phase was addressed; the optimization of the fleet size and the vehicle allocation in each station was studied with a mixed integer linear programming model (*99*). Testing new strategies, especially brand-new strategies, could be a difficult and resource-intensive task. For example, to set up pricing experiments in a real-world setting could require substantial disruption of carsharing operations. Considering that we are looking for emerging functions for a complex system with many variables and intertwined behavioral processes the use of a simulator is a valuable asset to get insights and can produce advanced screening of operational strategies.

The question behind this paper is the following: "is it possible to identify a maximum profit functional relationship for any given combination of demand, supply and price?". To answer this research question, we created an experimental method that maximizes the profit of a company for any given usage of the supply advising the price of every booking. Considering that the state of the supply is thoroughly known by the company at any given time, the formulation of the solution is conceived to be opportunistic and adaptable at any given moment, taking advantage of the circumstances, contrary to planned strategies that cannot be easily adapted if specific events happen.

To the best of the authors' knowledge, this work helps to bridge the gap between profit maximization problems and agent-based simulation applied to a real case carsharing scenario. The method hereafter exposed can be considered applicable to any round-trip carsharing service except for what concerns the calibration phase. To showcase the results in a realistic setting, the data used in this paper is extracted from the Munich dataset of Oply, a B2C carsharing company operating with a round-trip mixed system. Oply offered a two-way service using small areas instead of punctual stations.

7.2 Methods

7.2.1 Methodology

Even though carsharing has been around for quite some time, models able to fully assess its functionalities are not yet fully developed. A conventional four-step model makes use of data that is too aggregated, not allowing researchers to assess the peculiarities of a carsharing service. That is why, to appraise round-trip carsharing, an aggregated trip-based model cannot be able to reliably assess fundamental Key Performance Indicators (KPIs) such as service availability at a precise point in space and time (*36*), users spending, activities, service profitability and usage during a typical business day. Taking into account the limited numbers of carsharing vehicles and users, a mesoscopic or microscopic simulation is possibly the most suited approach. The most popular way to apply this criterion in order to capture trends and indicators resulting from individuals' activity travel behaviors is through agent-based modeling (*100*).

Addressing a relocation problem, agent-based simulation was used for choosing the fleet size of a carsharing service in Texas. Comparisons of a calibrated simulation with actual data from Austin's car2go confirm the applicability of the simulation approach, as stated in (*101*). A similar approach was applied to estimate travel demand for carsharing through an activity-based microsimulation. A phase of validation against customer data of a Swiss carsharing company following the simulation was shown to be able to give plausible results in terms of overall carsharing usage (*102*). The simulation of innovative transport modes with agent-based models has been proven useful because of their microscopic nature. That is, regarding carsharing, the peculiarity of the services offered can be modeled in a realistic way and can capture car availability at a given location at a given time. Among the various agent-based simulation platforms, MATSim (Multi-Agent Transport Simulation), while applicable on large-scale scenarios, is capable of providing a disaggregated representation of carsharing operations and use (i.e. single vehicle and single user level (*19*)). For all the above reasons, this approach has been also used in this study.

Even though the agent-based simulators offer available in the literature is relatively vast, we selected MATSim since, up to date, it is one of the few that already allows to simulate carsharing services (*102*). Its use related to the users' activity chain and its integration with the microscopic land-use simulation system SILO (Simple Integrated Land-Use Orchestrator) (*103*) make this agent-based simulator suited to our task. MATSim simulation is based on the co-evolutionary principle, for which "every agent repeatedly optimizes its daily activity schedule while in competition for space-time slots with all other agents on the transportation infrastructure"(*19*). That is, a MATSim simulation is based on multiple iterations of the same day with the goal of reaching a user equilibrium since the optimization is based on an individual scoring function.

The methods section is structured in three main parts: the first section concerns the methodology. The first sub-section explains the setup of an agent-based simulator and the generation of the synthetic population using SILO and a microscopic travel demand model (MITO) (*104*), the second one debates on the calibration method while the third sub-section explains the maximization method. The second section is dedicated to the case study and explains how the scenario is set up, it discusses the introduction of Oply's members in the simulation and, finally, explains the framework of the two experiments that will be carried out.

Simulation setup

MATSim is an open-source software, written in the Java programming language, used to run large-scale agent-based transport simulations. The basic input files used by MATSim are the following:

Network

The *network* file is usually obtained importing OSM (Open Street Map) data into JOSM (Java Open Street Map). This time, however, since we used SILO and MITO in order to generate the synthetic population that best suits our needs, we use the Munich network available in the SILO repository.

CSStations

A *CSStations* file consists of a list of all the stations and the vehicles available at the beginning of the simulation day. In our case, the station and vehicle distribution used by the company was employed. Oply introduces a slight modification of the round-trip system: it does not have a well-defined landmarked carsharing stations, but the customers are required to return the vehicle back to the zone, or a neighborhood, where the rent started. These areas were imported in QGIS and then converted into a MATSim-readable file where vehicles for every virtual station were introduced. A virtual station, hereafter defined as station, is a centroid representing a carsharing parking zone.

Synthetic Population Generation

As an agent-based simulator, one of the MATSim fundamental inputs is the synthetic population of agents that will move in our simulated network accomplishing tasks as written in their activity chain file (i.e., *plans*). To generate this file, we made use of SILO and MITO. SILO produces and updates the synthetic population for the study area, i.e. the city of Munich in Germany, using geographical data available from micro census and travel times applying an iterative proportional updating algorithm. The travel demand model MITO, using the synthetic persons generated in the previous phase by SILO, distributes all trips returning the plans file needed in MATSim. Using this approach and starting from the German census data of 2011, we obtained the population updated to the 2020 ready to be run on MATSim. The information regarding the households for the German population are available at the 2011 Household Census (*21*). The census takes place every 10 years.

Simulation Calibration

Table 1. Notation

α_{cs}	Calibration parameter
$\beta_{(c,cs)}$	Marginal utility of money
p	Price of one hour of reservation
t_r, T_r	Reservation time
pd	Price of one kilometre travelled
d	Total reservation distance
$\beta_{t,walk}$	Marginal utility of walking
t_a	Access time
t_e	Egress time
$\beta_{t,cs}$	Marginal utility of traveling with carsharing
t	In vehicle time
r,R	Revenue
D	Demand
S	Supply

Once obtained the pool of members, we passed to a calibration phase in order to make the base scenario of the simulation match Oply's performance for a given typical day. The two indicators that we needed to match in order to calibrate our simulation were: number of bookings and daily revenue. The value of these two indicators is obtained averaging them over a fortnight service. The procedure chosen to carry out the calibration is an iterative bilevel calibration approach. Using a quadratic regression two constants are iteratively estimated to match the number of bookings and the daily revenue.

Booking Time

An average weekday of operations in Munich could reach an amount of around 130 bookings resulting in a total time of 508.5 hours (1 828 980). In MATSim, a booking is a function of many variables. First of all, all agents, including carsharing members, don't have carsharing as their predefined transportation mode. During every iteration a specific "random trip to carsharing" module assigns, with a probability of 20%, the carsharing mode to a member. At the end of the iteration, the scoring is calculated and, if it is higher than the score obtained in the previous or next iteration, the modal choice is kept. The scoring of traveling with the carsharing mode is described in Equation 1, where α_{cs} is a constant which can be used as a calibration parameter. The description of all the other parameters is in Table 1, directly taken from the MATSim manual (*19*). The second and third terms refer to the time-dependent and the distance-dependent parts of the fee, respectively. The fourth term considers the walking path to and from the station. The latter represents the marginal utility of an additional unit of time spent traveling with the carsharing service.

$$S_{trav,q,cs} = \alpha_{cs} + \beta_{c,cs} * p_t * t_r + \beta_{c,cs} * p_d * d + \beta_{t,walk} * (t_a + t_e) + \beta_{t,cs} * t \quad (1)$$

The number of bookings is dependent on the score, that is why the Carsharing Constant (CsC) α_{cs} is used as a calibration parameter.

Daily Revenue

An average weekday of operations in Munich brings a revenue of 3500 €. The revenue is directly dependent on the booking time given that the service price is offered as euro per unit of time. Also, the time a vehicle is booked, depends on the utility (i.e., the score) an agent gets using the carsharing service which depends, in turn, on the CsC. That describes in what measure the cost of the carsharing impacts the users and, indirectly, modifies the final revenue.

1st Calibration Process

Here we propose a first approach for calibrating the agent-based simulator. The two variables that we needed to match in order to calibrate our simulation were: number of bookings and daily revenue. The value of these two indicators is obtained averaging them over a fortnight service. The procedure chosen to carry out the calibration is an iterative bilevel calibration. Using a quadratic regression two constants are iteratively estimated to match the number of bookings and the daily revenue.

The calibration process consists of an iterative procedure in which five simulations are run in parallel fixing one constant per time. For the first calibration round 5 ascending values of the CsC were chosen while the MUoM was fixed at 1. Since *Bookings = f(CsC)*, using a quadratic regression to fit the points we found the fitting line that gives us the equation to find the first CsC. We used this new constant to carry out the same procedure and to find the MUoM.

In Figure 1 we show the gradient bringing to the CsC that allows the simulation to produce 130 bookings.

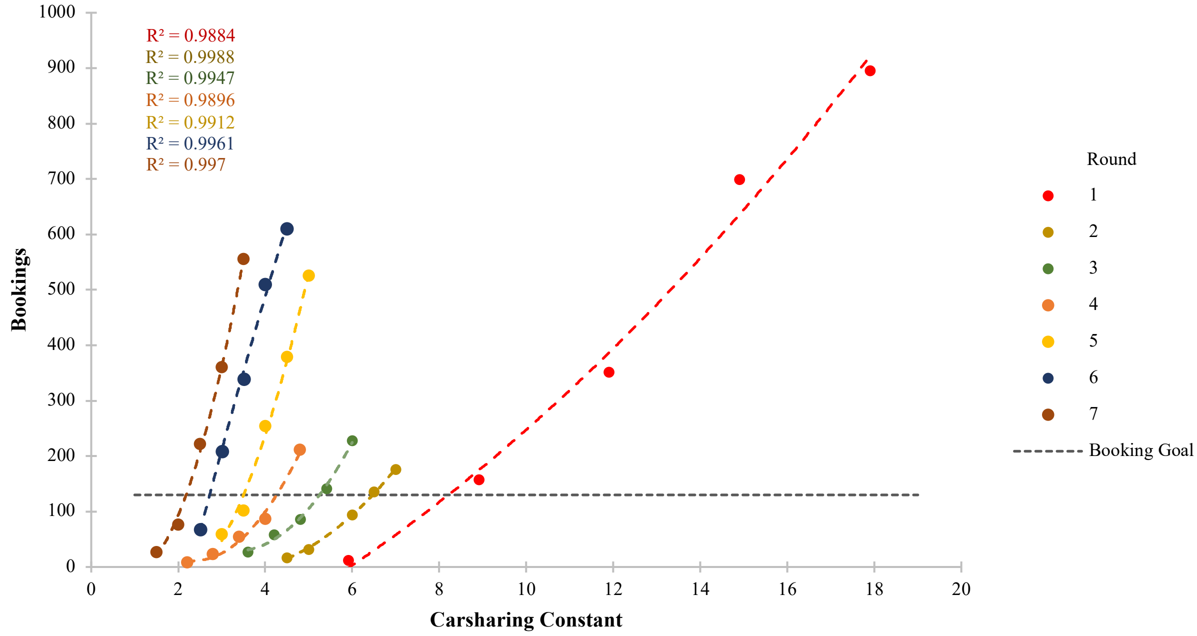

Figure 1 Calibration of the Carsharing Constant

Using the same procedure used to infer CsC, since *Revenue = f(MUoM)*, using a quadratic regression to fit the points we found the fitting line that gives us the equation to find the first MUoM.

In Figure 2 we show the gradient bringing to the MUoM that allows the simulation to generate a revenue of 3500€.

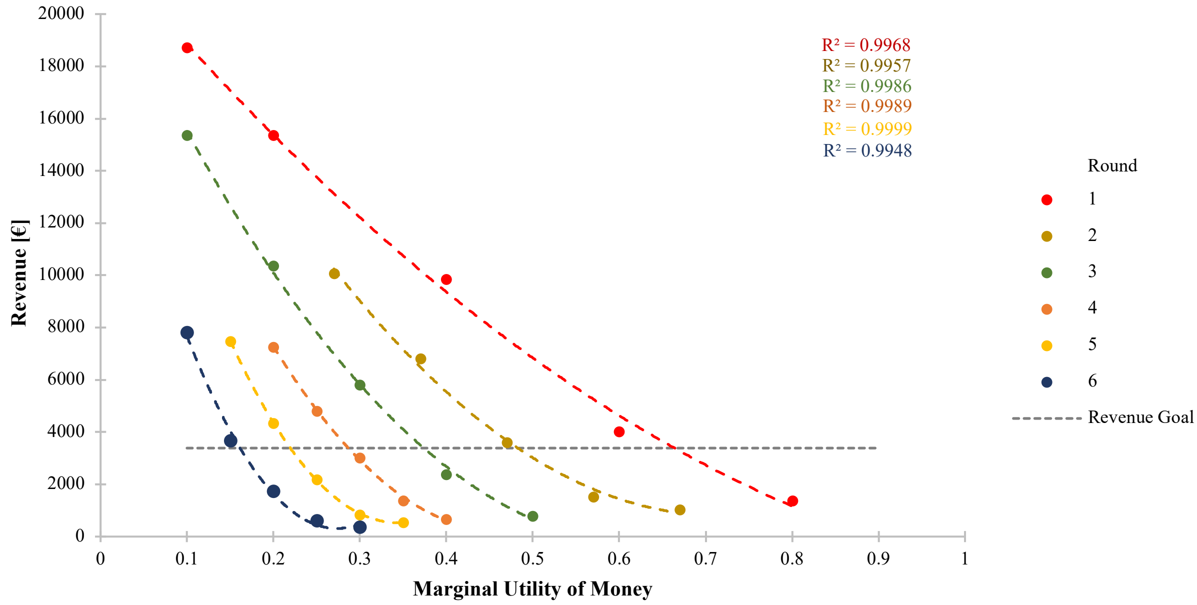

Figure 2 Calibration of the Marginal Utility of Money

We repeated the iteration process four times, that is until a new round of simulations returns nearly the same constant.

This approach has just been shown to be slow and suboptimal. First of all, it relies on the number of bookings and not on their duration, making the final calibration value inaccurate and, since the output values of the previous phase are used as input values of the next phase, this leads to a dilation of the calibration times. To speed up this phase, we propose a new calibration method below.

2nd Calibration Process

The calibration process consists in a procedure in which five simulations are run in parallel with different value of the CsC. The process behind the calibration presented in this paper takes its roots from simulation-based optimization (*106*) used to solve large-scale dynamic traffic assignment.

The goal of the calibration is to find a CsC that generates a revenue and a total booking time similar to the one observed during Oply's daily operations.

The first step consists in running five simulations with a different set of CsC and retrieve their relative booking times and revenues (Table 2).

Table 2. CsC calibration phase one

Simulation	α_{cs}	Revenue [€]	Booking Time [s]
1	5.0	25.93	11 972
2	7.0	230.71	102 117
3	9.0	1 193.25	498 955
4	11.0	2 063.02	887 936
5	13.0	4 396.72	2 035 090

We plot these points as shown in Figure 3.

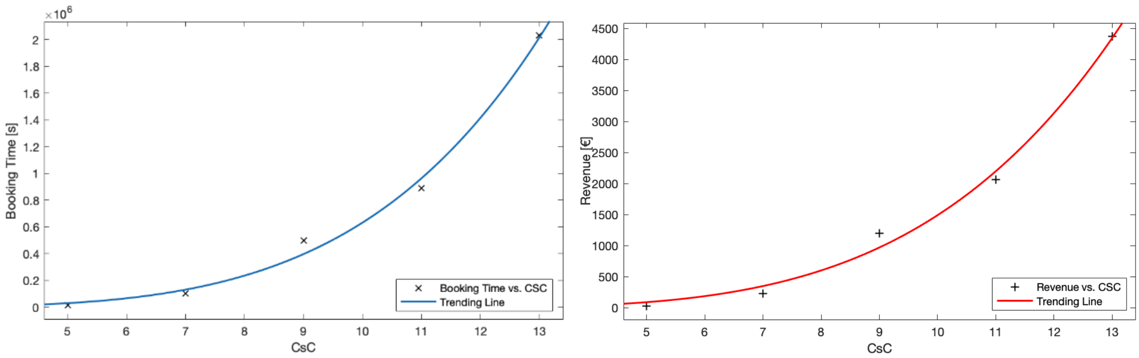

Figure 3. a) Booking Time vs CsC plot; b) Revenue vs CsC plot

We fit the point with two power trend lines described by Equation 2 and Equation 3.

$$\hat{t}_r = 23.85 * \alpha_{cs}{}^{4.423} \tag{2}$$

$$\hat{r} = 0.1249 * \alpha_{cs}{}^{4.0.77} \tag{3}$$

In order to find the values of booking time and the revenue we are looking for, we measure the root-mean square error (RMSE) between the two equations above and the observed valued T_r and R (respectively 508 hours and 3 412 €) in order to obtain Equation 4.

$$\hat{z} = \frac{(\hat{t}_r - T_r)^2 + (\hat{r} - R)^2}{2} \tag{4}$$

Applying a minimization method, we are able to find the α_{cs} that minimizes $\hat{z}$ (Figure 4). When α_{cs} = 12.7 $\hat{z}$ is at its minimum.

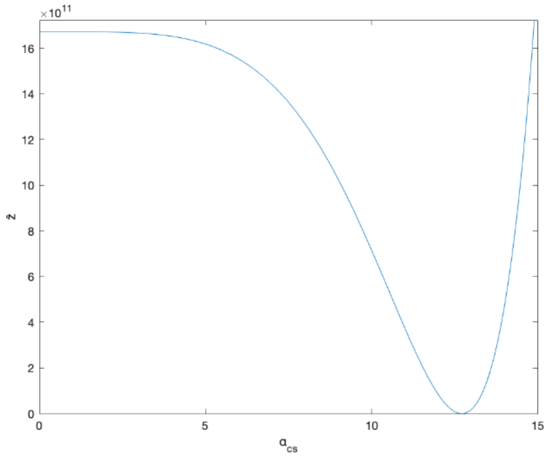

Figure 4. $\hat{z}$ function

We therefore use α_{cs} as the new CsC for the next simulations.

Profit Maximization

In carsharing operations, we can calculate the profit (*P*) as the difference between the revenue generated renting the vehicles and all the fixed and variable costs (*c*) sustained by the company. Revenue (*R*) is the gross income generated from the business operations and, in our case, it can be a function of:

- Demand (*D*), the number of members that will realize a booking.
- Supply (*S*), the number of hours we are able to sell to our customer base.
- Price (*p*), the cost of renting a vehicle by unit of time.

It is clear that, once the supply is fixed and the demand is known, different prices will lead to a different revenue that, once the fixed and the variable costs are known, will return a profit curve where *P=f(D,p).* The same can be said if the demand is considered fixed and the supply varies, once the fixed and the variable costs are known we can obtain a profit curve where *P=f(S,p).* The two types of costs (obtained from Oply) considered are:

- Variable costs linked to the utilization of one vehicle, including maintenance, fuel, wear of the vehicle estimated with an amount of 1.5€/h.
- Fixed costs for one vehicle, including insurance and leasing costs, estimated with an amount of 3€/day.

Following the research question stated in the introduction, we created an experimental method in order to calculate the two afore-mentioned functions.

7.2.2 Case Study

Scenario Setup

In Figure 5 we show the network and the distribution of the stations. The actual offer from Oply consists of 186 vehicles (4464 equivalent rental hours) distributed along 79 stations.

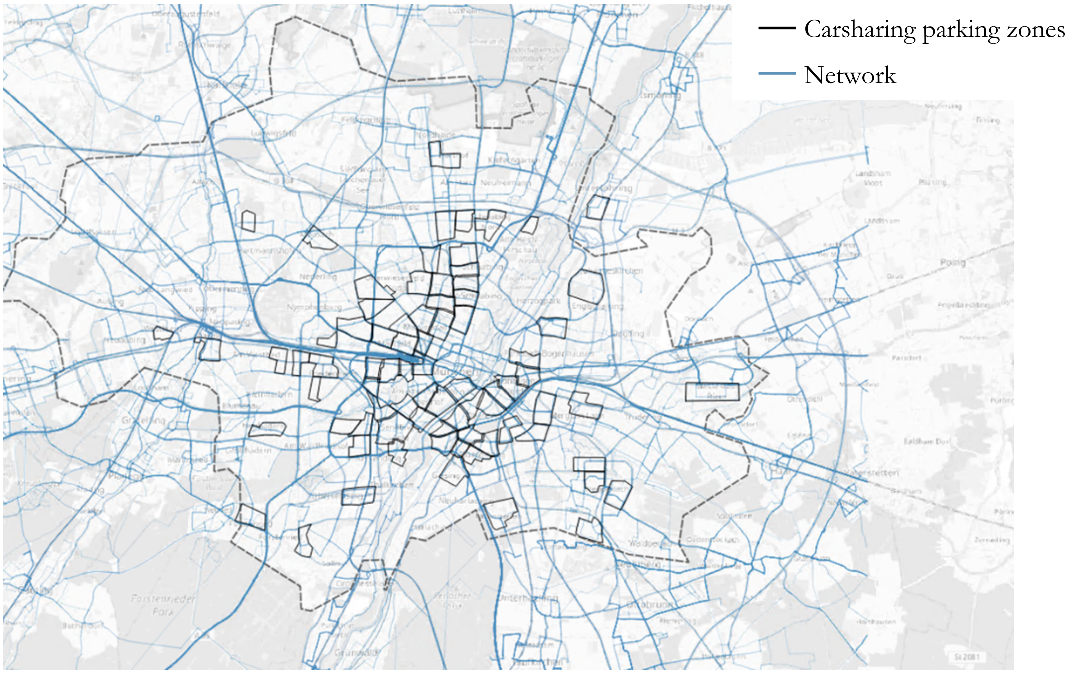

Figure 5. Network and Carsharing Stations

Regarding the population, we have generated the equivalent of the adult population of Munich, roughly 1385000 citizens. It is computationally challenging to simulate this number of agents, running a MATSim simulation on eight Xeon E5-2680v4 at 2.4GHz with 40 GB of RAM took almost 25 days. Considering that the scope of this paper is to assess indicators exclusively related to carsharing, we opted to simulate only the carsharing population, 14747 people, that is, the agents who are members of Oply. This assumption is considered reasonable given the goal already stated. Results may be limited since the use of a population smaller than the actual population of Munich will not generate any congestion at all. To fix that, we need to scale down the capacity of the network. To do so, we set the parameters "flowCapacityFactor" and "storageCapacityFactor" (*19*) in the configuration file to 0.011.

Oply's Members

Oply was a carsharing company operating in some major German and British cities until February 2020. Using the anonymized information of their members database we treated this data to fit the scope of our simulation. Using QGIS, a free and open-source geographic information system (GIS) (*107*), we imported the agents obtained in the previous sub-section. After that, we cropped down our population to the one living inside the Munich border. Once our synthetic population was prepared, we imported all Oply members into our geographic platform. In order to be able to simulate a typical day with MATSim we needed to infer the activity chain of these members and, moreover, we needed to make this activity chain readable by MATSim. To do this we proceeded to apply an Iterative Linking Algorithm (ILA) (Figure 6) based on the Euclidean distance within an agent created in the previous sub-section and Oply's members. The ILA allocates one agent (drawn from the whole population set) properties to the closest member and, once done so, it deletes the agent leaving only the member with all the desired attributes.

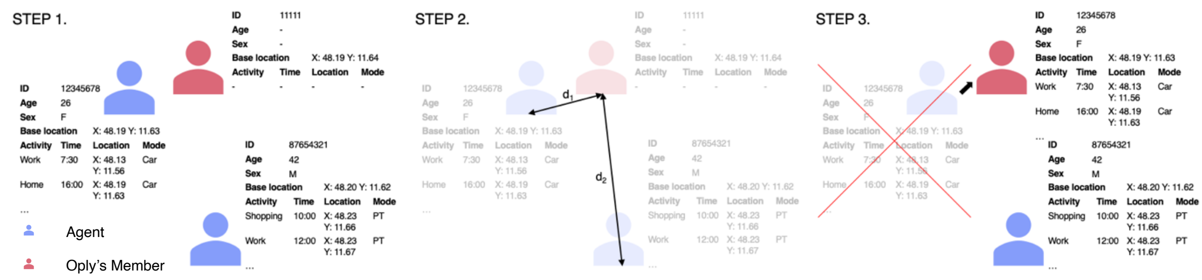

Figure 6. Example of the Iterative Linking Algorithm

This instance is repeated until all the members are embedded into the synthetic population of Munich (Figure 7).

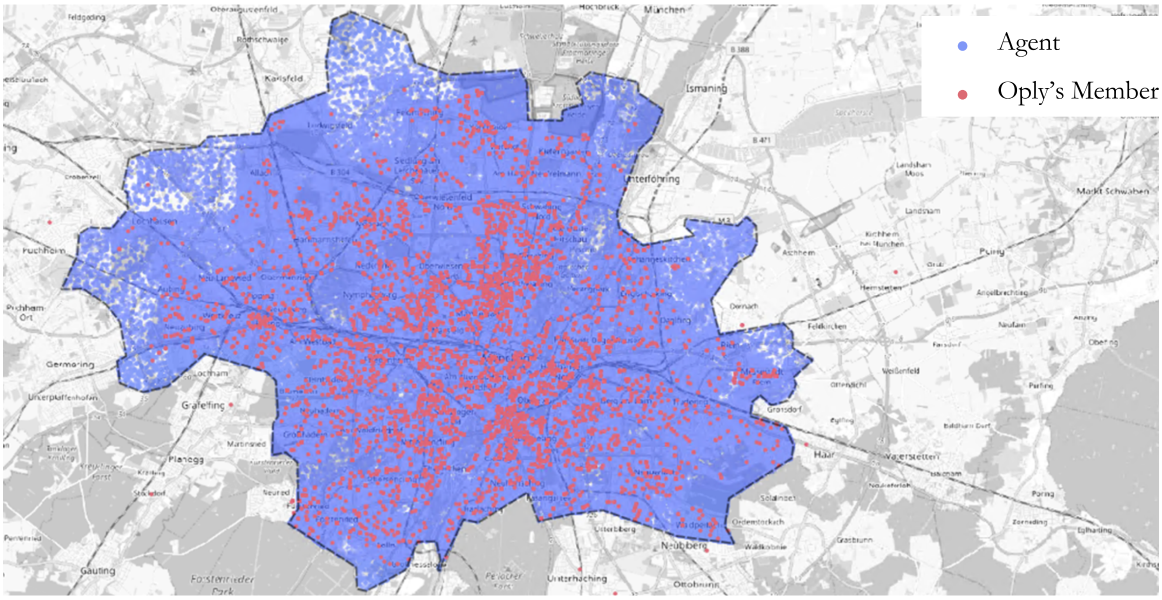

Figure 7. Distribution of the synthetic population and Oply's members

Fixing the Supply

In this experiment set the supply is fixed for an equivalent offer of 4464 rental hours (the actual offer from Oply). In order to vary the quantity of booked hours, which is an output of the simulation, we can change the number of members creating five different inputs (Table 3).

Table 3. Scenarios Definition for Demand Variation

Scenario Code	Number of Members	Difference from the original pool
×	11946	20% fewer
●	13273	10% fewer
■	14747	Original pool
▲	16221	10% more
◆	17843	20% more

Furthermore, we introduce ten different prices (Table 4).

Table 4. Price

Price [€/h]	Price [€/min]	Note
3	0.05	
4.2	0.07	
5.4	0.09	
6	0.1	Original Oply's pricing
6.6	0.11	
7.8	0.13	
9	0.15	
10.2	0.17	
11.4	0.19	
12	0.2	

The set of prices is conceived around Oply's pricing model. Currently, Oply offers a base price of 6€/h and unlimited mileage. Combining these inputs we obtain 50 simulations that we run in parallel on a High Performance Computing Platform (HPC) (*99*) using 4 cores and 40GB for each instance.

Fixing the Demand

Keeping the same prices, we set up another experiment in which we fixed the demand of 14747 members while changing the supply (Table 5).

Table 5. Scenario Definition for Supply Variation

Scenario Code	Supply [h]	Supply [car]	Difference from the original supply
×	936	39	80% fewer
●	2568	107	42% fewer
■	4464	186	Original supply
▲	6432	268	46% more
◆	8328	347	82% more

Combining these inputs with the 10 pricing values shown in Table 2, we obtain 50 simulations run in parallel on the HPC using the same above-mentioned computing power.

7.3 Results

The average computational time for every simulation is of 32 hours. Once the results are obtained, they are processed with MATLAB and gathered in a spreadsheet.

7.3.1 Fixing the Supply

Once the supply has been fixed and the number of members is varied according to Table 3, we evaluate the revenue and the profit reached for every set of simulations (Figure 8).

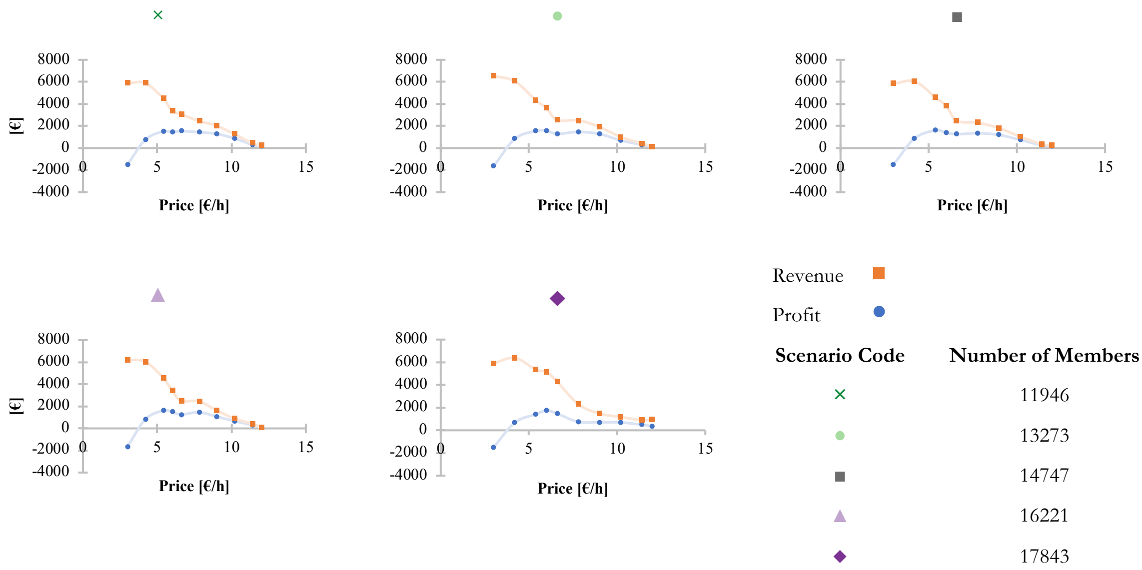

Figure 8. Revenue and Profit by Potential Demand Variation

It is noticeable how the shape of the profit function is not significantly affected by the variation of the potential demand. All the maximum points are always around 2000€. This result is reasonable and possibly caused by the fact that the demand is not varying significantly even though the range considered, especially the 3000 members of difference between the actual and the highest increment in number of members cannot be considered modest. Of course, this result is also related to the equilibrium reached with the available supply and, even though few more vehicles are rented, the marginal profit does not vary significantly as the additional demand is not compensating the increase in operational costs.

In order to further assess the trend of the profit once the number of members varies, we show in Figure 9 the profit curve in function of the potential demand and the price offered.

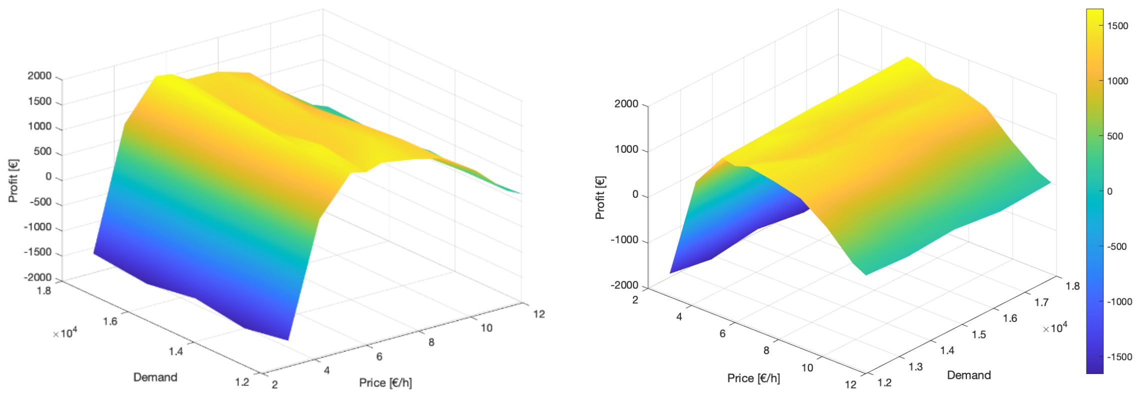

Figure 9. Dual perspective of profit as a function of the potential demand and price variation

The maximum profit is always reached when the price is between the 5.4€/h and the 6€/h. Anyway, for what concerns the profile of the surface, the profit slightly depends on the swing of the potential demand. The peak in the middle of the crest makes it clear that there is not a monotonic correlation, this makes it difficult to formalize a function that describes the relation between the two variables.

In Figure 10 we display the elasticity of the demand and how the amount of booking time (i.e., the total hours for which the fleet is booked) is not affected by the different quantities of members.

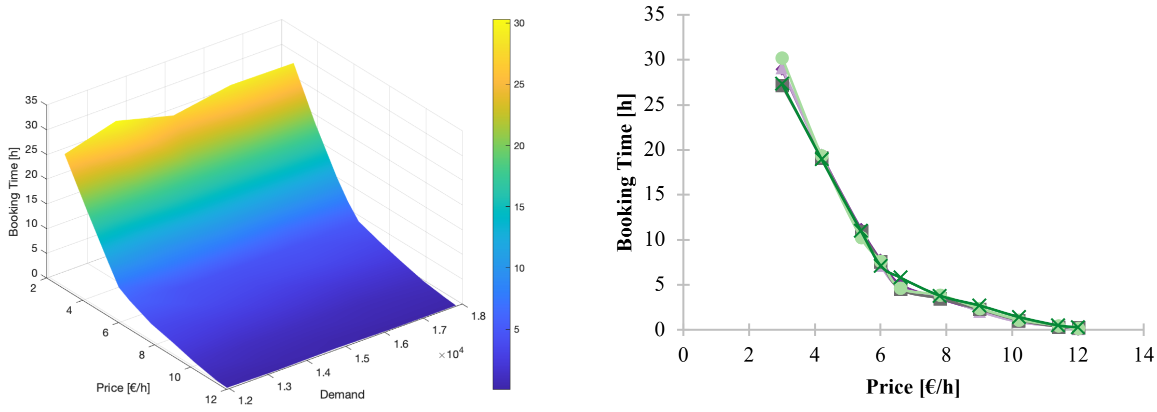

Figure 10 Demand elasticity

This specific shape of Figure 10 it's plausibly a result of the method used to create more demand. The members generated to increase Oply's customer base are randomly spawned in the Munich area and linked to the closest agent following the procedure shown in paragraph 2.3.

7.3.2 Fixing the Demand

Once the number of members is fixed and the supply is varied according to Table 2, we assess the revenue and the profit generated for every set of simulations (Figure 11).

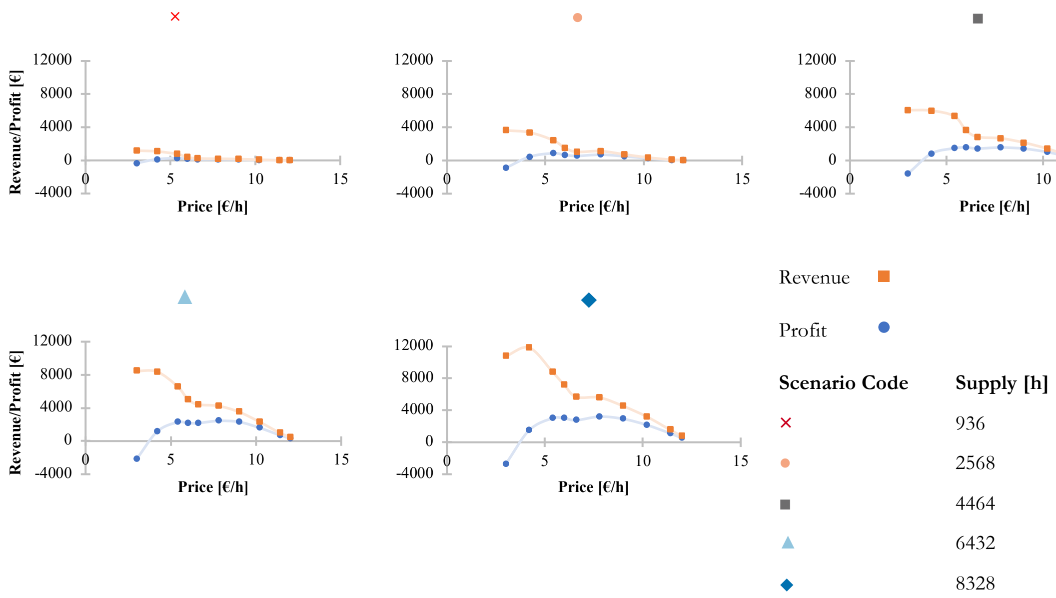

Figure 11. Revenue and profit by supply variation

Looking at how the dimension of the x-axis changes it is clear how the profit is strongly affected by the change of the supply. Scaling up the supply generates an increment of the revenue, this hints to a stronger relationship between these two variables compared to the one shown in the previous paragraph. In Figure 12 we show the profit curve in function of the supply and the price offered.

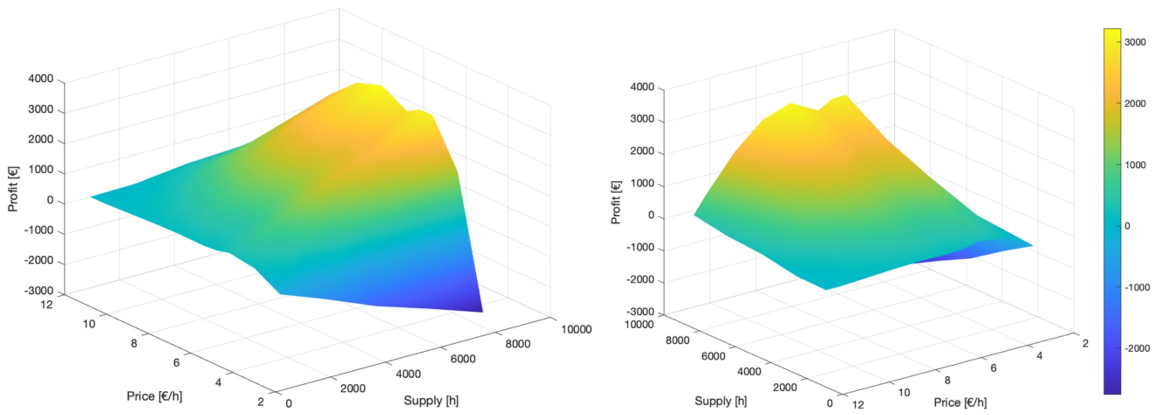

Figure 12. Profit in function of supply and price variation

The maximum profit is always reached when the price is between 5.4€/h and 7.8€/h. In this case, concerning the profile of the surface, the profit has a stronger dependence on the amount of supply offered and it doesn't change only in function of the price. Given the monotonic shape of the crest we assess the relation between the two variables (supply and profit) in a bidimensional space (Figure 13).

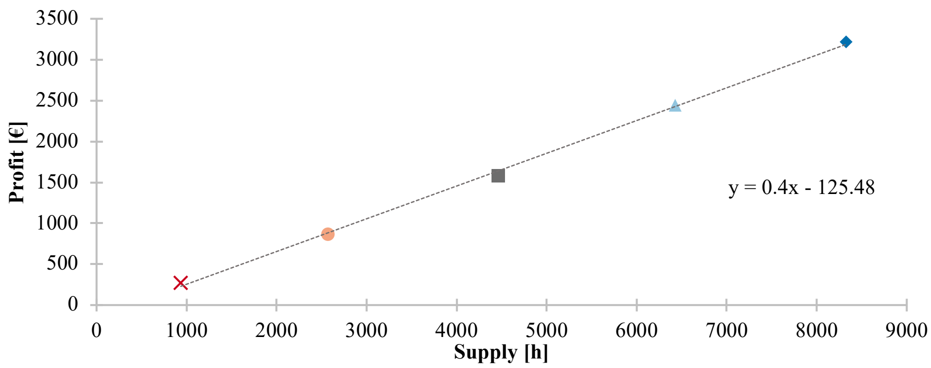

Figure 13. Linear regression of the profit in function of the supply

By performing a simple linear regression, it is possible to model the relationship between the dependent variable, the profit, and the explanatory variable, the supply. This model shows how every hour of supply offered generates a profit of 0.40 €. However, the prices that are generated by this line are various as shown in Figure 12. That is why, to show how the unitary profit changes throughout all the stages of the supply we show the maximum profit divided by the total number of hours supplied (Figure 14).

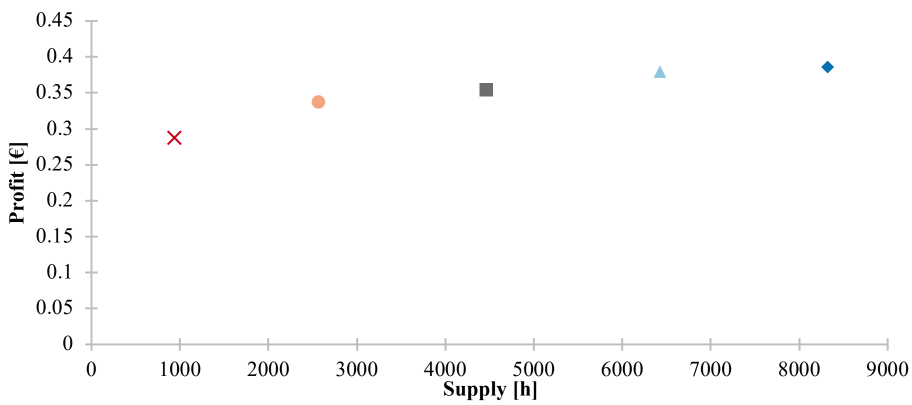

Figure 14. Profit gained for one hour of service offered

The trend of the marginal profit shown in Figure 14 is less than linear. An explanation of this behavior can be found in the overall usage rate. The usage rate (Figure 15), which is obtained as the ratio between the total number of hours booked when the profit is the highest and the number of hours supplied in the same simulation.

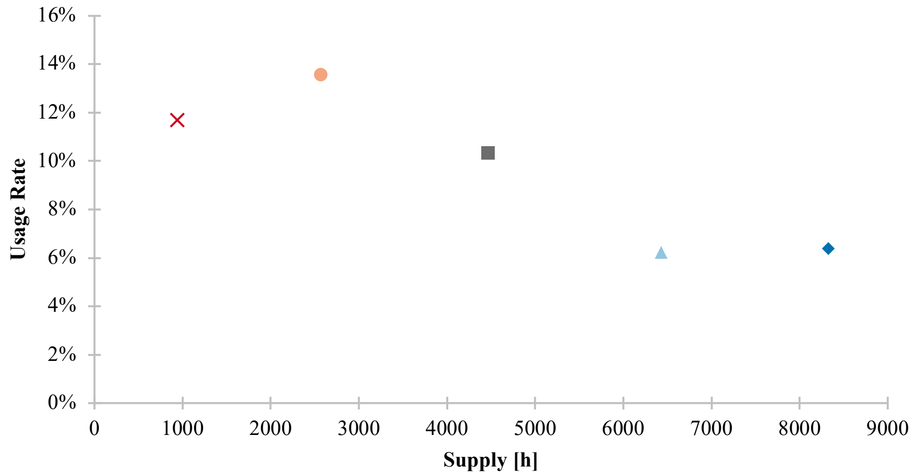

Figure 15 Usage rate

The decrease in the overall usage rate explains the less than linear growth of the marginal profit. Along with the increment of the supply and profit, the demand intercepted by the service moves towards an inelastic state, the usage drops since only people that must travel with the carsharing will use the service.

In Figure 16 we display the elasticity of the demand once the supply varies. The three-dimensional graph in Figure 16 left, displays the elasticity of the demand in a continuous fashion while the right figure shows its projection on the price-booking time plan. The five functions can be considered homothetic with the elasticity of the demand decreasing together with the supply: a lower supply intercepts an inelastic demand while a higher amount of supply induces a strong elastic demand intercepted for a price lower than 8€/h and a less elastic demand intercepted for a price higher than that.

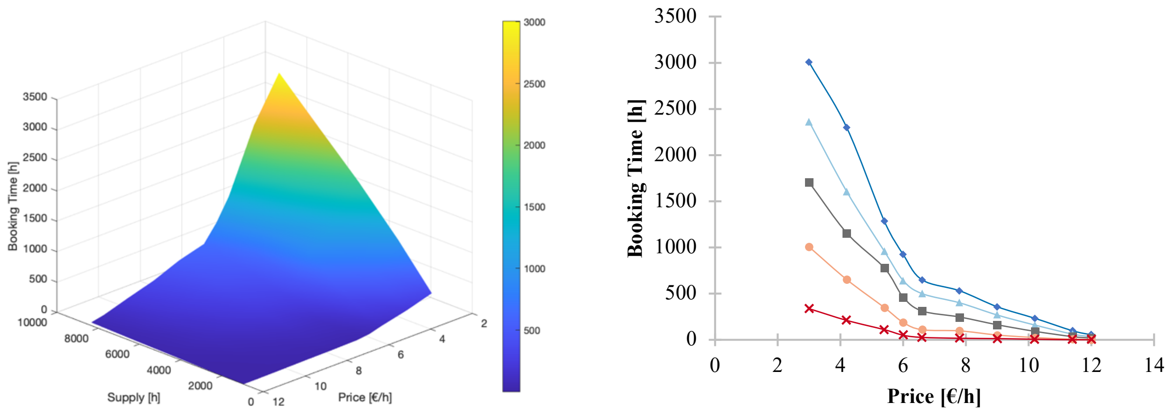

Figure 16. Demand elasticity

Being the profit function of both the supply and the price offered, we fit the data shown in Figure 13 as a three-dimensional surface (Figure 17).

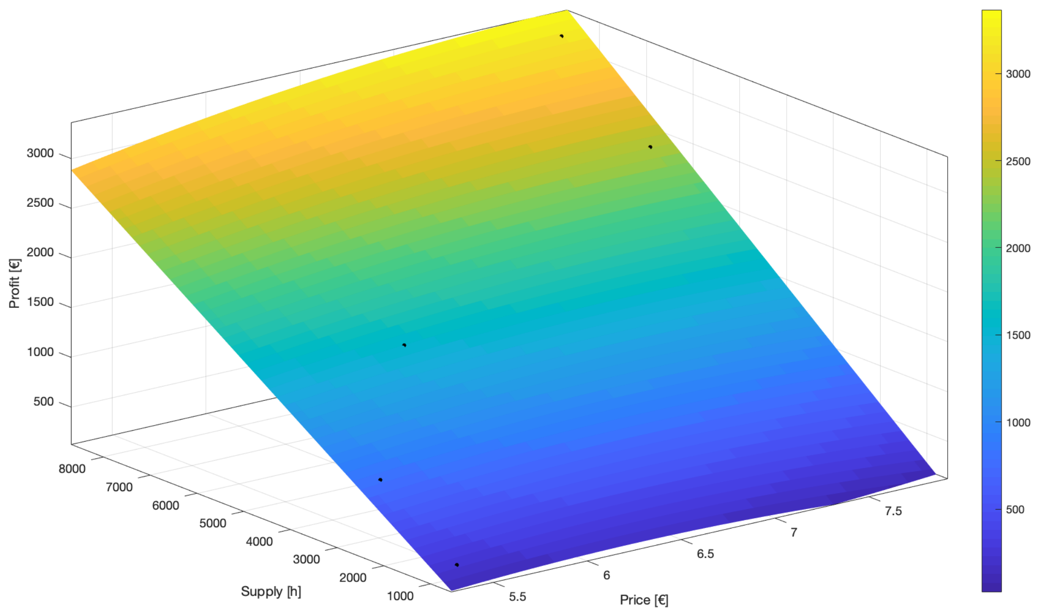

Figure 17. Three-dimensional plane of Profit - Supply - Price

Once the points of maximum profit are connected using a polynomial fitting function, we obtained a concave surface. With the use of this figure, it is possible to define the highest profit reachable for any given price once the supply is given. Through a quadratic interpolation we define the model in Equation 5.

$$P(p, S) = -60.29\, p^2 + 739.9\, p - 2287 + S\,(0.027\, p + 0.194) \tag{5}$$

where P is the *profit*, p is the *price* proposed per hour of service and S is the *supply* expressed in number of hours. Once the supply that can be offered is known, given the concave shape of the surface, it is possible to define the price solving the Equation 5 as an optimization problem as shown in Equation 6.

$$\begin{gathered} \max P(p) \\ 3 \leq p \leq 12\ [€/h] \end{gathered} \tag{6}$$

Since S is known at the moment of the booking, we treated it as an "undefined constant" in order to identify the line of maximum profit. We evaluate all the points where the derivative is equal to zero.

We calculate the first derivative which is set to zero in order to obtain the line of maximum profit as shown in Equation 7.

$$\frac{dP}{dp} = -120.52p + 0.027S + 739.9 = 0 \tag{7}$$

In Equation 8 we obtained the maximum profit line obtained and in Figure 18 it is shown its relative graphical form for the intervals *5.4≤p ≤7.8[€/h]* and *1000 ≤S ≤8000 [h]*.

$$p = \frac{0.027S + 739.9}{120.52} = 0.00022S + 6.13 \tag{8}$$

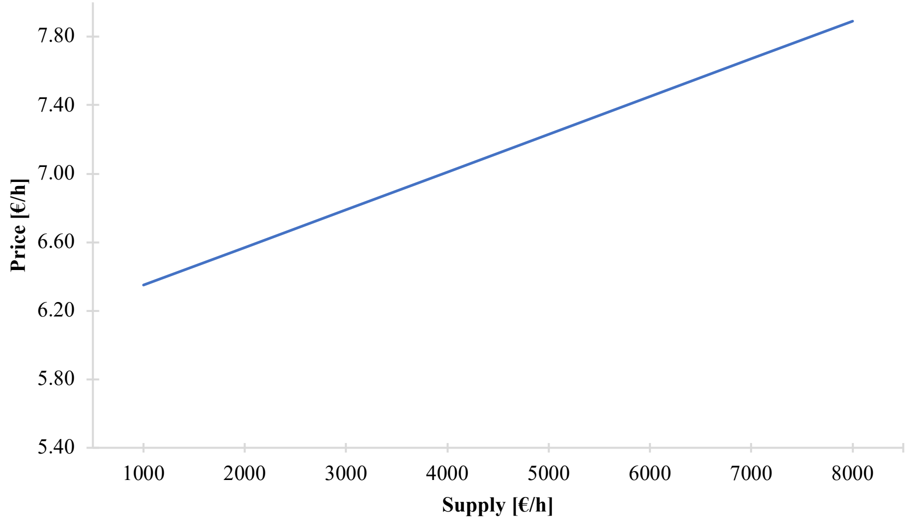

Figure 18. Line of maximum profit

The functional form here proposed links a state of the supply to a specific price. Given the specificity of the application, the equation is valid only for the scanned region of supply comprise between 1000 and 8000 hours. The result can be applied by a carsharing company in two different ways:

- Every time a vehicle is requested, the company scans its fleet, retrieves the number of hours that can be offered and offer the price that leads to the maximum profit.
- Know-how and how much the price should change if new vehicles are introduced or removed from their fleet.

7.4 Discussion

The results of this paper suggest that enlarging the supply leads to higher profit but, at the same time, the marginal profit gets smaller. The highest possible profit is reached when the system is able to capture the part of the demand that is more elastic, that is, more sensitive to vehicles' availability.

Results shows that, when the supply (i.e., the number of hours supplied) is fixed and the number of members of the carsharing service varies, the profit variable is not sensitive to changes in potential demand; the change in profit is mainly lead by the pricing offer. One possible way to interpret this is that, given the daily schedule of the agents, it is not possible to find vehicles available at the right time for the additional members. In other words, it would be possible to have more demand if the potential demand (the additional members) had schedules compatible (without overlapping) with those already using carsharing. The finding potentially has important implications for an operator. Once the operator should find itself on the desired point of the marginal profit curve, it should not invest too much (or even at all) in trying to attract other customers as it would not increase the usage rate of the vehicles and then of the profit. Instead, it would potentially generate unsatisfied customers. It should be noted, though, that this possibly, at least partly, the result of the method used to create more demand. In the scenarios with additional Oply members, they are randomly generated, picking from the synthetic population. As a result, although the method per se keeps being valid, in order to completely trust the results, the mechanism through which additional agents become members should be properly modeled instead of using a random draw.

When the potential demand is fixed and the supply varies, results show that the obtained profit is linearly dependent on the supply while depending on the price in a parabolic fashion. Another important observation is also that one will expect a deterioration of profit at some point if they keep adding cars with fixed demand. Although the image in Figure 12 seems to contradict this, it should be noted that in that figure the ascending part of a curve that later descents is represented.

One may argue that the functional form chosen leads to prices that, if offered to real carsharing customers, could generate confusion. To avoid this problem and offer a more user-friendly price, a round off could help simplifying operations and the customers' understanding of the service. The calibration here proposed is made on Oply carsharing operation. In order to apply this methodology to a different company and to maximize their profit, a possible tabled solution could be tailored.

The solution to reach the maximum profit here proposed employs a functional link between the three main variables: profit, supply and price. This results in a price that can change dynamically during the day, it is defined when a vehicle is booked, and it is function on the number of vehicles available at the moment of the booking. The way this price is determined is by checking the state of the supply (known by the operator) - that is the number of hours that the operator can offer - and to set the price in order to reach the maximum profit for that pair. Either way, even though the robustness of this function should be further assessed before its eventual application in business operations, is interesting to know that such number exist and that we can calculate it, if we can measure all the other values empirically

7.5 Conclusions

The idea behind this paper is that modeling the profit as function of the price and the demand $P = f(p,D)$ and as function of price and supply $P = f(p,S)$, it is possible to identify a maximum profit for a specific price p, demand D and supply S. A novel calibration method for carsharing use in the agent-based simulator MATSim has been proposed. This method employs data fetched from the carsharing operator Oply in order to define a main constant used for the evaluation of the number of bookings and the cost of the trip, respectively CsC (carsharing constant).

The function in Figure 18 has been calculated on the whole city, therefore, a lot of attributes are naturally embedded in it such as, density of the members around the station, proximity with other stations, modal offer in the surrounding area, etc. Questions that easily follow are how much these attributes affect the price or if focusing on one station can return different prices. Answering these questions is out of the scope of this paper but, future research will provide an application of the same process on singular station. Future contribution will focus to another feature of this procedure: reproducibility. While it is clear that this paper focuses on a particular case study, in a specific city and on a precise carsharing company, it is true however that the same procedure can be applied, with similar results, on other case studies. As described in the methodology section, the input needed are the potential demand (i.e., the number of members of the carsharing service) and the supply (i.e., the number of cars that make up the fleet).

Other future work can focus in a more punctual calibration taking into account not only the actual bookings in one specific station, but even other attributes such as, members density, modal offer, accessibility, etc. This method can bring a more precise maximization function that considers the station attractivity as independent from the others allowing for a punctual pricing strategy.

From an operational point of view, future works can take into account the diversity of the offer considering different composition of the fleet (i.e., different vehicle models) and possibly different kind of features such as specific on-board service, different cancellation policies, number of vehicles in a specific area or station. Furthermore, one issue that can be seen in offering this kind of dynamic pricing is that the client is not able to know the price until a rental request is made and that this type of pricing is suited only for spontaneous bookings. Planned bookings (usually made hours or days before the start of the rental) cannot be supplied with this kind of approach. To fix that, future research can focus on specific hybrid dynamic pricing based on supply availability and time of the day in order to maximize profit.

7.6 Appendix A

The price function shown in Figure 18 and described by Equation 8 is valid for the whole city of Munich but hardly interprets the differences among the stations (e.g., location, accessibility, number of vehicles, …) and the areas (e.g., population density, demographic, …). Overall, Equation 8 aggregates and averages all the different prices function that could be proposed at a station level. To show that it is possible to find a similar functional form at the station level we carried out the calibration and the modeling of 2 randomly drawn stations (Table A1). These two stations are located one in the center, in a high-density area and another one in a low-density neighborhood (Figure A1).

Table A1. Stations Characteristics

Station ID	Supply [h]	Revenue [€]	Within 800 meters radius	
			Members	Density [members/Km^2]
1209635	144	110	817	408
1212165	48	54	120	60

Figure A1. Stations Location

7.6.1 Station 1209635

Calibration

As shown in the paper we proceed to the calibration phase (Table A2).

Table A2. CsC calibration phase one

Simulation	α_{cs}	Revenue [€]	Booking Time [s]
1	11.0	6	2441
2	12.0	6	3332
3	13.0	36	18137
4	14.0	84.19	40563
5	15.0	108	52145

We plot these points as shown in Figure A2.

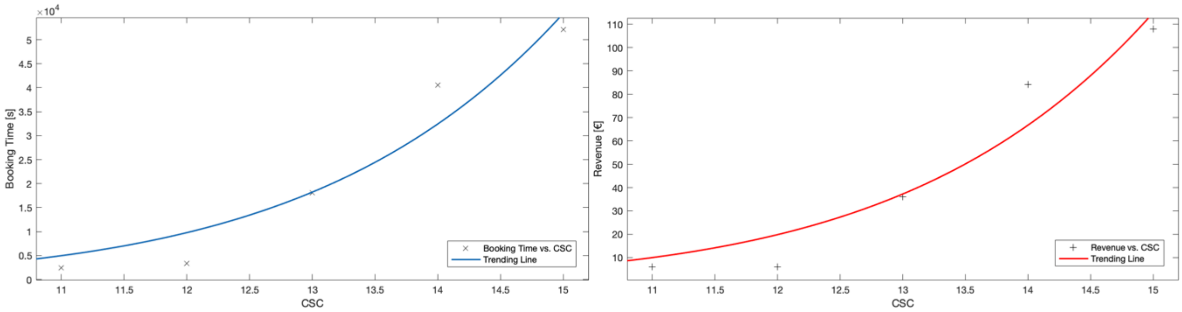

Figure A2. a) Booking Time vs CsC plot; b) Revenue vs CsC plot

We fit the point with two power trend lines described by Equation A1 and Equation A2.

$$\hat{t}_r = 3.904 * 10^{-5} * \alpha_{cs}{}^{7.782} \tag{A1}$$

$$\hat{r} = 6.277 * 10^{-8} * \alpha_{cs}{}^{7.786} \tag{A2}$$

In order to find the values of booking time and the revenue we are looking for, we measure the root-mean square error (RMSE) between the two equations above and the observed valued T_r and R (respectively 17 hours and 110 €) in order to obtain Equation A3.

$$\hat{z} = \frac{(\hat{t}_r - T_r)^2 + (\hat{r} - R)^2}{2} \tag{A3}$$

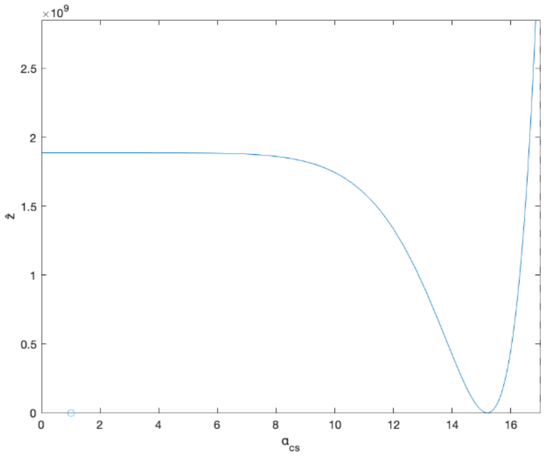

Figure A3. $\hat{z}$ function

Applying a minimization method, we are able to find the α_{cs} that minimizes $\hat{z}$. When $\alpha_{cs} = 15.19$ $\hat{z}$ is at its minimum (Figure A3).

Results

Keeping the same prices, we set up the experiment (Table A3).

Table A3. Scenario Definition for Supply Variation

Scenario Code	Supply [h]	Supply [car]
×	48	2
●	72	3
■	96	4
▲	120	5
◆	144	6

Combining these inputs with the 10 pricings values shown in Table 4, we obtain 50 simulations run in parallel on an HPC using 4 cores and 20GB of RAM for each instance.

Once the number of members is fixed and the supply is changed according to Table A3, we assess the revenue and the profit generated for every set of simulations (Figure A4).

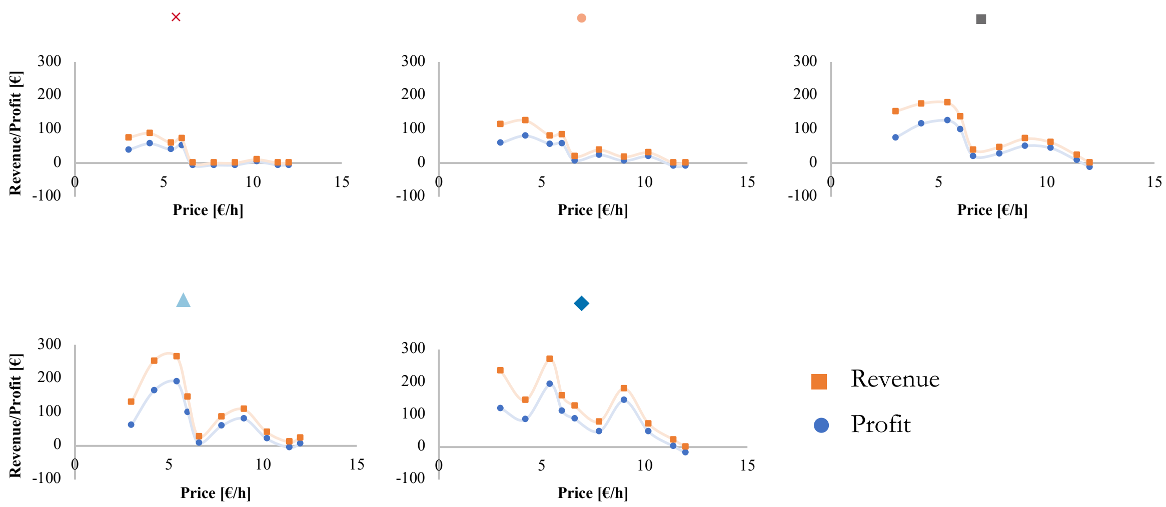

Figure A4. Revenue and profit by supply variation

When compared to the whole city, simulations running on one single station generate a more disturbed output. FigureA4 Shows that for a price around 6.6 €/h the revenue decrease before briefly inverting its trend. The cause of this behavior is to be found in the difference of booking time. The profit and revenue shapes shown in the paper (Figure 8 and Figure 11) are the result of a massive amount of members using the service while Figure A4 shows only the ones that can access station 1209635. The small number of agents used in the simulation causes members behavior (e.g., activity chain, schedule, …) to be more predominant and affected by the price. It's clear that in such situation the averaging effect given by the high number of members cannot be captured.

In Figure A5 we show the profit curve in function of the supply and the price offered.

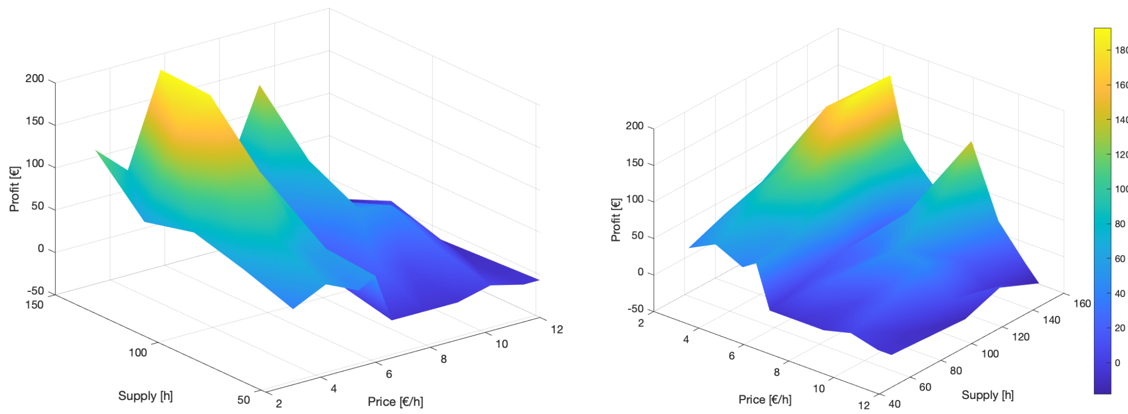

Figure A5. Profit in function of supply and price variation

The maximum profit is always reached when the price is between 4.2€/h and 6€/h.

Being the profit function of both the supply and the price offered, we fit the data use the same procedure used to create Figure 17 in order to generate Figure A6.

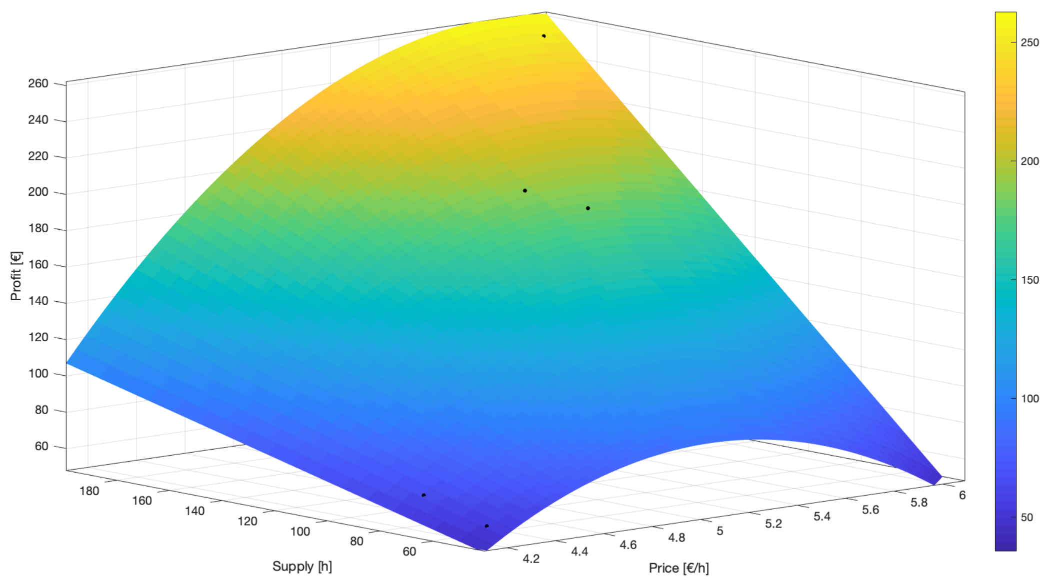

Figure A6 Three-dimensional plane of Profit - Supply - Price

Once the points of maximum profit are connected using a polynomial fitting function, we obtained a concave surface. With the use of this figure, it is possible to define the highest profit reachable for any given price once the supply is given. Through a quadratic interpolation we define the model in Equation A4.

$$P(p, S) = -48.58\, p^2 + 468.6\, p - 1074 + S\,(0.5263\, p - 1.783) \tag{A4}$$

Where P is the *profit*, p is the *price* proposed per hour of service and S is the *supply* expressed in number of hours. Once the supply that can be offered is known, given the concave shape of the surface, it is possible to define the price solving the Equation A4 as an optimization problem as shown in Equation A5.

$$\max P(p) \quad 3 \leq p \leq 12\ [€/h] \tag{A5}$$

Since S is known at the moment of the booking, we treated it as an "undefined constant" in order to identify the line of maximum profit. We evaluate all the points where the derivative is equal to zero.

We calculate the first derivative which is set to zero in order to obtain the line of maximum profit as shown in Equation A6.

$$\frac{dP}{dp} = -97.16p + 0.5263\,S + 468.6 = 0 \tag{A6}$$

In Equation A7 we obtained the maximum profit line obtained and in Figure A7 it is shown its relative graphical form for the intervals $4.2 \leq p \leq 6 [€/h]$ and $24 \leq S \leq 144\ [h]$.

$$p = \frac{0.5263S + 468.6}{97.16} = 0.00541S + 4.822 \tag{A7}$$

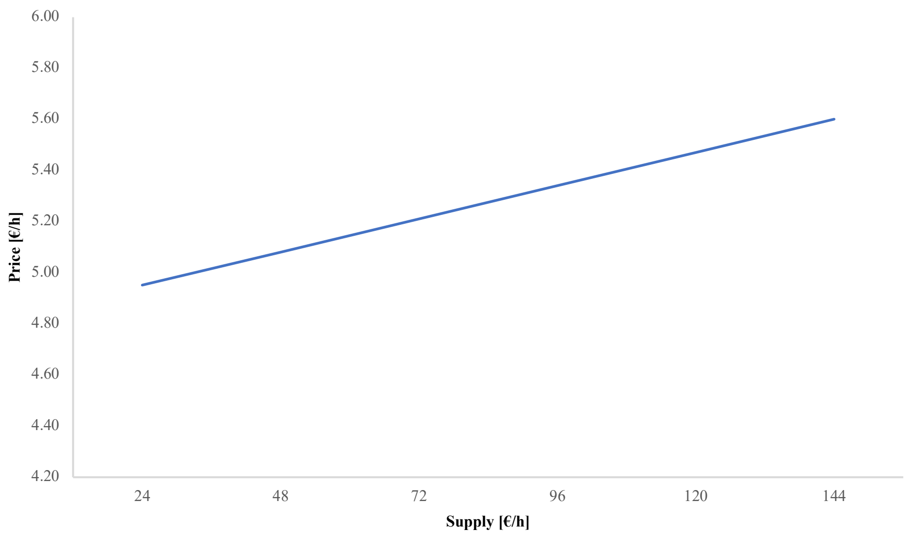

Figure A7. Line of maximum profit

7.6.2 Station 1212165

Calibration

As shown in the paper we proceed to the calibration phase.

Table A4. CsC calibration phase one

Simulation	α_{cs}	Revenue [€]	Booking Time [s]
1	11.0	6	3473
2	12.0	12	4875
3	13.0	24	10371
4	14.0	18	10163
5	15.0	72	35891

We plot these points as shown in Figure A8.

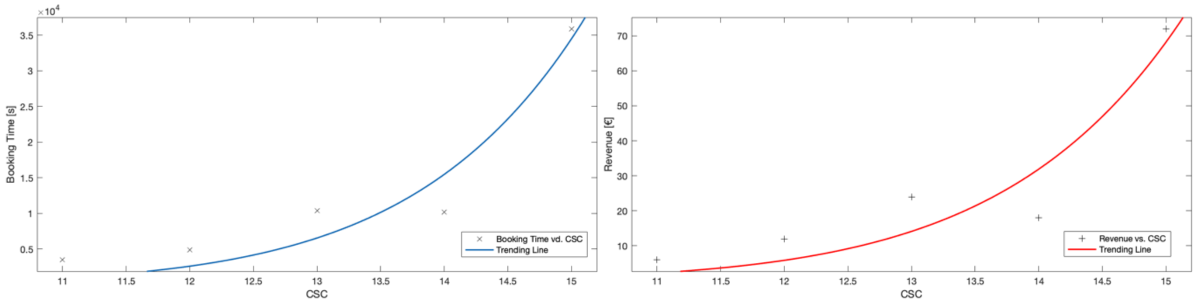

Figure A8. a) Booking Time vs CsC plot; b) Revenue vs CsC plot

We fit the point with two power trend lines described by Equation A9 and Equation A10.

$$\hat{t}_r = 7.266 * 10^{-10} * \alpha_{cs}{}^{11.63} \tag{A9}$$

$$\hat{r} = 7.733 * 10^{-12} * \alpha_{cs}{}^{11.01} \tag{A10}$$

In order to find the values of booking time and the revenue we are looking for we measure the root-square mean error (RSME) between the two equations above and the observed valued T_r and R (respectively 8 hours and 54 €) in order to obtain Equation A11.

$$\hat{z} = \frac{(\hat{t}_r - T_r)^2 + (\hat{r} - R)^2}{2} \tag{A11}$$

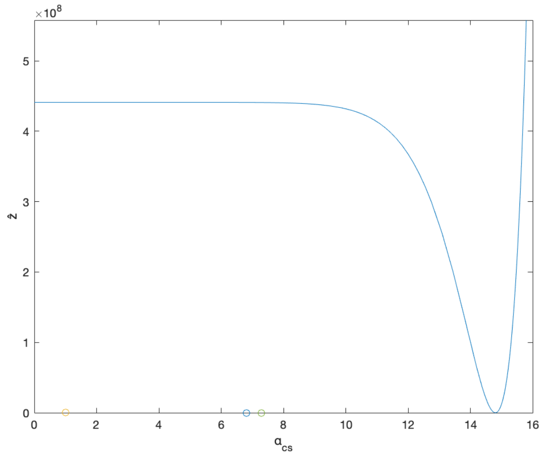

Figure A9. $\hat{z}$ function

Applying a minimization method, we are able to find the α_{cs} that minimizes $\hat{z}$. When $\alpha_{cs} = 14.8$ $\hat{z}$ is at its minimum.

Results

Keeping the same prices, we set up the experiment (Table A5).

Table A5. Scenario Definition for Supply Variation

Scenario Code	Supply [h]	Supply [car]
×	24	1
●	48	2
■	72	3
▲	96	4
◆	120	5

Combining these inputs with the 10 pricings values shown in Table 4, we obtain 50 simulations run in parallel on an HPC using 4 cores and 20GB of RAM for each instance.

Once the number of members is fixed and the supply is varied according to Table A5, we assess the revenue and the profit generated for every set of simulations (Figure A10).

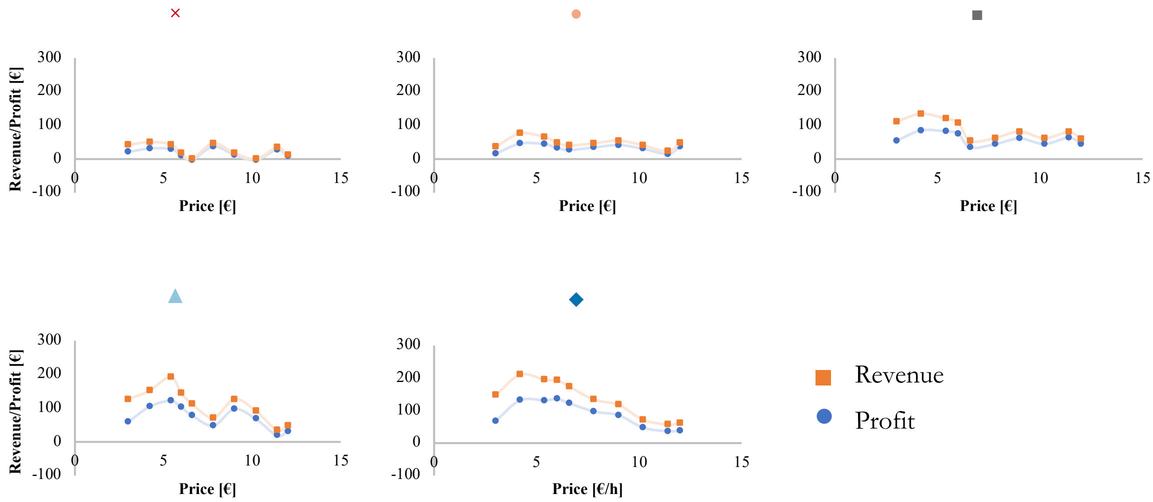

Figure A10. Revenue and profit by supply variation

In and Figure A11 we show the profit curve in function of the supply and the price offered.

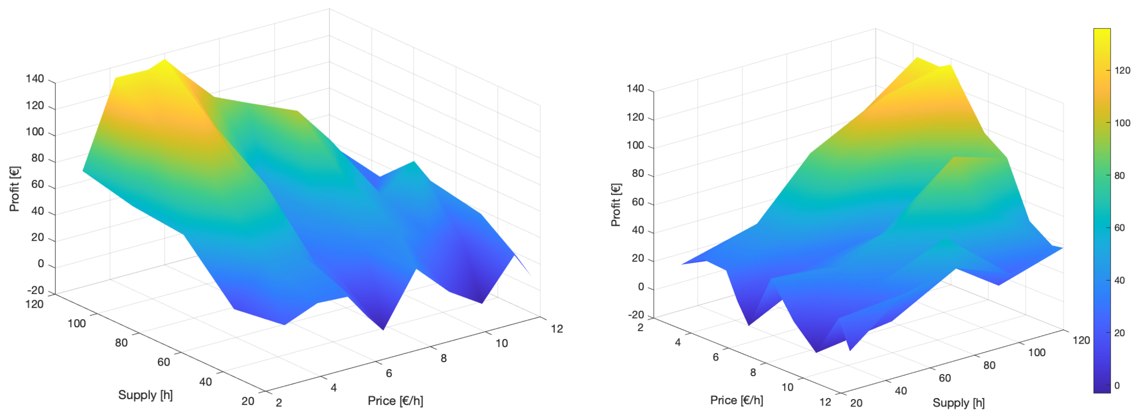

Figure A11. Profit in function of supply and price variation

The maximum profit is always reached when the price is between 4.2€/h and 6€/h.

Being the profit function of both the supply and the price offered, we fit the data use the same procedure used to create Figure 18 in order to generate Figure A12.

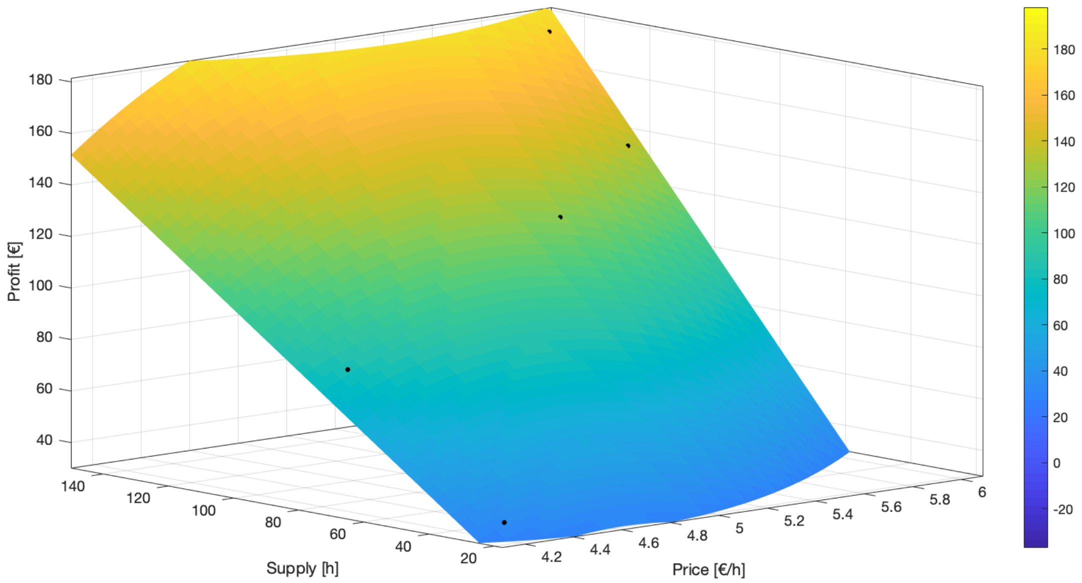

Figure A12. Three-dimensional plane of Profit - Supply - Price

Once the points of maximum profit are connected using a polynomial fitting function, we obtained a concave surface. With the use of this figure, it is possible to define the highest profit reachable for any given price once the supply is given. Through a quadratic interpolation we define the model in Equation A12.

$$P(p, S) = -31.2\, p^2 + 281.8\, p - 625.4 + S\,(0.339\, p - 0.4217) \qquad \text{(A12)}$$

Where P is the *profit*, p is the *price* proposed per hour of service and S is the *supply* expressed in number of hours. Once the supply that can be offered is known, given the concave shape of the surface, it is possible to define the price solving the Equation A12 as an optimization problem as shown in Equation A13.

$$\max P(p) \qquad 3 \leq \mathrm{p} \leq 12\ [€/\mathrm{h}] \qquad \text{(A13)}$$

Since S is known at the moment of the booking, we treated it as an "undefined constant" in order to identify the line of maximum profit. We evaluate all the points where the derivative is equal to zero.

We calculate the first derivative which is set to zero in order to obtain the line of maximum profit as shown in Equation A14.

$$\frac{dP}{dp} = -62.4p + 0.339\, S + 281.8 = 0 \qquad \text{(A14)}$$

In Equation A15 we obtained the maximum profit line obtained and in Figure A13 it is shown its relative graphical form for the intervals $4.2 \leq p \leq 6\,[€/h]$ and $24 \leq S \leq 120\ [h]$.

$$p = \frac{0.339\, S + 281.8}{62.4} = 0.0054S + 4.516 \qquad \text{(A15)}$$

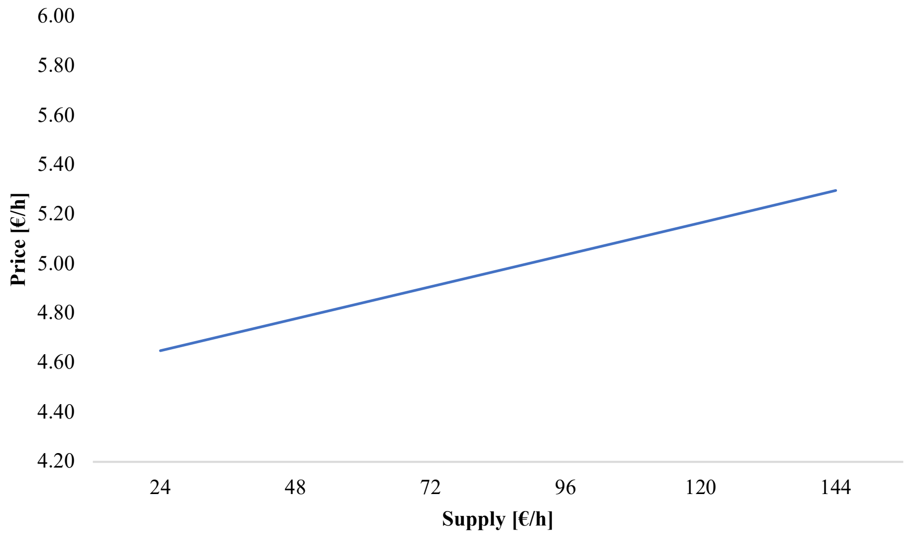

Figure A13. Line of maximum profit

8

Profit and Utility Optimization Through Joint Dynamic Pricing and Vehicle Relocation in Carsharing Operations

Pricing is one of the main determinants of a successful carsharing business plan. Companies develop different pricing strategies in order to increase attractivity, profit and service usage. The use of dynamic pricing strategies can lead to service gains in terms of profit and to an improvement of customer satisfaction. In this paper we develop two different hybrid pricing strategies in order to analyze key performance indicators related to carsharing business and its customer base, with the goal to increase companies' profit and users' utility. These two different hybrid pricing strategies are based on two different approaches: an approach based on demand information (i.e., fixed price and time-based dynamic price) and one based on supply's characteristics (i.e., maximum profit price and availability-based dynamic price). These strategies are simulated in an agent-based environment. Once these methods are applied, we show how it is possible to increase profit or utility using a hybrid pricing model. Furthermore, we show how it is possible to reach the best results when this gets structured using pricing strategies developed starting from the same base (i.e., demand-based with demand-based and supply-based with supply-based). Moreover, we show how an increment in profit corresponds to a reduction of the utility and vice versa. Additionally, we propose a relocation procedure for an agent-based simulation approach. Finally, we show how this approach leads to higher profit and customer satisfaction.

8.1 Introduction

Carsharing customers, once members of the service, gain access, typically in the order of magnitude of minutes or hours, to a pool of shared cars. This results in the possibility of accessing a car relieving the users from all the car-related fees such as maintenance, fuel, and insurance. The booking procedure, consisting of the car reservation and pick-up processes, is automatized to the point of making the carsharing offer a self-service process. Carsharing comes with a variety of forms, peer-to-peer (P2P) and business-to-consumer (B2C) (*109*). Focusing on B2C, carsharing comes in three main formats (*11*):

- Stations-based round-trip or two-way carsharing: the pick-up and return of the vehicle must happen at the same station or location.
- Station-based one-way carsharing: customers can pick-up a vehicle in any station and return in any other station.
- Free-floating carsharing: this format doesn't rely on stations; it employs a vast operative area in which users can pick-up and return vehicles.

The use of mobile apps and internet helped carsharing to prosper: these technologies are used for booking, to tailor the carsharing experience to the user, allows fast payments and make continuous operator supervision of the fleet available for the operator. Being not clear yet if this mobility service can be profitable (*16*), research is still focusing on ways to make more efficient the fleet management and targeting for profit or revenue maximization (*24*, *76*)

Pricing is one of the main connection points between the service provider and the final user and it is evident how its formulation impacts the relation between these two actors. This can affect spatially and temporally carsharing bookings influencing who, when and where the service will be eventually used (*77*). A well-structured offer can result in the success of a carsharing company or its eventual downfall. During the years, different pricing strategies have been proposed. With the goal of increasing profit, a mixed integer non-linear programming model was applied focusing on one-way carsharing and by proposing zone and time of the day price variations (*79*).

Understanding the relationship between price, supply, and demand to maximize profit while still offering an attractive service is not an easy task. Many variables have to be taken into account such as diverse characteristics of the demand (i.e., its elasticity, age and income of the users, trips purpose, etc.)(*30*), external requirements given by specific policies that could apply to the area of interest of the service together with specific stimuli for companies (*76*) and supply features like fleet composition, availability and eventual competition (*97*). Coming up with a simplified model that considers both demand and supply needs is not a trivial task, especially because, often, the maximization of profit for the company and the user's utility are two objectives that progress towards different directions.

Proposing a fleet of cars to customers is the core business of a carsharing enterprise. To manage their resources at best, different methodologies have been developed to address the vehicles relocation problem. The two main approaches used are analytical optimization algorithms and simulation. Optimization concentrates toward vehicle relocation problems (used for one-way models per their nature prone to unbalances). For instance, these algorithms are used to address pricing problems from a strategical and operational standpoint, mixing a trip-pricing problem with vehicle relocation and personnel assignment in order to develop a global optimization algorithm (*110*). While assessing the impact of different dynamic pricing strategies, this paper uses a simulation-based approach to describe how different pricing strategies impact both the demand and the supply. Simulation based strategies are often used to address this kind of problems. Today carsharing is a quite traditional concept but, nonetheless, models and strategies able to assess its impacts and functionality are still being developed. Based on previous studies on carsharing pricing, we compare the dynamic pricing strategies developed so far to create a hybrid pricing model (HPM) aiming at increasing supply and demand main key performance indicators (KPIs) such as profit and customer's utility.

When assessing the demand response, we studied multiple dynamic pricing strategies and how they impact the equity and the users' travel behavior. Findings demonstrate how a dynamic pricing scheme help to increase profit when compared to fixed pricing strategies (*41*). Simulation is often used to assess brand new strategies. On one hand, to deploy new schemes such as new pricing strategies in actual carsharing operations can be an expansive effort and, on the other hand, assess the satisfaction of the user can be a resource-intensive task. Hence, a simulator can be an asset to produce insights on new operational strategies. Continuing the stream of research that compares two different pricing strategies (*88*), one based on the supply availability and another one based on the hour of the day and, indirectly, on the carsharing demand profile, this work aims at the mixing the specificity of these two schemes in order to find a model increasing KPIs for both the demand and the supply.

This paper aims at answering to a specific research question: "is it possible to develop a single pricing model that incorporates the benefit of different dynamic pricing strategies?". To the best of authors' knowledge, the bond of different pricing strategies can offer an additional way to increase carsharing efficiency as in business efficiency while keeping the service interesting for the population. This study focuses on the impact of the introduction of these different strategies on carsharing operations, both from a business and management point of view and on the population and its different subset created by splitting it in different income groups. Furthermore, to show the results in a realistic setting, the real data used in this paper originates from Oply, a B2C carsharing company operating with a two-way round-trip system.

The remainder of this paper is organized in five different sections. The next section provides a methodology describing the various dynamic prices and the way they are expected to affect population's behavior; furthermore, the case study taken in exam is explained. Section 3 describes the outcome of the various scenarios from a business and demand point of view. Section 4 presents an examination of the results. Finally, section 5 proposes insights for future works.

8.2 Methods

Table 1. Notation

p_u	Price offered to the user u
V	Available Vehicles/Supply
s	station
t_h	Time of the day
S	Score/Utility
N	Number of activities
q	Performed activity
β_{dur}	Marginal utility of activity duration
t_{dur}	Performed activity duration
t_0	Duration when utility starts to be positive
α_I	Scale factor for the Income
I_u	Income of user u
FP	Fixed Pricing
TBDP	Time-based dynamic pricing
MPP	Maximum profit pricing
ABDP	Availability-based dynamic pricing
HP	Hybrid Pricing

When assessing punctual services with reduced vehicles flows, such as carsharing trips, traditional trip-based models (Cascetta, 2009) are not able to assess important KPIs related to single users (i.e., utility of the single user, intrazonal movements, spending power) and to the service (vehicles availability at a precise space and time). Considering the specific output we are looking for, which is the reaction of users to pricing policies, a mesoscopic approach can better capture emerging trends.

When evaluating a carsharing service, temporal and spatial resolution is of outmost importance and disaggregated methods becomes necessary. In this paper an agent-based simulator is employed called MATSim is used (*19*). The choice of this specific framework is given by the fact that, currently, is the most suited in providing a disaggregated representation of carsharing operations and use (*102*). Furthermore, the integration of the microscopic land-use simulation system (SILO) (*103*) make this simulator fit our needs since the possibility to recreate the synthetic population of Munich and their relative activity chains. MATSim is based on the co-evolutionary principle. The simulation consists of multiple iterations that allows agents to optimize their daily activity while in competition with other agents. These iterations have the goal of reaching a user equilibrium in terms of individual scoring. The score represents the utility of a given agent do specific travel choice for executing specific activities.

8.2.1 Methodology

In this paper, we introduce and compare four pricing strategies that can be ascribed to two groups: demand-based and supply-based.

Demand-based pricing

Prices based on demand are all those prices that can be obtained from market surveys based on preferences and revealed behaviors

Fixed Pricing

The simplest pricing scheme available is the Fixed Pricing (FP). Evaluated from market surveys or by analogy from competitors. Even though this price is influenced by production costs and supply, for this paper's sake, we include the FP in the demand-based pricing because it is not affected by the rate at which vehicles are requested.

Time-Based Pricing

Time-Based Dynamic Pricing (TBDP) is a price that changes in function of the time of the day. The conception of this pricing model comes from the idea of making resources more expensive at specific times of the day, usually when they are more requested. The TBDP model used in this paper is directly derived from the demand profile obtained from the usage of the FP as shown in Figure 1.

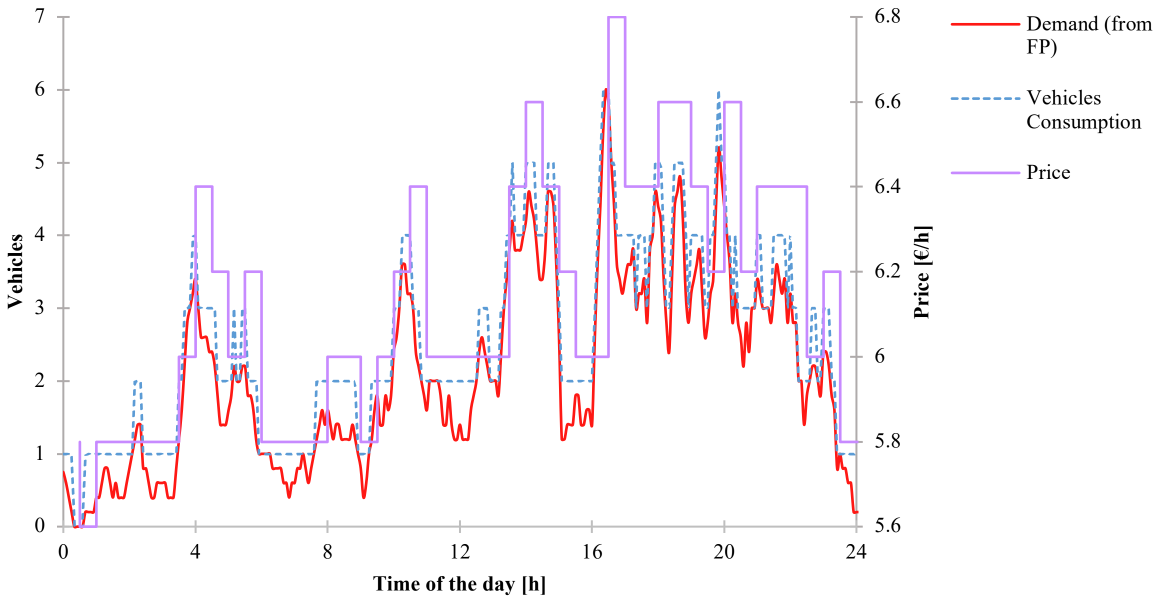

Figure 1. Example of TBDP creation

As it can be seen from the previous figure, the more cars are booked the higher the price gets. This kind of pricing has the effect to level the consumption of resources lowering price when they are not used and increasing it when they are more requested.

Supply-based pricing

Prices based on supply are all those prices that are established based on how the supply is used. One of the most common pricing based "on the option value of future sales, which varies with time and units available" (*98*) is the dynamic pricing (or dynamic price discrimination scheme) conventionally used in the airline industry. This kind of price can be used to address incomplete markets or steer demand behavior. In this case we developed two different dynamic prices that are based on supply availability at city level and at the station level.

Maximum Profit Pricing

The idea behind this price model is that it is possible to model profit as a function of the supply and to identify a maximum profit for a price given the number of car-hours the operator can offer. Using different couples of supply-price values where both are increasing within a specific range, it is possible to find a profit, output of the simulation that variates in function of these two inputs. Furthermore, is possible to plot these outputs on a three-dimensional graph (Figure 2) and, using a metamodel, it is possible to find a Maximum Profit Price (MPP) (*111*) interpolating these points.

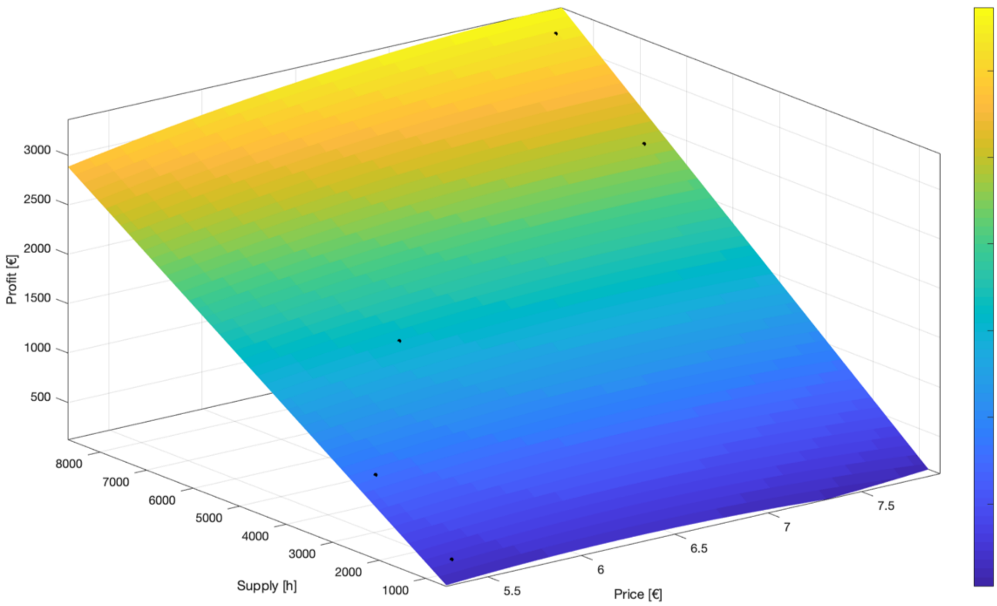

Figure 2. Example of three-dimensional plane of Profit-Supply-Price

Once these points are connected, we obtain a concave surface where it is possible to define the highest profit reachable for any given price once the supply is given. Given the concave shape of the surface, it is possible to define the price that gives back the highest profit once the supply is known calculating the first derivative of the surface in Figure 2 and setting that equal to zero. The result gives price shown in Equation 1.

$$p_u = 4.28 + \left[0.0001929 * V_{city} * (24 - t_h)\right] \quad (1)$$

It is important to note that this equation is valid for the Oply service in Munich. In the case the context would change (a different city, another composition or distribution of the fleet) we would expect a similar equation but with different parameters. The price shown has the peculiarity to change in function of how many car-hours the carsharing company can still offer until the end of the day, hence it is also dynamically changing. This kind of price is introduced in the planning phase since, to be created, needs multiple simulations and well-known description of the demand (as in the members characteristics of the carsharing service members) and of the supply (i.e., number of cars and their location).

Availability-Based Dynamic Pricing

Similar to the one introduced in the previous section, the availability-based pricing strategy is based on the idea that a vehicle becomes more expensive as fewer cars are available at the station when a booking gets executed. Figure 3 shows an example of an Availability-Based Dynamic Pricing (ABDP), the function is a power line where on the x-axis we have the number of vehicles available while on the y-axis there is the price.

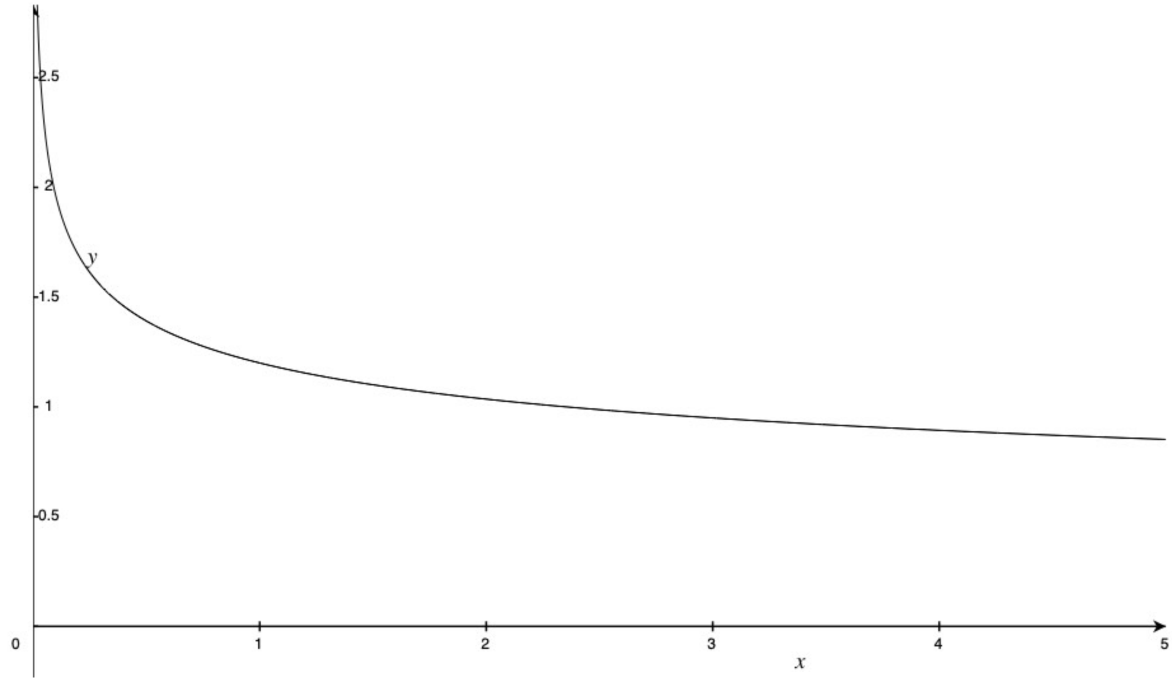

Figure 3. Example of ABDP strategy

Hybrid Pricing Model

The ideation of the Hybrid Pricing (HP) is made to answer the problem raised in the introduction: "is it possible to develop a single pricing model that incorporates the benefit of different dynamic pricing strategies?". The HP is conceived as a sequence of different stages in which a specific pricing is applied as shown in Figure 4.

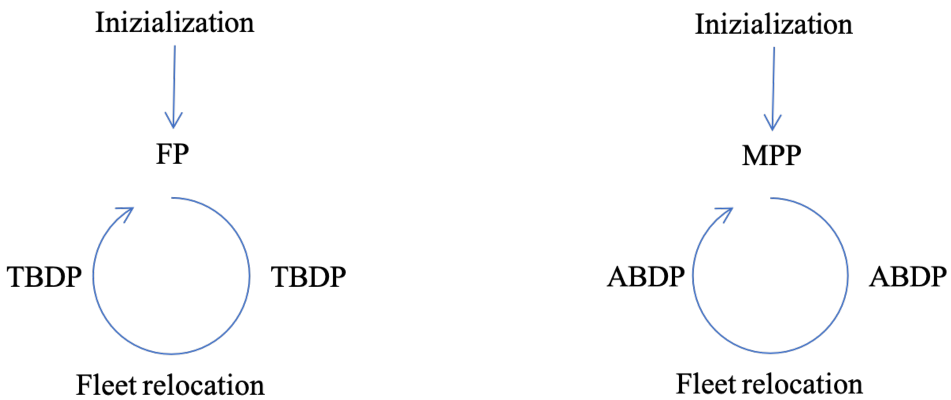

Figure 4. Day-to-day pricing and relocation loop

Figure 4 represents a day-to-day process. This means that the information is collected using a specific strategy for the whole duration of the day, analyzed, and used as input in a successive step.

Simulation Assessment

To assess the quality of service from the point of view of the operator and the user, we refer to a quantitative method of measurement. Here, we subdivide measures in two different KPIs, one group related to the company and another related to the demand.

User's KPIs

We consider the score, or otherwise the utility, the main KPI related to the demand. In MATSim the score is the evaluation of the agent's daily plan, and it is divided in two fundamental parts, the former related to the activity and the latter to the performed trips as shown in Equation 2.

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \quad (2)$$

Overall, when making their choice, the agents, singularly, try to maximize their score during their daily operations. This happens between every iteration of the simulation. In one iteration the plan is executed and, at the end, evaluated; in the next iteration a similar plan is executed as well and, by performing a multinomial logit model the selection between plans happens (*19*). Besides this main indicator, modal split, walking time to the station and modal choice are also chosen as additional KPIs.

Operator's KPIs

In this paper we consider the profit as the main KPI. Profit is the result of the difference between the revenue, generated by renting cars, and the costs, variable and fixed. Revenue is calculated by multiplying the hourly cost of the offer for the rental time. Costs (obtained from Oply), are divided in:

- Variable costs: linked to the utilization of the vehicle, it includes maintenance, wear of the vehicle, fuel and estimated around 1.5€/h per vehicle.
- Fixed costs: include insurance and leasing cost, estimated with an amount of 3€/day per vehicle.

Other indicators used to assess the goodness of the carsharing service are the booking time, and the number of bookings, directly related to the profit, the demand profile, needed to create the TBDP and a measure of when vehicles are used the most during the day and, finally, the station utilization, needed mainly to assess the situation before the relocation of the vehicles.

Relocation Phase

Even though not part of the pricing model, relocation is a step that can lead to further improvement of both the profit and the score. In this paper, we show how, with the simulation output, is possible to forecast where and when cars will be likely requested from a user. This is possible thanks to a specific output: the daily station utilization and the MATSim events file. Thanks to this file we can know when and where a customer tried to book a vehicle and the eventual outcome of the booking procedure. This way, we know when vehicles were not available, meaning that the service was not able to satisfy the user need.

The relocation phase is explained in Figure 5. It begins with the evaluation of the HP procedure assessing the two main KPIs described above: profit and utility. A score from 1 (lowest) to 4 (highest) is given to the dynamic pricing simulations run in series to the FP and the MPP simulations. The one that receives the highest total score, results of the addition of the two scores described above, gets the chance to be run again, this time, with the vehicles relocated.

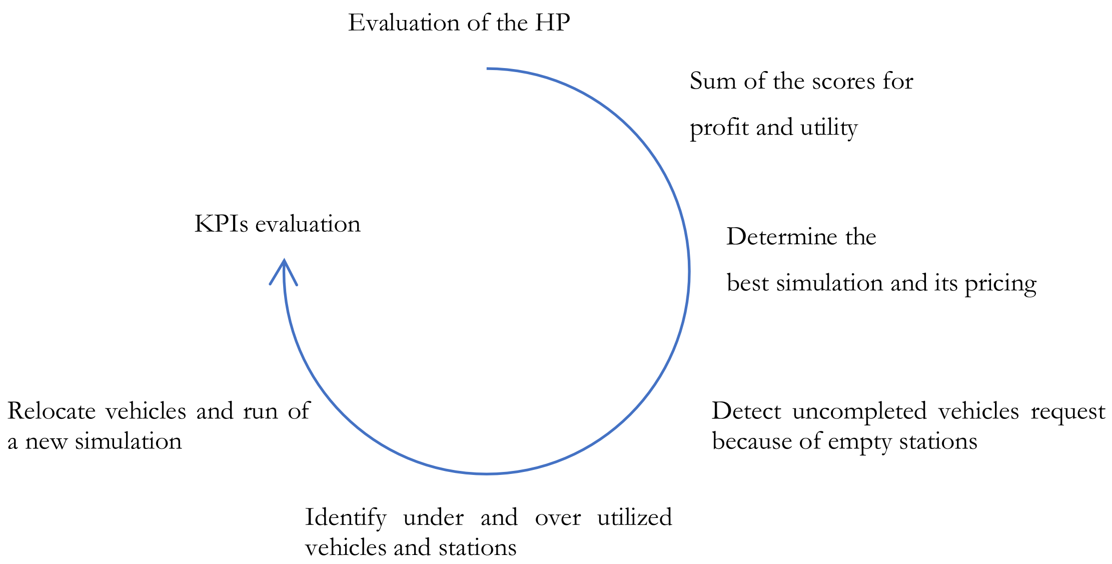

Figure 5. Identification procedure of the best simulation and vehicle relocation

8.2.2 Case Study

Figure 6 shows the network of the city of Munich, used for the simulation, together with Oply's carsharing stations (in blue) and the agents, members of the carsharing service (in green). The case study consists in a population of 14747 agents and 186 cars unevenly distributed in 79 stations.

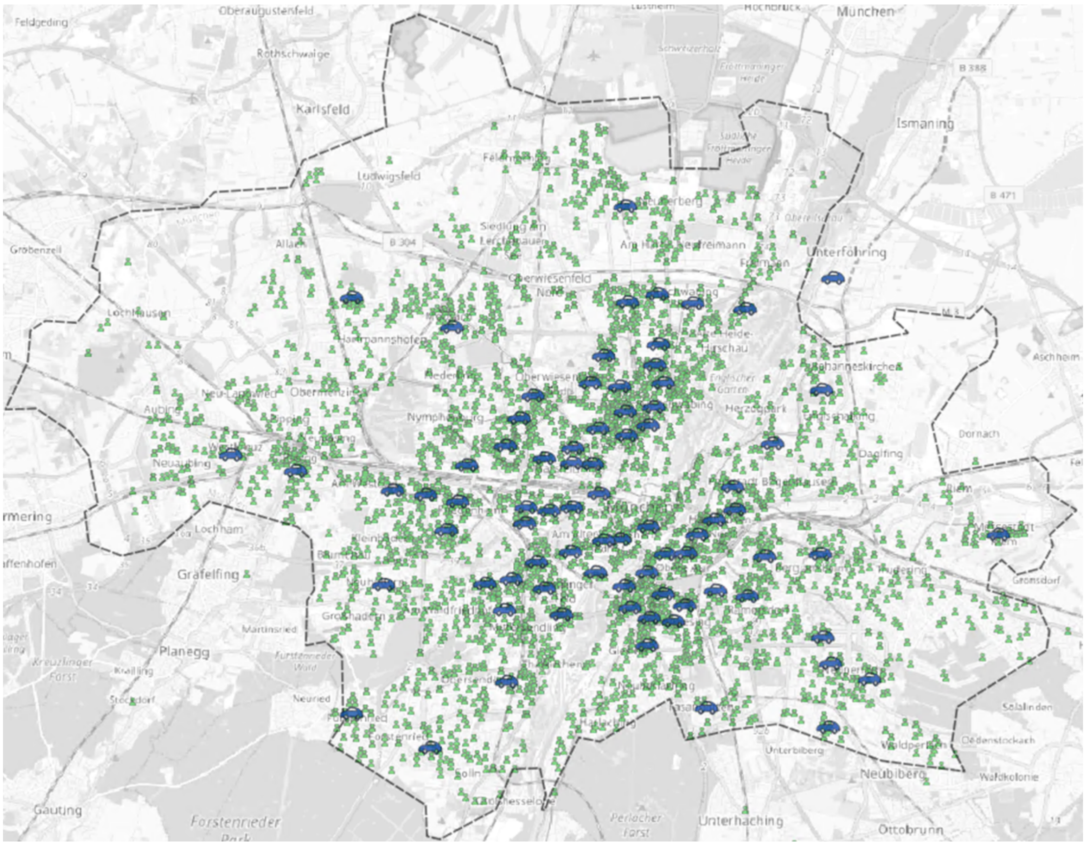

Figure 6. Network, stations and carsharing members

We define the different scenarios in Table 2.

Table 2. Scenarios Identification

Scenario Name	Pricing Strategy	Color Code
FP	Fixed pricing	
MPP	Maximum profit pricing	
TBDP010	Time-based pricing with a 0.10 € step	
TBDP030	Time-based pricing with a 0.30 € step	
ABDP105	Availability-based pricing with a 5% price increment of the fixed price for the last vehicle	
ABDP120	Availability-based pricing with a 20% price increment of the fixed price for the last vehicle	
FPRelocation	Fixed pricing after relocation phase	
MPPRelocation	Maximum profit pricing after relocation phase	
TBDP010Relocation	Time-based pricing with a 0.10 € step after relocation phase	
ABDP105Relocation	Time-based pricing with a 0.30 € step after relocation phase	

Demand-based pricing setup

In this subsection we explain how the demand-based pricings are developed. This kind of pricings are based on location and density of the population, journey behavior and market analysis.

Fixed Pricing

The price developed by Oply consists in a flat rate of 6 €/h. The price is paid by the hour, and it is not divisible. To avoid paying a full hour for small delays a grace period is introduced. The grace period is defined as a time of five minutes in which, any booking closed within this time is not subject to the full hour payment (e.g., a booking that lasts 64 minutes will cost to the user 6€ while a booking that lasts 66 minutes will have a total cost of 12€).

Time-Based Dynamic Pricing

The development of the TBDP follows the demand profile of a previous simulation or, in case, the demand profile observed from carsharing operations. In this specific case we developed one TBDP from the output of the FP scenario and one from the output of the MPP scenario.

The carsharing demand is averaged with bins of 30 minutes and three measures are considered to develop the TBDP:

- The maximum number of cars booked in any of the 30 minutes bin,
- The average number of cars booked during the day,
- the base cost, 6€/h for the FP scenario and 5.15€/h for the MPP.

For the FP scenario, being the price fixed the result is 6€/h; otherwise, for the MPP scenario the price depends on the number of vehicles available at city level, i.e., the average number of vehicles booked (for the explanation of the MPP price development for this case study refer to section 2.2.2). Once the price for the average vehicles is set, we create two scenarios in which we variate the price of 0.10 and 0.30 € for every vehicle unit diverging from the booking average as explained in Table 3 and Table 4.

Table 3. TBDP from FP scenario

Number of bookings	Variance from the mean	TBDP010	TBDP030
0	-2	5.8	5.4
1	-1	5.9	5.7
2	0	6.0	6.0
3	1	6.1	6.3
4	2	6.2	6.6
5	3	6.3	6.9
6	4	6.4	7.2

Figure 7 shows the demand and price profile of the TBDP010 (Figure 7a) and the TBDP030 (Figure 7b) developed from the FP demand profile.

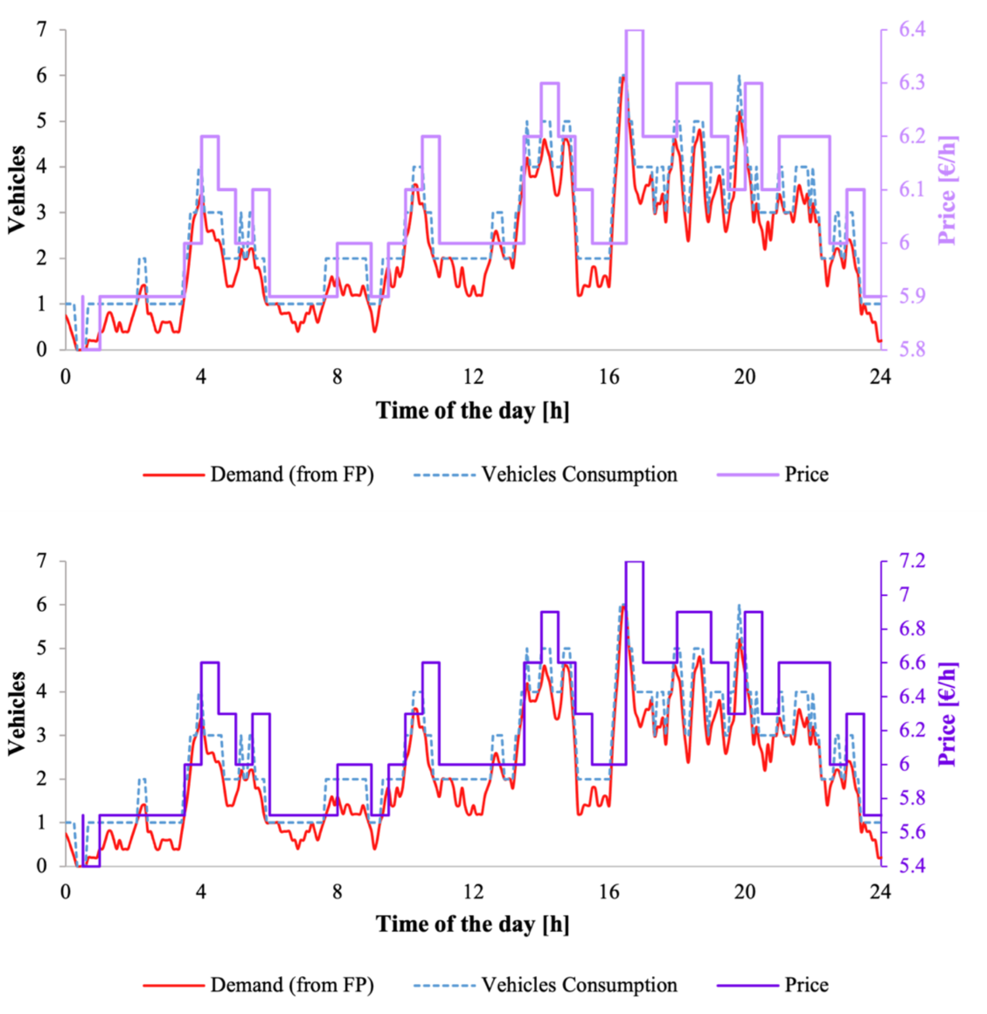

Figure 7. (a) TBDP010; (b) TBDP030

Table 4. TBDP from MPP scenario

Number of bookings	Variance from the mean	TBDP010	TBDP030
0	-4	4.74	3.94
1	-3	4.84	4.24
2	-2	4.94	4.54
3	-1	5.04	4.84
4	0	5.14	5.14
5	1	5.24	5.44
6	2	5.34	5.74
7	3	5.44	6.04
8	4	5.54	6.34
9	5	5.64	6.64
10	6	5.74	6.94
11	7	5.84	7.24

The TBDP exploits the higher competition of customers in specific times of the day and attracts customers in low demand periods. Figure 8 shows the demand and price profile of the TBDP010 (Figure 8a) and the TBDP030 (Figure 8b) developed from the MPP demand profile.

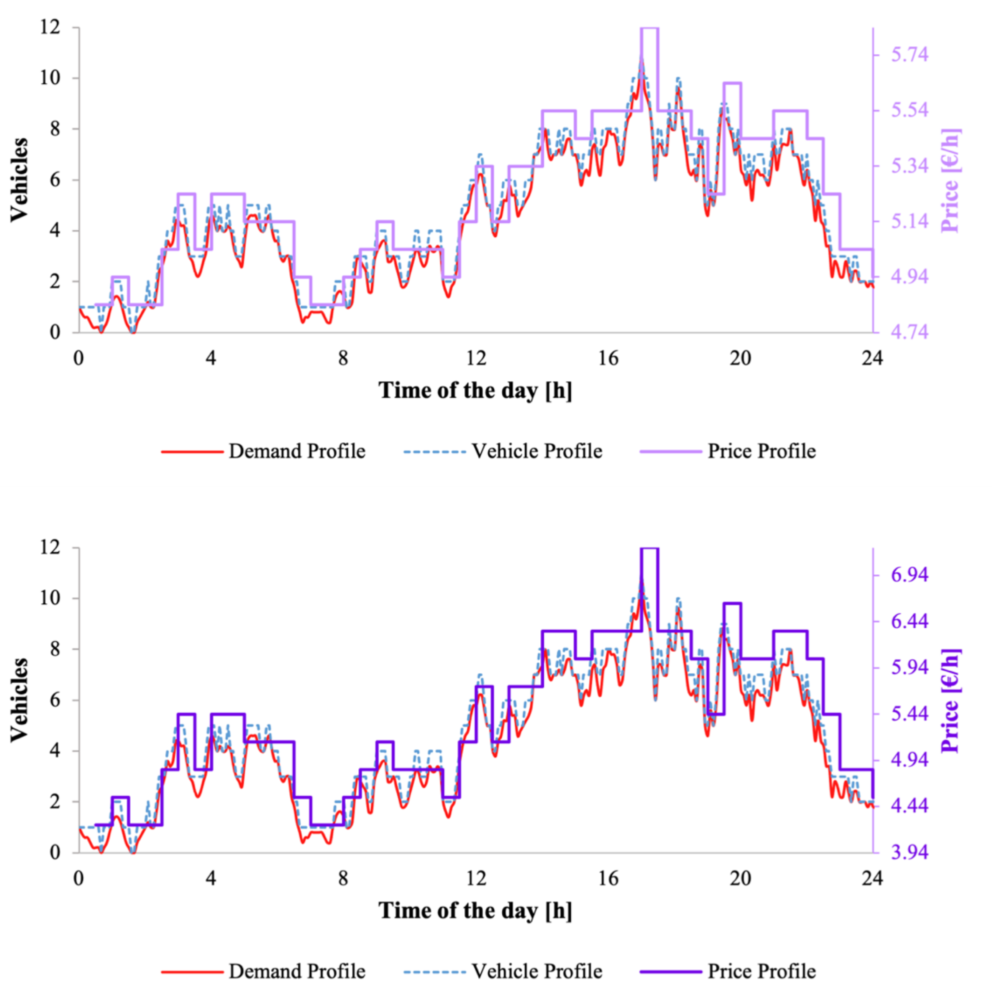

Figure 8. (a) TBDP010; (b) TBDP030

Supply-Based Pricing Setup

In this subsection we show the criteria behind the supply-based pricings. This kind of pricings are based on different factors bookings rate at station and city level and fleet size

Maximum Profit Pricing

The MPP is an optimal price that can be used as an ideal reference. Once demand characteristics (i.e., location, demographics, activities executed during the day) and supply characteristics (vehicles and stations location) are known, it is possible to follow the procedure explained in Giorgione et al. (2021) to obtain Equation 1. This equation shows the variation of the price in terms of how many vehicle-hours the company can still rent until the end of the day.

To explain the values in Table 4, to find a price of 5.14€/h we solved Equation 3 with $V_{city} = 186$ and $t_h = 0$.

Availability-Based Dynamic Pricing

The ABDP is similar, conceptually, to the price discrimination applied in airline business (*98*). For stations with overlapping catchment areas, there is the possibility to push customers from stations with low availability to those with higher availability. We calculated the average number of vehicles per station. This is to find the point in which the hourly cost of a booking will for the ABDP will be equivalent to the price of the FP (and the MPP later).

$$\bar{V} = \frac{\sum_s V_s}{\sum s} = \frac{79}{186} = 2.3544 \tag{3}$$

To find the price variation, as we chose a power curve, we need another point. The aggressiveness of such strategy is decided by the carsharing company whether they want the price to increase faster or staying close to a fixed pricing strategy. In this case, referring to the price for the last vehicle, we defined two prices: the first with an increase of 5% (Figure 9a) and another with an increase of 20% (Figure 9b) as shown in Figure 9. Once the base strategy is chosen (FP or MPP), to obtain the ABDP we multiply them for the amount y shown in Figure 9[I].

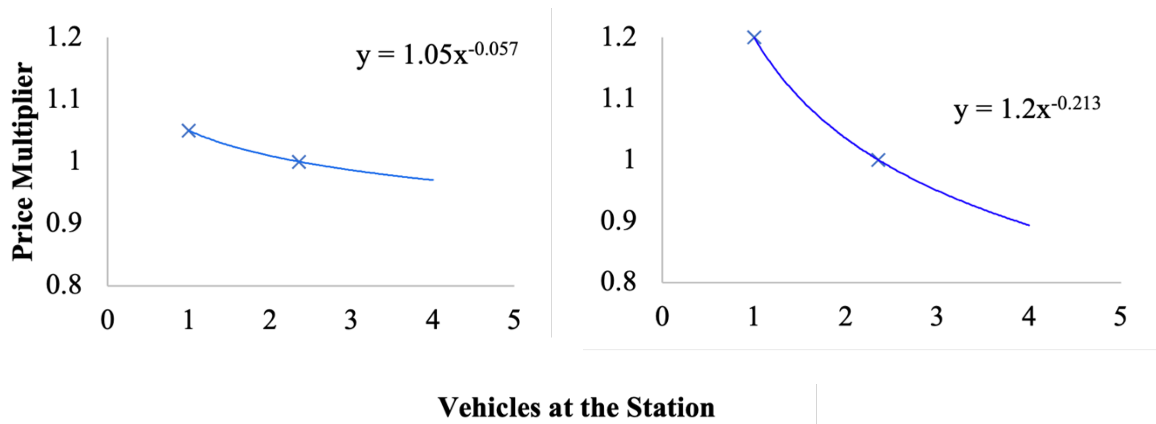

Figure 9. (a) ABDP105; (b) ABDP120

8.3 Results

The average computational time for every simulation is of 32 hours. Simulations are run with a PC with an i7-8700 CPU @ 3.20GHz, 3192 MHz, 6 Core(s), and 64Gb of RAM. the results are obtained, they are processed with MATLAB, Python and Tableau.
Results will be assessed separately for the supply and the demand-based pricing.

[I] On the left axis there is the price multiplier starting from 0.8 for a better and easier graphical representation.

8.3.1 Demand-Based Pricing

In this section, FP is used as baseline for other scenarios. Once all the simulations are over, we asses, as first, the resulting demand profile (Figure 10).

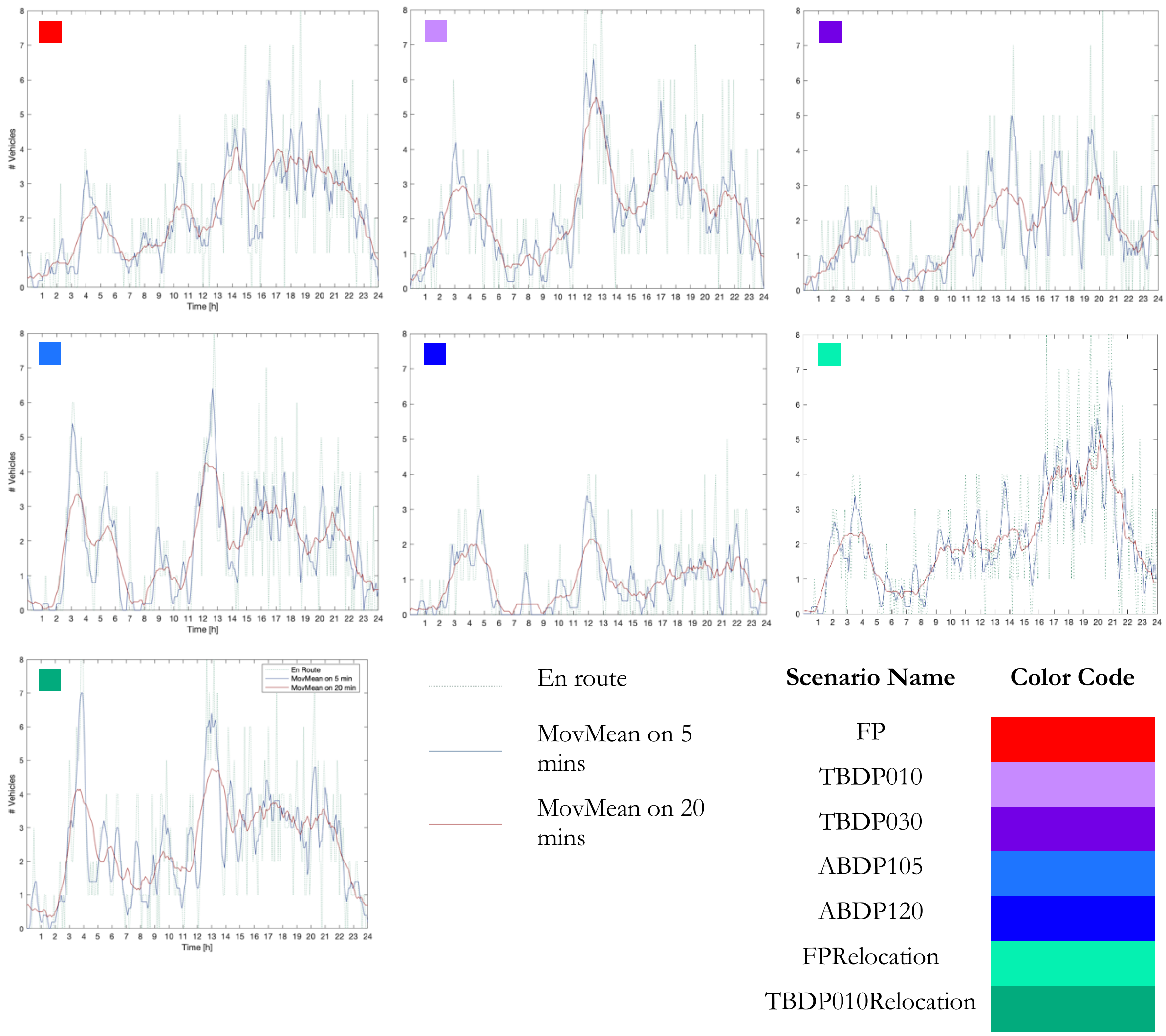

Figure 10. Demand Profile - FP

Figure 10 shows how different pricing strategies impact carsharing usage. TBDP induces a peak of bookings where price is low while ABDP shows peaks after periods of low usage. This is given by the fact that the more vehicles are at the station, the higher the price. Together with Figure 11, we can see how increasing the impact of the dynamic pricing (i.e., we refer to TBDP030 and ABDP 120) pushes away members from the service.

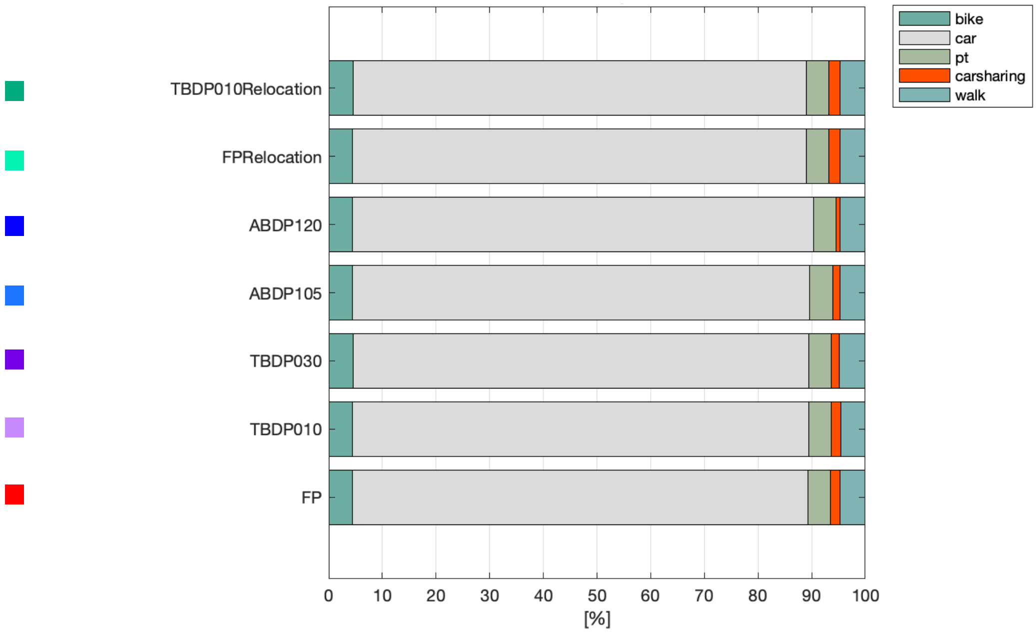

Figure 11. Modal Share

Figure 11 shows how, in terms of carsharing use, the FP and the TBDP010 are the pricing strategies that manage to attract more people (relatively 1.81% and 1.82%). Relocating vehicles manage to increase this carsharing share up to 2.05% and 1.98% meaning that the relocation was effective. The same effect can be noticed in Figure 12 where we show the score in a normal distribution for every scenario.

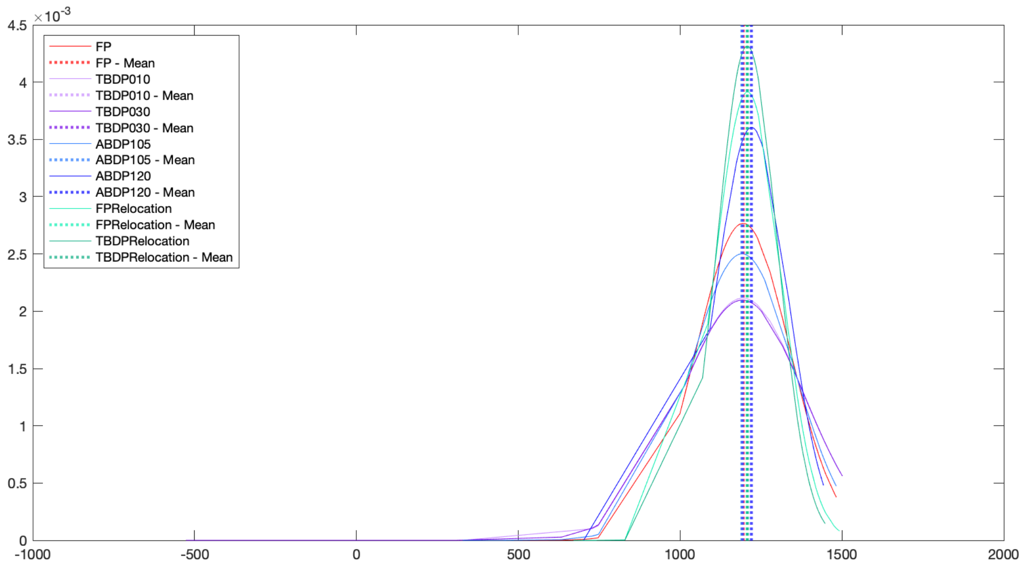

Figure 12. Normal Distribution of the Score

Figure 12 shows how, besides the relocation scenario, every pricing strategy lowers the score except the ABDP120. Since in this scenario we observe fewer bookings (see Figure 10), the only members that use the carsharing service are the ones that are greatly benefitting from it, that is why the average score tends to increase. Even though this may seem a good strategy to increase user's satisfaction, the fact that the number of bookings decreases strongly makes believe that a service using this strategy will have the result to push people towards other modes. Another representation of the score, in this case divided by income group is given in Figure 13.

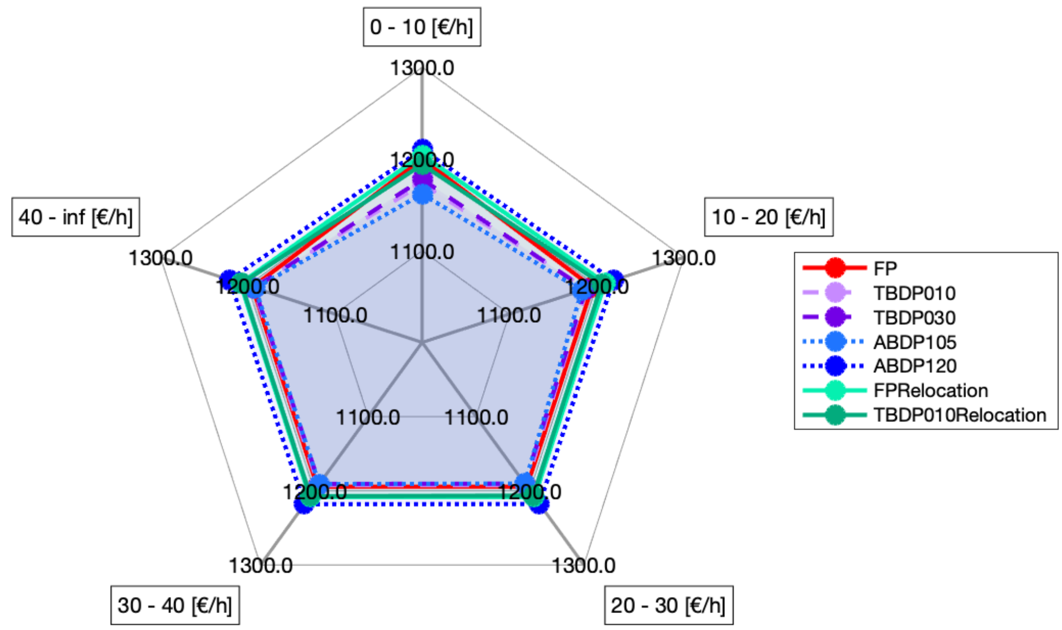

Figure 13. Score per Income Group

In line with the results in our previous works (*88*), we see how, when compared to the other scenarios, the FP strategy is the only one in which the average score for the lowest income group is higher than the others (2.5% higher). For all the other scenarios, the score tends to increase with the income. A similar plot can be used to explain the supply KPIs as in Figure 14.

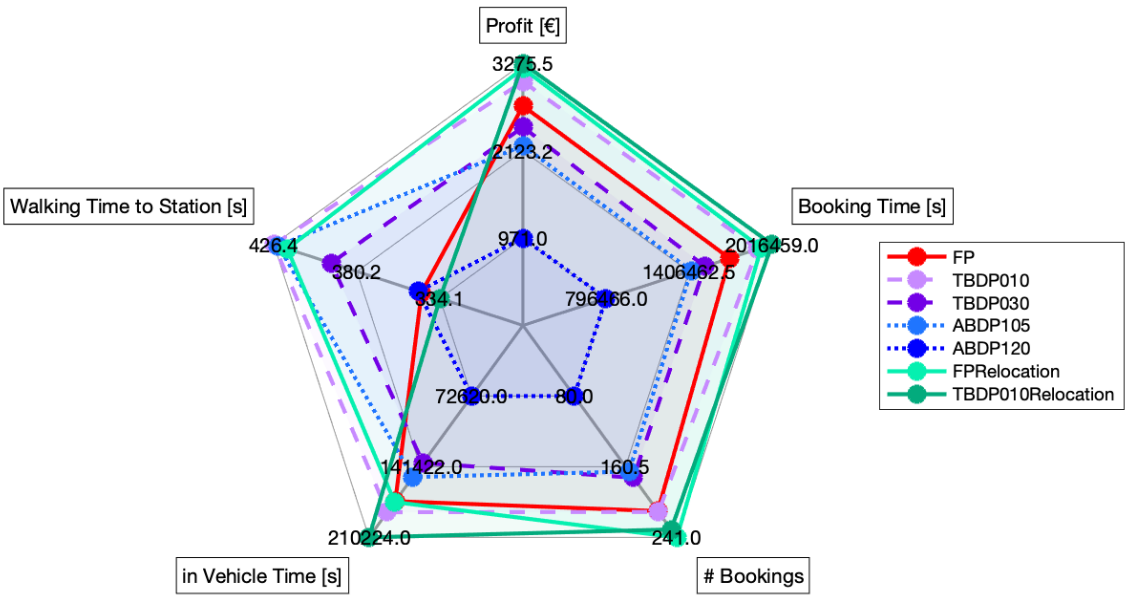

Figure 14. Supply KPIs

Figure 14 shows how it is possible to increase the profit passing from a FP to a TBDP strategy. The same happens after the relocation. The change in strategy results in a similar amount of bookings and time spent driving but, the fact that the price adheres better to the demand leads to a higher profit and utilization. Once the vehicles are relocated, more members can find cars where and when they are needed. This additionally increases the profit. Once vehicles are relocated the average walking time to reach the station increases, this is because people leaving far from the stations, this time, can find cars once they arrive to the station and are not forced to use another mode.

8.3.2 Supply-Based Pricing

At first sight the demand profile (Figure 15) has an increase in the number of vehicles used during the day only for some specific scenarios. When a strategy as we have previously defined with the name of supply-based pricing is implemented, the number of reservations is the highest. Here, starting from the MPP, we have an inverse effect if compared to the demand-based pricing. In this case, the TBDP doesn't manage to flatten the demand increasing it when the price is low. The only effect coming from this pricing strategy is to cut the carsharing demand during the peak hours. The ABDP (especially the ABDP105) strategy manages to have plenty of bookings but it doesn't achieve the same amount as the MPP.

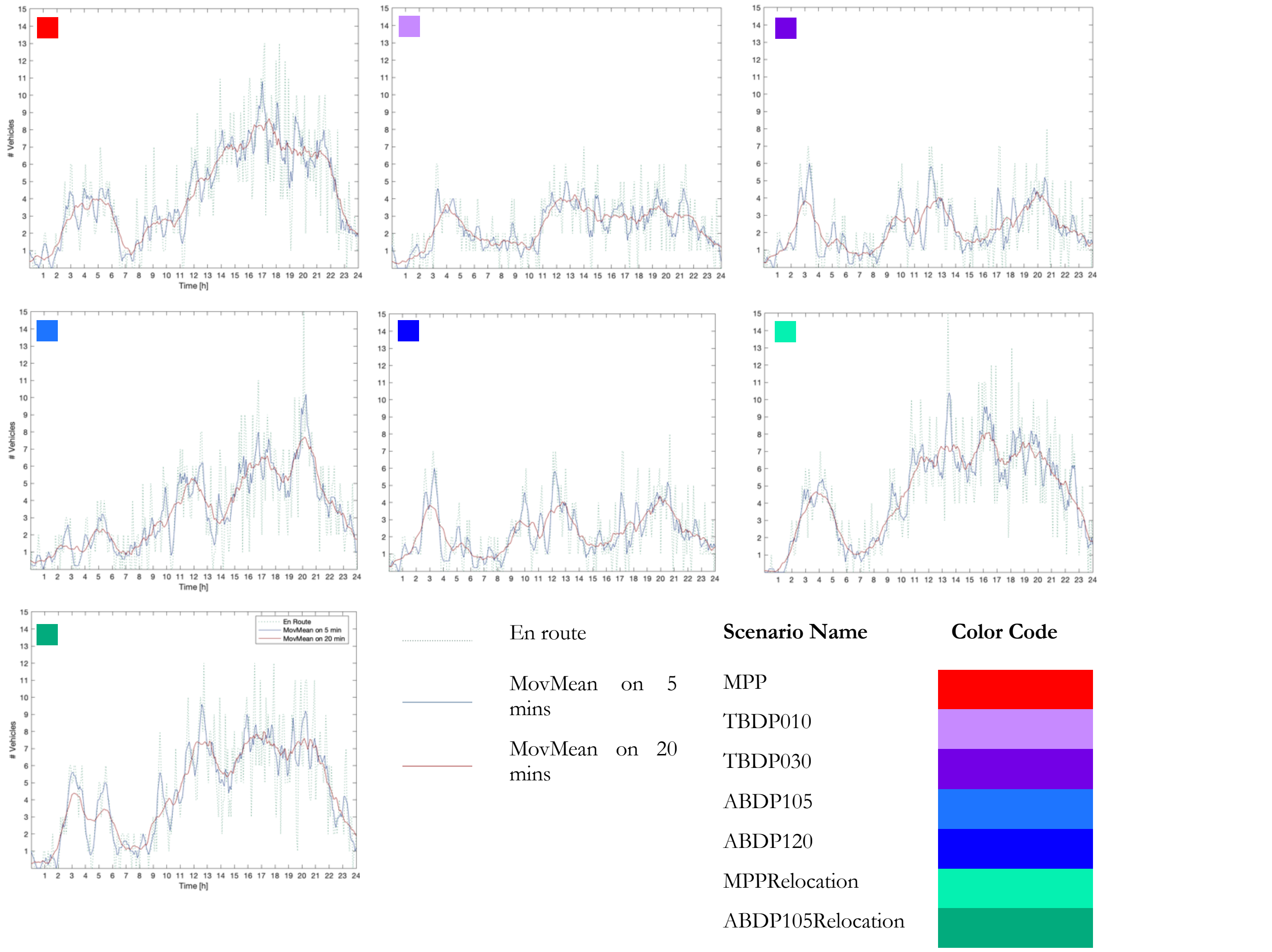

Figure 15. Demand Profile – MPP

This statement becomes clearer in Figure 16. MPP and ABDP are the strategies that result in the highest share in carsharing (relatively 3.93% and 3.44%). As in the other case, when relocated, the carsharing usage rises to 4.16% for the MPPRelocation and 4.07% for the ABDP105Relocation.

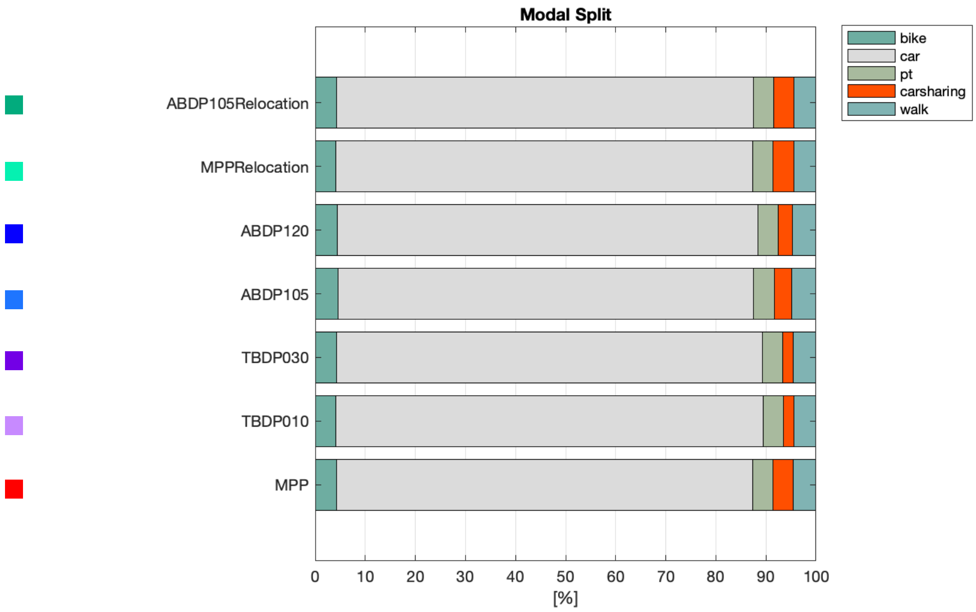

Figure 16. Modal Share – MPP

While both MPP and ABDP105 manage to increase carsharing modal share, they get a higher variance when we represent the score as a normal distribution as in Figure 17.

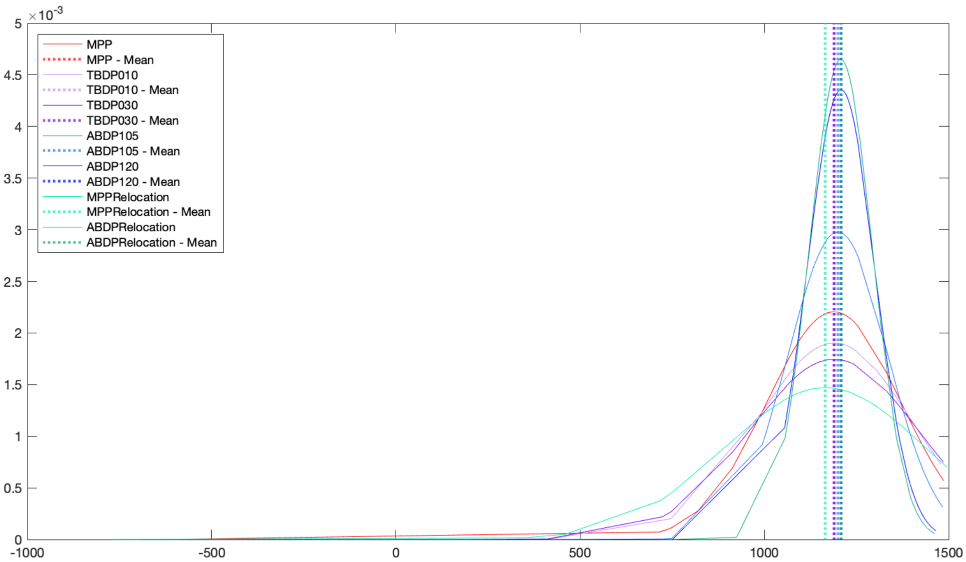

Figure 16. Normal Distribution of the Score

MPP, both in the original version as in when the relocation strategy is applied, has a bigger variance in score when compared to all the other scenarios, especially to the ABDP105. This means that the ABDP105 intercepts all those members that, at the end of the simulation, will reach a specific degree of utility. Even on average, the MPP registers a lower mean. When we deconstruct the score by income group, we can see different income groups reacting to the different pricing scenarios (Figure 18).

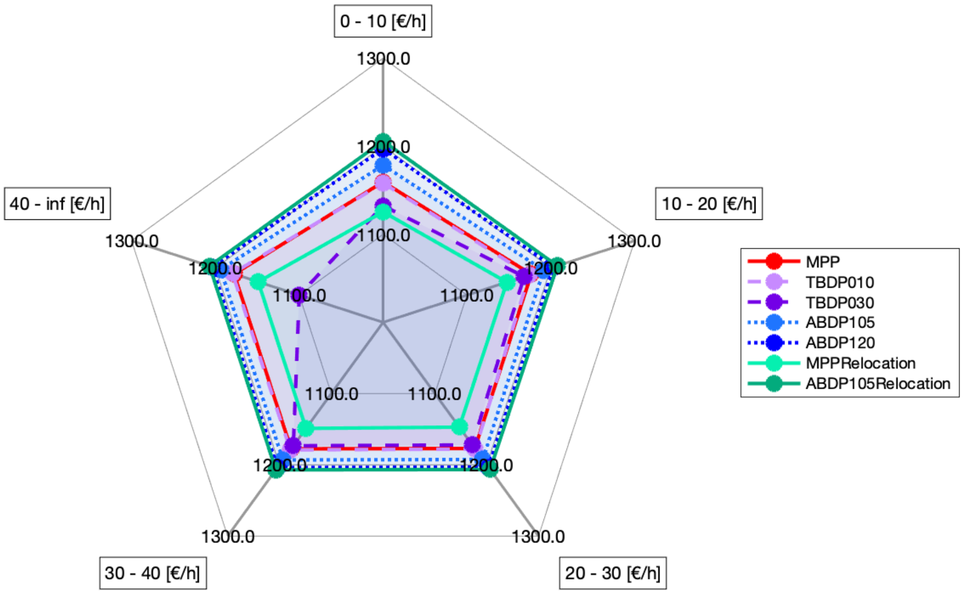

Figure 18. Score per Income Group

Also here, the higher the income groups the higher the score is. This discrepancy is stronger in the MPP where we registered score variations between +1.5% and +2% from the first income group. In the ABDP105 we have the same behavior but with an average score that is systematically higher. The moment we relocate vehicles the average score drops with an average of -3%. This happens since the new strategy allows more agents to find available vehicles at the station, resulting in a greater variety of plans. The moment the ABDP105 strategy is activated, both in the first and in the relocation phase, we see how the average score increase while the number of bookings drops as shown in Figure 19.

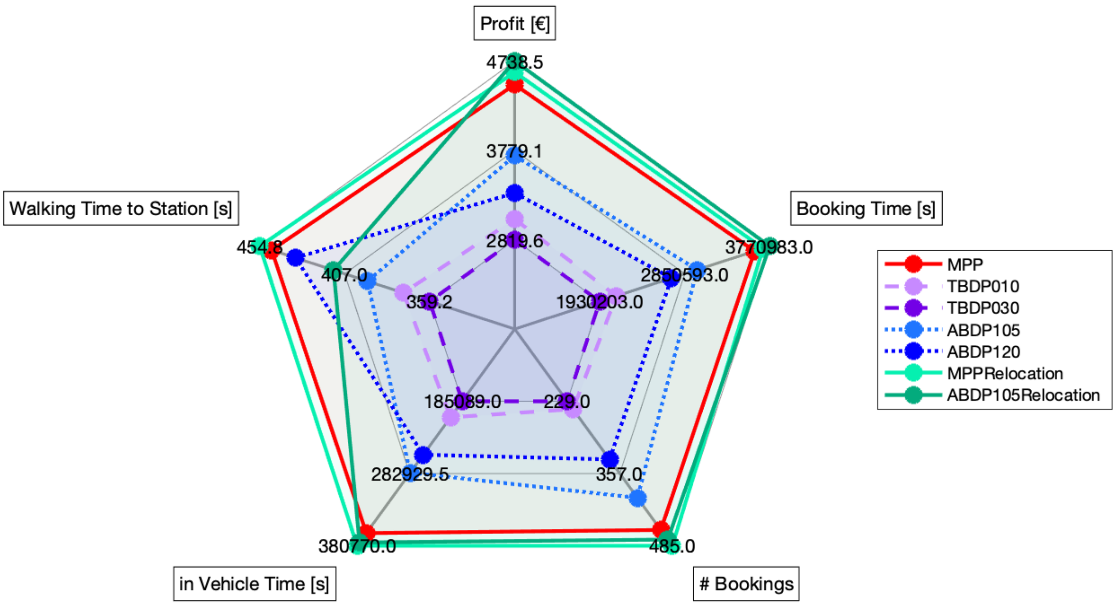

Figure 19. Supply KPIs

Here we can see how the booking time, from MPP to ABDP105, decreases of 21% while getting an increment of the average score of 1% and a variance passing from 180 to 133. When the relocation is done, we manage to increase the booking time of 2.5% (from MPP to

MPPRelocation), to increase the profit of 3% at the expanses of a decrease in the average score of 2%

8.4 Discussion

Table 5. Pricing strategies output

	AVG Score	Var Score	Profit	BookingTime	Bookings
FP	-	-	-	-	-
TBDP010	-0.08%	23.40%	10.55%	10.78%	0.47%
TBDP030	-0.17%	24.21%	-11.48%	-11.98%	-21.97%
ABDP105	-0.17%	9.43%	-23.94%	-19.87%	-27.11%
ABDP120	2.21%	-29.73%	-179.63%	-114.02%	-163.75%
FPRelocation	1.16%	-42.57%	15.38%	12.00%	12.45%
TBDP010Relocation	1.08%	-56.52%	17.11%	15.46%	9.05%
MPP	-	-	-	-	-
TBDP010	0.08%	13.88%	-47.57%	-70.90%	-88.07%
TBDP030	0.00%	21.40%	-59.10%	-86.92%	-99.56%
ABDP105	1.00%	-35.34%	-20.52%	-20.86%	-14.25%
ABDP120	1.66%	-97.80%	-35.03%	-33.30%	-37.65%
MPPRelocation	-1.97%	33.58%	2.88%	2.46%	5.77%
ABDP105Relocation	1.57%	-111.76%	5.33%	4.32%	3.59%

The pricing strategy based on booking time, given that by its nature tries to interpret and follow the demand for carsharing, manages to increase the variance of the score and, at the same time, the profit. Even if the number of bookings remains the same, their time increases.

The only pricing strategy that manages to significantly increase both the score and the profit are those applied after the relocation. As in the pre-relocation state, applying a time-based pricing strategy leads to an increase in profit in the face, however, of a slight decrease in the number of bookings. In the second group of scenarios, starting from the MPP, we show how it is not possible to increase profit by changing only the pricing strategy. This makes sense considering how the MPP is designed. Nonetheless, ABDP is capable of increasing scoring much more than a TBDP strategy. When you relocate, you can increase your profit. This demonstrates how MPP is a profit-optimizing price given a given network configuration and which must be recalculated in the event of any changes to the fleet. However, the introduction of an ABDP strategy after the relocation can increase both profit and score.

8.5 Conclusion

In this paper we developed an approach designed to optimize the profit (for the operator) and usefulness (end-user) of a carsharing service. The considered strategies are practical and essentially data driven. In both cases, in the application of these procedures, the data used that is normally in the possession of the carsharing companies (i.e., historical number of booking, availability of vehicles in real time, distribution of members on the territory). In both cases, we have shown that there is need for a car-sharing demand forecasting model. Taking TBDP as an example, in a practical application, one should consult the use of carsharing cars in the previous day to decide the price of the following day using with a day-to-day approach. The ABDP, on the other hand, is an online model. This can be applied directly as it only depends on the actual consumption of resources. Furthermore, the relocation results in an increase in the main KPIs. Its simplicity is mainly dictated by the fact that what happens is the marginal calculation of the impact of moving the vehicle from one station to another. This approach is also data-driven. In the simulation it is in fact possible to evaluate the potential impact of the vehicle that will be moved. Finally, this paper is strongly practical-oriented. Any carsharing company that can collect these types of data can, in principle, apply these models quite easily.

Possible future works can be developed around the booking forecasting system. It can help to have a fleet distribution that best adheres to member behavior using an active approach. Predictive systems of this kind can decrease the time it currently takes to generate a new fleet configuration based on the detected vehicle consumption. Furthermore, the various pricing strategies applied there can be studied in view of the implementation of carsharing (or other sharing services such as bikesharing or scootersharing) in synergy with other transport modes to optimize not only the single service, but this service in relation to a wider modal offer.

VI. Conclusions and Future Works

This part concludes the dissertation by presenting a summary of the conclusions leaving the reader with possible future research directions.

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9
Conclusions and Future Works

9.1 Conclusions

This dissertation dealt with various aspects concerning carsharing business and operations. The research has moved towards the description of the interaction between demand and supply and how to optimize the car sharing system according to objectives pursued by these two entities. A literature review on carsharing has shown how this business model, while still growing, leads to very low marginal gains. Moreover, even if car sharing tends to satisfy a small part of the daily modal choice, it has been shown how this mode of transport can make a valuable contribution to the environmental sustainability of the transport system. The study presented here involved an extension of the already existing multi-agent transport simulator MATSim by introducing dynamic pricing strategies and new simulator calibration methods regarding the extension of carsharing.

The main purpose of this thesis was to create a practical decision support system (DSS) for carsharing business providers. The idea behind this DSS is to adopt and extend an already existing agent-based simulator to create realistic what-if scenarios based on different characteristics of the territory and of the service. This DSS aims to optimize business strategies around the customer's needs by suggesting the correct business model for the service provider. To achieve this, we have answered four research questions, already formulated in the first part of this dissertation:

RQ 1: Given a certain territory and population, is it possible to identify a carsharing system that is optimal for both users and the service provider?

Creating a simulation based DSS allowed us to assess and identify ways to increase user utility while optimizing supply resources. This question carries with it several facets. Here three main factors are identified: The territory, the demand, and the supply system. In the third part of this thesis, we identified what are the characteristics of the demand that could influence the eventual success of a specific carsharing business model. In chapter 2 we highlighted the qualities and shortcomings of two different types of car sharing introduced in the Berlin area highlighting how the one-way service offers more flexible options to service users. This leads to greater use and integration with other modes of transport. In contrast, however, a two-way system, used for rentals of longer duration, tends to generate more profit and a simpler model to handle for the carsharing company. In chapter 3, we conducted an exploratory analysis, in addition to verifying the coherence of the simulator with the data already present in the literature. In the fourth part, specifically in chapter 6, we expand the concept of optimality considering the impacts generated by a carsharing service on the population. To better study its nature, we have shown how the introduction of the income into the utility function can lead to the identification of problems concerning vertical equity and how the poorest users are the ones who find the hardest time to manage the introduction of this type of service on the land.

RQ 2: Is it possible to maximize profit in carsharing operations through a simulation approach?

If based on the supply available, it is possible to create a meta-model aiming at profit maximization. In the fifth part of this work, specifically in chapter 7 and 8, we studied how it is possible to create a method that maximizes the profit generated by the rental of the vehicle fleet. The concept behind this operation is as follows: profit is essentially composed of two parts, one positive, the revenue, and one negative, the cost. the cost is also divided into two parts, a variable which is a function of actual use, and another fixed which is independent of how much a given resource will be used. It is therefore clear how the item "costs" grows differently according to the use of vehicles and increases more or less quickly according to the size of the fleet. Inversely, revenue, in a system where demand is elastic, tends to grow as a function of price until, once the proposed price is too high (i.e., greater than the utility of using that particular service), begins to drop. This means that, mathematically, it is possible both to find that price which, in a given situation, brings the revenue to be maximum and that price that brings the costs (due to use) to be minimum. But revenue and costs, as we have said, do not depend only on the price but also on the size of the fleet. We must therefore also take into account the consumption of the vehicle fleet, that is, of the supply. By evaluating various combinations of price and supply we can, finding the profits generated by these pairs, generate a surface on which we can identify, once we know the status of the supply (number of machine hours that the company can offer) the price that will correspond to the maximum profit obtainable in that situation. At the end of the fifth part, we demonstrated how this type of price can work during normal daily operations. One of the main flaws of this method lies in the difficulty of having complete information on the behavior of the demand without which, it is difficult to create a sufficiently reliable simulation in order to obtain the aforementioned surface.

RQ 3: how can a dynamic pricing strategy be developed to increase the profit of the company and, at the same time, improve the utilization of the fleet?

This research question has been addressed in the third part of this dissertation, specifically in chapters 3 and 4 we have introduced the various indicators used for the evaluation of dynamic pricing strategies. Subsequently, in chapter 5 we applied this know-how in evaluating the impact of different pricing strategies on different distributions of homogeneous income. The lessons learned of this part were introduced in a more complex system in the fifth part, in chapter 8. From this procedure it appears that the success of such a strategy, where success indicates an increase in profit and secondarily an increase in the use of the fleet, depends on the amount of data held by the company and that can lead to different ways of deploying resources. In the fifth part of this dissertation, we define how, given the amount of information that the carsharing company has, which is the approach that generates, in terms of profit and use, the best outcome. We have also shown how this is possible by using specific pricing strategies, and how this is possible by hybridizing different types of prices. Pricing based on demand (whether it is a fixed price based on surveys placed at potential members of the service or prices based on the times the resources are used) can be constructed with few knowledges of the network and be used for planned and spontaneous booking models. Supply based dynamic pricing such as prices function of the resources available, need a thorough knowledge of the demand and the supply state and are more suited to spontaneous bookings. Given their nature, the introduction of pricing strategies based on the time of day, if properly developed, increase the profit generated by the rental of the fleet and, at the same time, they also manage to increase its utilization. Resource-based dynamic pricing strategies, even if they greatly increase profit, generate underutilization of resources. As described in chapter 8, vehicle reallocation processes bring the greatest benefit in terms of fleet booking time. The goodness of the outcome lies on the knowledge of the territory from the company. If the company has a poor knowledge of the competition and of the demand, strategies like fixed pricing or time-based dynamic pricing leads to higher profit. These strategies don't need a thorough knowledge of the territory and are based only on superficial knowledge of the demand. Such strategies, even if not optimized, can lead to better acceptance of the service especially if assisted with ad-hoc relocation strategies that, the creation of this decision support system, can advise with a simulation approach. Also, such strategies are offline. This implies a lower need for an advanced IT structure with the ability to receive timely information on both the fleet and its movements and consumption. Secondly, the better the knowledge of the territory better the possible outcome in terms of profit and service acceptance. When the company has an in-depth knowledge of the demand (i.e., spatial distribution of their members, insights on their travel patterns), strategies like maximum profit pricing can increase profit. To increase profit beyond this point, strategies like relocation and availability-based pricing help to intercept the mismatch created by the new distribution of the vehicles without the need of using time greedy procedures for the calibration of the decision support system. Strategies of this type are based on sudden online price changes. These responsive methods need a good IT structure capable of handling more advanced calculations based on the state of the network.

Finally, we have shown how this decision support system, together with the procedures defined in this dissertation, can help a carsharing business to achieve success based on how much knowledge the company has of the territory and its fleet, how demand is distributed and to its intrinsic properties. Each type of carsharing model has its own prerogatives, each type of demand distribution causes a certain success of the pricing strategies and a specific level of knowledge of the supply-demand system corresponds to a specific type of price that is able to maximize the operational profit of the service.

RQ4: Is it possible to assess the quality of a business model in a multi-criteria and multi-actor analysis framework?

In the second and third part, specifically in chapter 2 and 5 of this dissertation, we have developed a multi-criteria approach to estimate how user behavior changes. These indicators concern both the temporal effect and the economic effect on demand. First of all, in the second part we show how it is possible to analyze both the outcome of a price strategy variation for the company and how, always this same price variation, brings a change in the modal choice habits of users and how specific chains of activities are more or less favored. The multi-criteria analysis makes it possible to immediately identify, for example also using dashboards that can display multiple indicators, the impact that the choices recommended by the decision support system will have both on users and on the supply. In part three, we show how an extension of these indicators is possible for those magnitudes that further and more deeply characterize the behavioral differences of individuals, disaggregating, in this case, by wage group. Overall, the development of these indicators follows, in addition to the quantitative approach based on the physical quantities of the indicators themselves, also a qualitative approach. Their development is based on a concept of visuality that can allow, through the creation of a possible dashboard, to immediately understand the quality of the choices recommended by the decision support tool.

9.2 Main Findings

The practical implications and scientific contributions made by this research are summarized below.

9.2.1 Practical Contributions

Development of a practical decision support system

Business decisions, more often than not, are decisions that involve a huge consumption of financial and economic resources. The ability to test these decisions in a sandbox without having to do it directly in the field can bring a considerable competitive advantage. The decision support system introduced in this work makes it possible to evaluate the introduction of different types of prices, different business models and the introduction of a service from scratch considering the characteristics of the territory and of the population. Using a simulation approach allows you not to have to use huge resources for testing phases that could prove to be too expensive for the company.

Development of a maximum profit pricing strategy

The business of carsharing, given its nature and the competitiveness present today, is a type of business that tends to have small profit margins. In this thesis we have shown how, given a comprehensive knowledge of the pool of members and the supply situation, it is possible to develop a dynamic price that allows maximizing profit. This type of price implicitly carries information relating to the user base and is created through a simulation approach.

Estimation of the impact of introducing dynamic prices

The introduction of dynamic pricing in carsharing is no longer a novelty, but the way and the method by which the impacts of this strategy are assessed is not yet consolidated. In this thesis we have concretized a methodology that allows to estimate the impacts through a simulation approach and that allows to have an overview of both the user side and the supply side.

Business models development

In addition to the development of the decision support system, in this thesis, we also tested its functionality by implementing different pricing strategies on different territories and different population distributions. We have evaluated the quality of different business models and explained how it is possible to build different strategies thanks to the use of this tool.

Introduction of new ways to develop and assess realistic scenarios

Having a general tool that is versatile enough to evaluate similar services which are introduced in different territorial and demographic contexts is not trivial. It goes without saying that as scenarios tend to be more realistic this assessment becomes more complex and more prone to error. In this work we have shown how it is possible to assess different scenarios with different degrees of complexity and what are the procedures to be implemented to simplify too complex scenarios.

9.2.2 Scientific Contributions

Introduction of the income in the utility model

The development of the decision support system is based on an agent-based framework which is interpreted by a transport simulator which, in the case of this thesis is MATSim. To increase the ability of this software to describe the user and generate behaviors that are as similar as possible to reality, we have introduced an income value in the utility function. The introduction of this attribute allows a more disaggregated and precise evaluation of the user's behavioral component and therefore allows to describe the impact that the different modes of transport have on the user's choices not only from a temporal or spatial point of view but also from an economic point of view.

Calibration of an agent-based simulator for carsharing

Methods of calibrating a carsharing service, especially when it comes to agent-based models, are quite rare. The main problems are the difficulty in finding data and the rarity of simulators that allow to replicate this specific mode of transport. In this dissertation we have identified a simulator calibration procedure using an approach based on the consumption of resources and the revenue generated by one day of service activity.

Profit Maximization Method

Even if the maximization of profit has rather practical implications, the methodology with which this problem was faced has produced a scientific contribution. Depending solely on the consumption of resources (i.e., vehicles) we have developed a method of maximizing profit which, through the creation of a metamodel that can be generated by simulating multiple configurations of the service, is able to return a formulation that incorporates within, in an implicitly way, the demographic and fleet characteristics.

Methodological contribution valid for other mobility services

In this paper we described how the approach used here is scalable to be applied in different cities and, above all, it can be applied to various carsharing models. The generality of the criterion used in the creation of the methodology allows its introduction for other types of shared mobility (eg, bikesharing, scootersharing), it can be applied independently of the technology used by these systems (i.e., for autonomous or electric vehicles) and can finally be extended for mobility studies based on MaaS.

9.3 Future Work

Although this thesis was able to answer the different research questions proposed in the introduction, further efforts aimed at generalizing the decision support system, refining the pricing strategies, and further assessing other factors that influence the success of a carsharing company are possible by following these possible search directions:

- Advanced fleet allocation,
- Machine Learning,
- Extension to Free-Floating and One-Way,
- Extension to other mobility services and MaaS,
- Extension of the calibration process.

Advanced Fleet Allocation

In this thesis we used a relatively simple responsive approach: the position of vehicles is changed when we know that a user has searched for a vehicle in a certain area and cannot find it. Booking forecasting systems can help to have a fleet distribution that best adheres to member behavior using an active approach. Predictive systems of this kind can decrease the time it currently takes to generate a new fleet configuration based on the detected vehicle consumption. A possible method of recognizing usual booking patterns can be constructed using machine learning.

Machine Learning

Machine learning can help in finding behaviors that we cannot recognize at the moment in the population. For instance, in this thesis specific exogenous conditions such as, for example the weather, have not been treated. The implementation of machine learning techniques in this decision support system can lead to the identification of attributes that are not easily identifiable in the simulation that can best describe the behavior of the demand in such a way as to adapt the offer to the contingent situation.

Extension to Free-Floating and One-Way

the extension of the strategies evaluated in this dissertation can be applied to other carsharing models: free-floating and one-way. In these cases, we expect the results to differ from those reported due to the diversity of use of this service by end users. Given the use of a higher number of vehicles, pricing strategies such as availability-based dynamic pricing may be better. This intuition is supported by the well-known application of these strategies in the sale of airport tickets. A higher number of assets can trigger better competition for cheaper booking between neighboring areas or stations given the wider range of price variations.

Other Sharing services and MaaS Extension

Similar to the Free-floating and one-way extension, a possible addition to the calibration algorithm used in this thesis can be applied for simulation in other sharing models and mobility as a service. The various pricing strategies applied there can be studied in view of the implementation of carsharing (or other sharing services such as bikesharing or scootersharing) in synergy with other transport modes in order to optimize not only the service, but this service in relation to a much wider modal offer.

Extension of the Calibration

In this work we have presented a first possible approach to the calibration of the MATSim agent-based simulator with regards to a carsharing service. This calibration was carried out at city level and considering revenue and the number of hours rented by users as objective. Although this approach is a good starting point because of its generality and simplicity of execution, another and more thorough calibration method can be constructed to calibrate the carsharing system at the area or station level and including different vehicles and features.

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