Diana Rita Ramos Jorge

OPTIMIZATION AND SIMULATION OF ONE-WAY CARSHARING OPERATIONS

PhD Thesis in Transport Systems supervised by Professor Gonçalo Correia and Professor Cynthia Barnhart, presented to the Department of Civil Engineering of the Faculty of Sciences and Technology of the University of Coimbra

September 2014

· U C ·

Universidade de Coimbra

Diana Rita Ramos Jorge

OPTIMIZATION AND SIMULATION OF ONE-WAY CARSHARING OPERATIONS

PhD Thesis in Doctoral Program in Transport Systems supervised by Professor Gonçalo Correia and Professor Cynthia Barnhart, presented to the Department of Civil Engineering of the Faculty of Sciences and Technology of the University of Coimbra

September 2014

• U C •

UNIVERSIDADE DE COIMBRA

To my mother

Financial support

This research work was conducted under the MIT-Portugal Program and financed by "Fundação para a Ciência e a Tecnologia" (FCT, Portugal) through the Ph.D. grant with reference SFRH / BD / 51328 / 2010, and was co-financed by the European Social Fund (ESF) within the "Programa Operacional Potencial Humano" (POPH), by project InnoVshare - Viability analysis of different carsharing system configurations through an innovative large scale agent based simulation model (PTDC/ECM-TRA/0528/2012), and by project EMSURE - Energy and Mobility for Sustainable Regions (CENTRO-07-0224-FEDER-002004). The POPH research program is integrated in the "National Strategic Reference Framework 2007-2013 - Tipologia 4.1 – Formação Avançada" (QREN 2007-2013).

MIT Portugal

FCT Fundação para a Ciência e a Tecnologia
MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E ENSINO SUPERIOR Portugal

POPH PROGRAMA OPERACIONAL POTENCIAL HUMANO

QREN QUADRO DE REFERÊNCIA ESTRATÉGICO NACIONAL PORTUGAL 2007.2013

UNIÃO EUROPEIA
Fundo Social Europeu

Acknowledgements

Firstly, I want to thank Professor Pais Antunes for playing the most important role in my decision to pursue this PhD. You have always believed in my abilities and transmitted the priceless confidence I needed to succeed. I am grateful for your support and encouragement throughout the past years, as a teacher and as a friend.

My deepest gratitude goes to Professor Gonçalo Correia for permanent guidance, availability and support. You shared your knowledge, stimulated my critical spirit and willingness to always go further, and had a crucial role in the development of this work. Thank you Professor, for helping me accomplish my goals.

I sincerely thank Professor Cynthia Barnhart for receiving me at MIT and supporting my research. I benefited so much from your vast knowledge on operations research, providing me unique and valuable insights essential to guide my work in a favorable way. Despite an extremely full schedule as yours, you have always managed to make the time to help me by addressing my questions.

I would also like to thank Fundação para a Ciência e Tecnologia (FCT) and MIT-Portugal Program for their financial support that has allowed me to continue my studies both in Portugal and at MIT. Furthermore, it was essential for me to be able to present my work in major conferences worldwide. A special reference must be made to the Faculty of Sciences and Technology of the University of Coimbra for all the institutional and logistics support.

My thankfulness goes also to Lourenço Dantas from the Boston Logan Airport and to my colleague Jóni Santos for providing me essential data for one of the case studies. Without you, I would not be able to present such a realistic case study.

To my colleagues and friends at the Department of Civil Engineering, especially to Melissa, Joana Carreira, Inês, Sílvia and Joana Cavadas, thank you for the great times together and for the support I always felt to be present from your behalf. Joana Cavadas, despite your late show in my life, I am certain you know how important you are to me.

Regarding my stay in the United States, I want to thank Ta for his imperative help and availability, which played an important role in the development of my work. To Irene, thank you very much for all the good moments we had together, your friendship and support. You are one of the best people I have ever had the pleasure to meet.

Mark, you became one of the most important persons in my life. Living with you in Boston and traveling with you throughout the country was privilege. I never thought it would be such a life changing experience. Thank you so much, for everything we've been through, and everything that is still ahead.

To my friends, Catarina, Sara, João and Filipe, I am grateful that you were able to listen to me constantly talking about my work and constant concerns, and still decided to stick around. Thank you for the support and the great moments we had together, in person and online. You are all very important to me.

Acknowledgements

I want to express my profound gratitude to my father Valdemar, my sister Márcia and to my grandparents Preciosa, and José. I owe you everything I am, and what I have accomplished until today. Your love and support have been essential throughout my entire life, and I am so very lucky to have you all with me.

Finally, I want to dedicate this thesis to my mother, Maria.

Contents

List of Figures

List of Tables

Abstract

Carsharing is a transportation option with great potential, allowing people to use a private vehicle without having to own it. Nowadays carsharing systems are implemented almost all over the world, being the round-trip system the most predominant. However, the implementation of one-way systems has been expanded considerably since 2008. Despite the proliferation of carsharing, there are few analytical studies addressing its management. One-way systems offer users more flexibility. Contrarily to the typical round-trip systems, one-way systems allow users to pick up the vehicles at one station and deliver them to a different station from the one where they were picked up. This flexibility poses added management complexities which have never been solved completely. Most of the existing studies cannot accurately represent the reality of these systems, due to algorithmic, structural, and functional complexities. Therefore, carsharing is an interesting topic to be addressed under an operations research perspective.

This thesis has two main objectives. The first objective consists in assisting one-way carsharing companies to plan and manage their systems in a more profitable way while at the same time offering users a good quality of service. The second objective targets helping round-trip carsharing companies to start offering one-way trips, taking full advantage of idle fleets and offering users a transportation option for other trips than just shopping or leisure. Three optimization models as well as a simulation model have been developed to reach the previously defined objectives.

In this thesis, we consider the perspectives of two main stakeholders: the carsharing provider and the carsharing user. It is our belief that the improvement of carsharing systems from these two perspectives is also relevant to transportation authorities and to local and central governments, since it provides a complement to existing private and public transportation modes.

The greatest problem of one-way carsharing companies is associated with the imbalance of vehicles across stations. This is due to the imbalance inherent to trip patterns in most of the cities worldwide. In this work, the two approaches proposed to mitigate this problem are: vehicle relocation between stations through a staff of drivers, and changing the price of the trips according to its effect on system balance. With respect to relocation operations, both an optimization model and a simulation model are developed. For the second approach, only an optimization model is proposed. Given the complexity inherent to this optimization model, we resorted to an iterated local search meta-heuristic algorithm. All of the developed models aim at maximizing the profit of the carsharing companies taking into consideration the revenue obtained through the trips paid by carsharing users, and the costs involved, namely fleet, stations and relocation operations costs. For the trip price changing approach, costs associated with relocation operations are not considered since vehicle relocation is not considered.

As one-way carsharing systems present greater flexibility in terms of trip purposes (for example, commute, shopping, and leisure), round-trip companies have started to consider providing one-way trips. For instance, in 2014, *Zipcar* began accepting some one-way trips. Notwithstanding, as it was previously said, one-way trips are more difficult to manage than the round-trip ones. Thus, there is the need to study the integration of both carsharing types, which is another objective of this thesis. For this purpose, an optimization model is developed with the same goal as the previous, the maximization of carsharing companies' profit.

All the models are applied to realistic case studies. For the approaches studied to balance the vehicle stocks in one-way carsharing systems, the municipality of Lisbon, in Portugal, is used. For the integration of both round-trip and one-way carsharing, the *Zipcar* round-trip carsharing service in Boston, Massachusetts, USA, is considered. The developed methodological approaches are able to deal with the size and complexity of the case studies considered, as all the applications reached satisfactory results and some of them achieved optimal results. Results show the usefulness of these methodologies as viable tools to help carsharing companies plan and manage their systems, improving the level of service offered to the users.

Resumo

O carsharing é um modo de transporte com grande potencial, permitindo o uso de um carro sem os custos inerentes à sua aquisição e manutenção. Atualmente, os sistemas de *carsharing* existem em praticamente todo o Mundo, sendo o sistema de *round-trip* o mais predominante. No entanto, a implementação de sistemas de *one-way carsharing* tem-se expandido consideravelmente desde 2008. Apesar da proliferação do *carsharing*, ainda existe um número reduzido de estudos analíticos que tentem resolver os problemas relacionados com a sua gestão. Contrariamente aos sistemas tradicionais de *round-trip carsharing*, os sistemas de *one-way carsharing* oferecem aos utilizadores uma maior flexibilidade, permitindo aos utilizadores recolherem os veículos numa estação e devolverem-nos em outra diferente da inicial. Esta flexibilidade implica problemas adicionais para as empresas na gestão da sua frota, os quais nunca foram totalmente solucionados. A maioria dos estudos existentes não consegue representar fielmente a realidade destes sistemas, devido à sua complexidade algorítmica, estrutural e funcional. Deste modo, o *carsharing* torna-se um tópico interessante de estudo sob uma perspetiva de investigação operacional.

Esta tese tem dois objetivos principais. O primeiro objetivo consiste em auxiliar as empresas de *one-way carsharing* a planear e gerir os seus sistemas de uma forma mais lucrativa, oferecendo, ao mesmo tempo, uma boa qualidade de serviço aos seus utilizadores. O segundo objetivo visa ajudar as empresas de *round-trip carsharing* a oferecer viagens *one-way*, tirando completo proveito da sua frota enquanto oferecem aos seus clientes uma alternativa de transporte para outras viagens que não as de compras ou lazer. Três modelos de otimização e um modelo de simulação foram desenvolvidos para alcançar os objetivos referidos. Nesta tese, as perspetivas de dois intervenientes principais nestes sistemas são considerados: a das empresas, e a dos utilizadores. A melhoria dos sistemas de *carsharing* consoante estas duas perspetivas é relevante para as entidades locais e centrais que gerem os transportes, já que estes sistemas constituem um complemento ao transporte privado e ao transporte público existentes.

O maior problema que as empresas de *one-way carsharing* enfrentam prende-se com o desequilíbrio de *stocks* de veículos nas estações. Este surge devido ao desequilíbrio no padrão de viagens existente na maioria das cidades. Nesta tese, as duas abordagens propostas para combater este problema são: operações de relocalização de veículos entre estações através de um conjunto de condutores contratados pela empresa de *carsharing*, e variação dos preços das viagens de acordo com o seu efeito no equilíbrio do sistema. No que se refere à primeira abordagem, um modelo de otimização assim como um modelo de simulação são desenvolvidos. Para a segunda abordagem, um modelo de otimização é desenvolvido. Dada a complexidade inerente a este modelo, recorremos a uma meta-heurística de procura local com iterações para a sua resolução. Todos os modelos propostos têm como objetivo a maximização do lucro obtido pela empresa, considerando a receita obtida através das viagens pagas pelos clientes, e todos os custos envolvidos, nomeadamente os custos relativos à frota de veículos, às estações e às operações de relocalização. Para a abordagem correspondente à variação dos preços das viagens, os custos das operações de relocalização não se consideram, visto que estas não são efectuadas em simultâneo com a política de preços.

Devido ao facto do *one-way carsharing* apresentar uma maior flexibilidade relativa aos motivos de viagem (por exemplo, pendulares, compras e lazer), as empresas de *round-trip carsharing* começaram a pensar oferecer viagens *one-way*. Em 2014, a *Zipcar* começou a providenciar este tipo de viagem. Não obstante, como já foi referido anteriormente, estas viagens são mais difíceis de gerir do que as viagens de *round-trip*. Desta forma, existe a necessidade de estudar a integração de ambos os tipos de *carsharing*, o que constitui outro objetivo desta tese. Com esta finalidade, um modelo de otimização é desenvolvido com o mesmo objetivo dos anteriores, a maximização do lucro da empresa.

Todos os modelos desenvolvidos foram aplicados a estudos de caso realistas. Para as abordagens propostas para equilibrar os *stocks* de veículos nos sistemas de *one-way carsharing*, é utilizado o município de Lisboa, em Portugal. Para o estudo da integração de ambos os tipos de *carsharing* é considerado o serviço de *round-trip carsharing* da *Zipcar* existente em Boston MA, EUA. As metodologias desenvolvidas são capazes de lidar com a dimensão e complexidade dos estudos de caso considerados, já que todas as aplicações alcançaram resultados satisfatórios, sendo mesmo possível atingir resultados ótimos em algumas delas. Os resultados mostram a utilidade destas metodologias como ferramentas viáveis para ajudar as empresas de *carsharing* a planear e gerir os seus sistemas.

OPTIMIZATION AND SIMULATION OF ONE-WAY CARSHARING OPERATIONS

Chapter 1

Introduction

1.1 Background

In the last decades, the way urban transportation is seen has changed. In the beginning, private transportation provided greater accessibility and flexibility to its users. However, in the long-run, several negative externalities have been noticed, namely pollution, and excessive consumption of energy and persons' time due to traffic congestion (Schrank et al., 2010). Moreover, vehicle ownership costs are not recoverable, for example insurance, even if the vehicle is no longer used (Mitchell et al., 2010). With respect to parking, private vehicles' utilization rates are very low, for example, in the US, automobiles spend around 90% of their time parked (Hu and Reuscher, 2001). This creates opportunity costs associated with using urban land for parking spaces instead of other more productive activities. Thus, public transportation could constitute a good alternative. Nevertheless this also suffers from several shortcomings, for instance: poor service coverage, schedule inflexibility, lack of personalization, and inefficiency due to the need of providing enough vehicles for the peak hour demand, which will then be idle during the remaining periods of the day.

Taking into consideration the advantages and disadvantages of private and public transportation exposed above, there is the need to find compatible and alternative transportation modes that aim at minimizing the negative aspects of the traditional ones and that at the same time provide the travelers the mobility they need when necessary. One of these alternatives is carsharing which may be classified somewhere between private and public transportation. Carsharing systems involve a small to medium fleet of vehicles available at several stations or parking spaces spread across a city to be used by a relatively large group of members. Through these systems, a person can access a fleet of shared-used vehicles and benefit from almost all the advantages of private transportation, without the costs of owning a car (Shaheen et al., 1999).

These systems have a positive impact on urban mobility. Mainly through a more efficient use of automobiles (Litman, 2000; Schuster et al., 2005) since they have much higher utilization rates than private vehicles. That is, in the medium to the long-run they can dilute the sunk costs and decrease the land needed for parking. Typically the use of carsharing systems corresponds to a decrease on car ownership rates and as a consequence a reduction on car use as the main transportation mode (Celsor and Millard-Ball, 2007; Schure et al., 2012; Sioui et al., 2013). This illustrates the potential of carsharing systems as a strong transport demand management measure available to transportation and municipality authorities. Moreover, some recent studies concluded that carsharing systems would have positive environmental effects, allowing the reduction of greenhouse gas emissions (Martin and Shaheen, 2011; Firnkorn and Müller, 2011).

With respect to the operating model, there are two main types of carsharing systems: round-trip (or two-way) and one-way. Round-trip carsharing systems require users to return cars to the same station where they were picked up; while one-way carsharing systems offer users the flexibility of picking up a car at a station and return it to a different one. Thus, round-trip services may not be attractive if a trip requires spending a long time parked at a location other than the vehicle's home location, being mostly used for short trips in which vehicles are parked for a short duration, typically for leisure, shopping and sporadic trips (Barth and Shaheen, 2002; Costain et al., 2012; Balac and Ciari, 2014). On the contrary, one-way carsharing may be used for all trip purposes, even commuting (Balac and Ciari, 2014; Ciari et al., 2014; Schmoller et al., 2014). Although Balac and Ciari (2014) concluded that the demand for round-trip carsharing did not decrease significantly with the introduction of one-way carsharing, showing that both services are complementary. Recently, a particular case of one-way carsharing appeared, in which the vehicles are scattered in parking spaces within a city, the so-called free-floating carsharing (Ciari et al., 2014; Schmoller et al., 2014), which can be called a generalization of the one-way carsharing.

Despite being an advantage for the user, one-way carsharing systems bring the complex question of how to manage fleet imbalances, since demand for vehicles and free parking spaces fluctuates throughout the day. Therefore, clients may not find vehicles or parking spaces available at the time they need them. Several approaches have been proposed in the literature to address the imbalance problem, such as: operator-based relocations (Kek et al., 2009); price incentive policies for the users to accept choosing another drop-off station (Febbraro et al., 2012); price incentives for grouping and ungrouping parties of people (Barth et al., 2004); accepting or refusing each trip (Fan et al., 2008); station location (Correia and Antunes, 2012); and changing the trip prices considering both origin and destination stations simultaneously (Zhou, 2012). These approaches have mainly been studied using optimization and/or simulation methods.

However, all of the approaches previously studied present problems related to the approach itself or to the methodology followed. With respect to the approaches: operator-based relocations present additional costs to the operator, while user-based relocations are limited to the value that users give to affordability versus convenience. The same happens with the price incentives for grouping and ungrouping people. Moreover, refusing trips can damage the image that users have about this type of system, and just locating carsharing stations is not by itself able to increase the profitability of the system. Finally, changing the price of each trip according to its potential to balance the vehicle stocks has not yet proved to be able to solve this problem. Regarding the methods used: optimization algorithms usually entail great computational complexity, which makes it difficult to perform a complete analysis, integrating several planning and/or operational decisions; and simulation does not lead to optimal solutions.

1.2 Short history of shared vehicle systems

Shared-use vehicle systems were originated in 1948, in Zurich, Switzerland with a cooperative known as *Sefage*, and expanded to other European countries, namely France and The Netherlands in the 1970's (Shaheen et al., 1999). However, all of these systems failed and only in the 1980's successful programs were implemented, which benefited from the knowledge acquired from previous experiments and the advancement of communication technology. In the United States these systems appeared much later, in 1983, with the *Mobility Enterprise* program. This concept of shared vehicles began gaining popularity in the US only in the 1990s. More recently, these systems were also implemented in Asia, for instance in Japan and Singapore (Kek et al., 2006), and in Australia (Flexicar, 2014) and New Zealand (Cityhop, 2014). Moreover, start-ups are being explored in several African countries, such as Kenya and South Africa (Shaheen and Cohen, 2007).

Nowadays, carsharing is implemented in approximately 1100 cities in 27 countries worldwide and has an estimated 1,788,000 members sharing over 43,550 vehicles (Shaheen and Cohen, 2013). Currently, the world's largest carsharing company is *Zipcar*, which was founded in 2000 and purchased by *Avis Budget Group*, in 2013. It has a fleet of 10,000 vehicles shared by 850,000 members in the United States, the United Kingdom, Canada, Spain, and Austria (Zipcar(a), 2014), and operates mainly as a round-trip carsharing company. Considering the Portuguese case, there are currently two round-trip carsharing providers: *Mob Carsharing* that operates in Lisbon since September 2008, and *Citizenn Carsharing*, which appeared later in Oporto. *Mob*

Carsharing has 9 vehicles scattered around 8 stations (mobcarsharing, 2014), while *Citizenn Carsharing* has 8 stations and a total fleet of 10 vehicles (citizenn, 2014). Moreover, it is important to note that these two companies have a partnership, allowing the clients of each of them to use both services.

Despite round-trip systems being the predominant type of carsharing (Barth et al., 2006; Enoch and Taylor, 2006; Shaheen et al., 1999; Shaheen and Cohen, 2007), one-way systems have been expanded considerably since 2008. Currently, as far as we know, there are six one-way carsharing systems operating worldwide. One created by the *Daimler* carmaker group, *car2go*, started in October, 2008, in Ulm, Germany. Now *car2go* operates in other German cities, the US, Canada, the Netherlands and Italy (car2go, 2014). Another created by *BMW*, which is called *DriveNow*, was started in April, 2011, in Munich, Germany (AutoExpress, 2011). *DriveNow* is also operating in other German cities, as well as in San Francisco, the US (DriveNow, 2014). Moreover, one-way carsharing is being offered by *Communauto* (Auto-mobile vehicles) in Montrèal, Canada (Communauto, 2014), and by *Autolib'* in Paris, France (Autolib', 2014). *Zipcar*, the biggest round-trip carsharing company, is also offering one-way trips in Boston, the US (ZipcarOneWay, 2014). This service started in March 2014 (autobloggreen, 2014). With respect to Portugal, very recently in June 2014, *Mobiag* (Mobiag, 2014) appeared in the city of Lisbon. The objective was to manage the fleets of the different carsharing operators in an integrated way, providing them the necessary technological tools. Currently, *Mobiag* manages, for example, *CityDrive* (CityDrive, 2014), a free-floating carsharing service, and a total fleet of 40 vehicles (Exameinformática, 2014).

Furthermore, other vehicle shared systems growing fast are bikesharing systems, which grew from about 60 programs in 2007 to about 500 programs in 2012 all over the world (USnews, 2013). These systems started in Europe and then spread to other continents, namely America, Asia, and Oceania (Larsen, 2013). A bikesharing system is planned for South Africa (GoogleMaps(a), 2014). In January 2014, there were over 700 cities worldwide offering bikesharing services (The Bikesharing Blog, 2014). The world's largest bikesharing program was launched in Wuhan, China, with 9 million clients sharing about 90,000 bicycles (Larsen, 2013). In Europe, the largest bikesharing program is Vélib, implemented in 2007, in Paris, France. It started with 10,000 bicycles scattered around 750 stations, doubling the size quickly (Larsen, 2013). Both round-trip and one-way bikesharing systems exist. However, it is important to refer that one-way bikesharing systems are easier to manage, because bicycles' relocations may be simply done by loading them onto trucks (Mitchell et al., 2010).

The growth in the implementation of these systems worldwide demonstrates their great potential. Moreover, there are few analytical studies in this field, as referred in the previous section. And these few do not allow solving the existing problems completely, predominantly the ones related to providing more flexible systems without losing a profit. These two aspects combined make this an interesting topic to be addressed under an operations research perspective.

1.3 Research objectives

The general objective of this thesis is to provide new tools, namely optimization and simulation models, to help manage one-way carsharing systems. In this thesis, models are developed taking into consideration the carsharing operators' perspective in their planning and operational decisions with the goal of achieving the highest possible profit, but always considering that their major purpose should be providing their clients (carsharing users) the highest possible level of service.

Considering this, the first objective of this thesis is to set out a comprehensive review of the research that has been conducted on this alternative transportation mode, mainly in the last few years. This review focuses on the models that address carsharing demand modeling and ways of balancing vehicle stocks across stations with the objective of identifying the existing research gaps and to decide paths for future development in this field. This review laid the path for the other research objectives which try to bridge some of the identified gaps.

Through the previous, it was concluded that one of the main existing gaps in the literature is the lack of methods to define operating principles for managing one-way carsharing systems. Therefore, the second objective of this thesis is to develop methodological approaches that aim at balancing vehicle stocks across one-way carsharing stations. These should be easy to apply to real systems in order to increase the profitability of the company and the quality of service to the users.

The third objective of this work is to address the process of integrating both types of carsharing (round-trip and one-way). This is relevant given that round-trip systems are more frequently found in cities and they are easier to manage, but clients are demanding more flexible systems with no mandatory return to the original station and even without stations.

The objectives will be pursued by developing and applying optimization and simulation methods to realistic carsharing networks. These networks were mainly chosen taking into consideration data availability, but also its appropriateness to study the specific problem at hand. It is important to note that, despite the effort made in having access to real-world information to represent the problems as realistically as possible, there was the need in some cases to resort to hypothetical data.

1.4 Outline

This thesis is divided into 6 chapters, Chapters 1 and 6 are the thesis introduction and conclusion, respectively. The four main chapters, Chapters 2 to 5, are all written in the format of a scientific paper. Some have already been accepted for publication, and others have been submitted recently, where editorial decisions are expected in the next few months. This means that all chapters can be read in succession or independently. For this reason, there are some repetitions in respect to the concepts as well as the background information throughout the document that cannot be avoided. Despite the independence between chapters, this thesis is not merely a collection of papers, since they form a logical evolution that is related. In Figure 1.1 the thesis flowchart is shown.

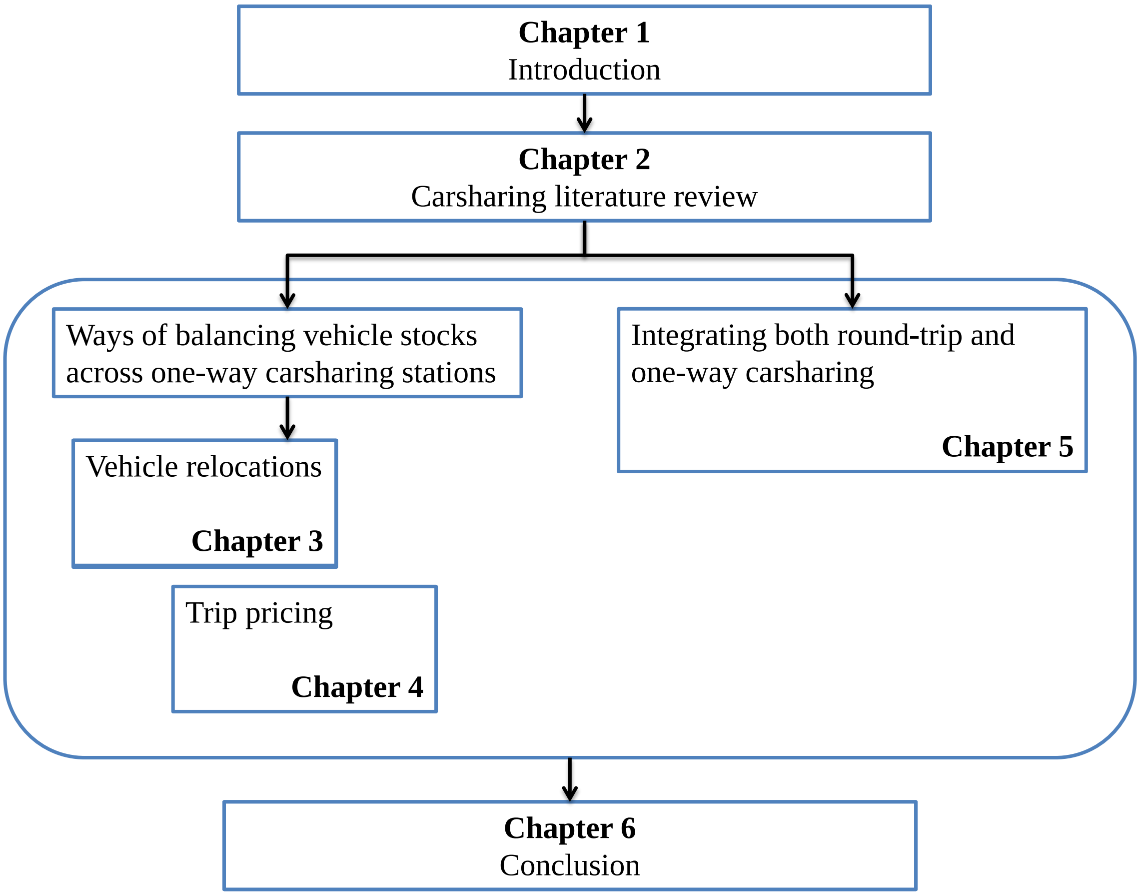


Figure 1.1 - Schematic figure of the thesis outline

Chapter 2 is the result of a comprehensive literature review of research articles and scientific reports that have been done on carsharing, mainly during the last years and until the publication date of the paper (Jorge and Correia, 2013). This chapter focuses specifically on: carsharing history and trends, carsharing demand modeling, and one-way carsharing systems modeling in terms of explaining the vehicle imbalance problem, its performance, and the ways of solving the vehicle imbalance problem. A primary focus is on the mathematical models developed so far with the objective of identifying the existing research gaps and finding possible paths to devise better operational principles for carsharing operators to manage these systems. It should be noted that since 2013, the publication date of the paper presented in this chapter, some new studies have appeared about carsharing that can help bridge the gaps previously identified. The new studies are referred to in chapters 3, 4, and 5.

Chapters 3 and 4 present ways of managing imbalance of vehicle stocks in one-way carsharing systems. The methodological approaches to address these issues are optimization (mathematical programming models) and simulation.

Chapter 3 introduces relocation operations of vehicles between stations using a staff of drivers as a way to solve vehicle imbalance issues. With this objective, two tools are developed: a mathematical programming model to optimize relocation operations that maximizes the profitability of the company; and a simulation model that allows testing different real-time relocation policies. The profitability combines the trips paid by customers, and the costs of running the system, such as: relocation, vehicle maintenance, vehicle depreciation, and station parking maintenance. In these models, all demand between existing stations must be satisfied. The real time relocation policies are based on historical data and some of them also use some of the results achieved with the optimization model as basis for obtaining better solutions. Both mathematical and simulation approach results are compared using trip data from the city of Lisbon (Portugal). The optimization results are the best ones possibly obtained, but simulated relocation policies are much more applicable in reality, because in the existing carsharing systems the travelers do not have to reserve their vehicles in advance.

Chapter 4 presents the use of trip pricing to balance one-way carsharing systems. We formulate a mathematical programming model with the decision being to increase or decrease the price of travelling from an origin zone to a destination zone according to the vehicle stocks in the origin and destination zones. We consider that there is a negative price elasticity of demand, which allows changing demand for balancing vehicle stocks. In this model, the goal is again to maximize the profitability of a carsharing company considering the revenues obtained through the trips paid by clients, and the costs of vehicle maintenance, vehicle depreciation, and station maintenance. Given the dependence between demand and price, the model is non-linear, which leads to the need of creating a solution algorithm to solve it. Therefore, a meta-heuristic is developed for solving the problem. As in Chapter 3, the model was applied to the case-study of Lisbon (Portugal).

To the best of our knowledge, Chapter 5 introduces, for the first time, the integration of both round-trip and one-way carsharing. The objective of this chapter is to study if a round-trip carsharing system is able to be profitable by allowing one-way trips for specific origin-destination pairs, considering that the round-trip service already exists and for this reason should be served in priority. An integer programming model is developed to decide which one-way trips to/from a major trip generator should be allowed in a round-trip service in order to maximize the profit of the company. This profit is computed taking into consideration the revenues that are obtained through the trips paid by the clients, and the costs that correspond to maintenance of the vehicles used for the one-way service, high demand generator station parking, and vehicle relocation when these are being considered. Two assumptions are considered for this model: the number of parking spaces in each existing round-trip station is not increased; and the fleet of vehicles is limited to the number of vehicles currently existing in the round-trip service. This model was applied to the case study of the Logan Airport in Boston, United States of America, considering that one-way trips are allowed from the existing Zipcar stations in the city (Zipcar(b), 2014) to the Airport and vice-versa.

Finally, Chapter 6 summarizes the work developed throughout this thesis and presents the main conclusions withdrawn from it.

1.5 Publications

As mentioned, this thesis is organized as a collection of papers. Therefore, we refer here the research papers that have resulted from the thesis, and where they have been published or where they have been submitted in the case of the last two.

All papers have been submitted to international peer-reviewed journals. They have not been altered in any aspect, with the exception of some layout-specific issues. Hence, some notation may differ from chapter to chapter of the thesis. The references for these chapters are as presented in Table 1.1.

Table 1.1 - Publications

Title	Authors	Journal	Status
Chapter 2 Carsharing systems demand estimation and defined operations: a literature review	Diana Jorge Gonçalo Correia	*European Journal of Transport and Infrastructure Research*	Published (2013, Volume 13, Issue 3, pp. 201-220)
Chapter 3 Comparing optimal relocation operations with simulated relocation policies in one-way carsharing systems	Diana Jorge Gonçalo Correia Cynthia Barnhart	*IEEE Transactions on Intelligent Transportation Systems*	Published (2014, Volume 15, Issue 4, pp. 1667-1675)
Chapter 4 Trip pricing of one-way station-based carsharing networks with zone and time of day price variations	Diana Jorge Goran Molnar Gonçalo Correia	*Transportation Research Part B: Methodological*	Submitted
Chapter 5 Assessing the viability of enabling a round-trip carsharing system to accept one-way trips: application to Logan Airport in Boston	Diana Jorge Cynthia Barnhart Gonçalo Correia	*Transportation Research Part C: Emerging Technologies*	Submitted

Beside the journal papers, most of the research developed in these last 4 years has been presented and discussed in several international and national conferences between 2012 and 2014. These are listed below:

- *9º Encontro do Grupo de Estudos em Transportes* (9º GET), January 5-6, 2012, Tomar, Portugal – Chapter 3;
- *25th European Conference on Operational Research* (XXV EURO), July 8-11, 2012, Vilnius, Lithuania – Chapter 3;
- *15th Edition of the Euro Working Group on Transportation* (15th EWGT), September 10-13 , 2012, Paris, France – Chapter 3;
- *1st European Symposium on Quantitative Methods in Transportation Systems* (1st LATSIS), September 4-8, 2012, Lausanne, Switzerland – Chapter 3;
- *Institute for Operations Research and the Management Sciences Annual Meeting 2012* (INFORMS 2012), October 14-17, 2012, Phoenix, USA – Chapter 3;
- *Transportation Research Board 92nd Annual Meeting* (92nd TRB), January 13-17, 2013, Washington DC, USA – Chapter 3;
- *13th World Conference of Transport Research* (13th WCTR), July 15-18, 2013, Rio de Janeiro, Brazil – Chapter 3;
- *11º Encontro do Grupo de Estudos em Transportes* (11º GET), January 6-7, 2014, Covilhã, Portugal – Chapter 5;
- *17th Edition of the Euro Working Group on Transportation* (17th EWGT), July 2-4, 2014 Seville, Spain – Chapter 5.

Chapter 2

Carsharing Systems Demand Estimation and Defined Operations: a Literature Review

2.1 Introduction

In recent decades there have been some changes in how the use of urban transportation is viewed. At first, the increasing use of private transportation in industrialized countries provided greater accessibility. In the long-term, however, it has resulted in serious negative externalities, such as pollution, and excessive consumption of energy and time due to congestion problems. This has happened mainly in urban areas where demand is concentrated in peak hours (Schrank et al., 2010). Moreover, land prices and vehicle ownership costs such as fuel, parking and the cost of purchasing and insuring the vehicle itself are increasing. 'These last costs are sunk costs even before a mile is driven' (Mitchell et al., 2010), which means that they are unrecoverable, even if the vehicle is no longer used. In addition each vehicle use is very low. In America, for example, automobiles spend around 90% of their time parked (Hu and Reuscher, 2001). Public transportation could be a good alternative, but it has several shortcomings. For instance, coverage does not allow a door-to-door service even in those European cities that have an outstanding public transportation network. Moreover, schedules are not flexible and services lack personalization. Providing public transportation for the peak hour demand also means that vehicles are idle for the rest of the day, which decreases its efficiency.

Since all these issues matter to society they have been handed over to policymakers, who should act in the public interest. It is now generally agreed that strategies are needed that will minimize these impacts while simultaneously allowing people to participate in the same activities as before. One strategy that has been indicated to manage demand is providing a transportation alternative in the form of carsharing which is a system that is somewhere between private and public transportation. The classical definition of carsharing states that it is a system that involves a small to medium fleet of vehicles, available at several stations, to be used by a relatively large group of members (Shaheen et al., 1999).

2.1.1 Round-trip versus one-way carsharing

Traditional carsharing system operators require users to return cars to the station where they were picked up. These are round-trip carsharing systems, which simplify the task of the operators because they can plan stocks based on the demand for each station. But it is less convenient for the users. Better suited to personal needs are one-way carsharing systems. In one-way carsharing, users can pick up a car from one station and leave it at a different one. If they need a vehicle later on, they can pick up another one. Therefore, in theory, one-way carsharing systems allow more trips to be captured than the alternative round-trip system, which can only be used by a small market share for leisure, shopping and sporadic trips (Barth and Shaheen, 2002). Firnkorn and Müller (2011) concluded exactly this through a survey that shows that market penetration of *car2go*, a German one-way carsharing company is about 0.37%, which is 25 times higher than the market penetration of round-trip carsharing in Germany. However, it is relevant to note that this figure depends on their computation process, which was based on member subscriptions and not on the number of active members.

A study based on a stated-preference survey performed in Greece (Efthymiou, 2012) (respondents were aged between 18 and 35) also concluded that the flexibility to return the vehicle to a station different from the one where it was picked up is a critical factor to joining a carsharing scheme. Although stated-preference only shows how things could be and not what would really happen if they were implemented. Costain et al. (2012) studied the behavior of a round-trip carsharing company in Toronto, Canada, and concluded that most trips are made for grocery or other household shopping purposes, which supports the idea that reasons for making trips are limited.

Despite the apparent advantages of one-way systems they do present the operational problem of creating unbalanced vehicle stocks in the stations due to the uneven nature of the trip pattern in a city. Nevertheless, a great effort has been made to provide these flexible systems for users in recent years. One notable example is the *car2go* company (car2go, 2012), implemented first in Germany by the Daimler carmaker and recently extended to some other European and North American cities.

2.1.2 Motivation

The complexity of managing carsharing systems, especially one-way trips, is directly linked to the interplay effect of supply and demand. One must be able to accurately model the demand and supply of these systems to better operate carsharing and estimate its effect on mobility management and the accessibility that it provides in urban areas.

Carsharing has gained great momentum in the European Union as a measure to manage transportation demand, resulting in the implementation of a very significant number of private and public carsharing initiatives. For instance the Covenant of Mayors' initiative was created to get European municipalities to work to reduce vehicle emissions by 20% by 2020, and one of the measures that repeatedly appears in the plans presented by cities is the promotion of carsharing systems. However, despite the interest shown in carsharing, there are not yet many instruments to measure the impact of carsharing systems on the sustainability of urban mobility. Moreover, it is often difficult to define their operational principles, especially in the fastest growing market of one-way carsharing systems.

This chapter sets out to give a comprehensive overview of the research that has been conducted on this alternative transportation system, mainly in the last few years. The focus is on the mathematical models developed so far, especially those that address demand modeling and ways of balancing vehicle stocks across stations in one-way carsharing systems. The objective is to create a milestone, identifying the existing research gaps and proposing possible paths for future development in this field. Our strategy consisted of reviewing all the research articles and scientific reports on carsharing, especially those that use mathematical modeling to understand the behavior of these systems and devise better operational principles for managing carsharing.

The chapter is structured as follows. The next section gives the background to carsharing systems. This is followed by a review of the research that has produced models to characterize carsharing demand. Then the models that have been developed to study one-way carsharing systems are reviewed, but specifically focused on creating ways to solve the vehicle imbalance problem, which is one of the major issues with running these systems. After that we have a tabular summary of the studies that have been carried out so far. The chapter ends with a section where we point possible ways to plug the gaps in the literature, thus identifying potential paths of future research in this field.

2.2 Carsharing: history and trends

The origins of shared-use vehicles can be traced back to 1948, when a cooperative known as *Sefage* set up services in Zurich, Switzerland (Shaheen et al., 1999). These first experiments were mainly motivated by economic reasons. Elsewhere, a series of 'public car' experiments were attempted, but failed. Among the failures were a carsharing initiative known as *Procotip*, which began in Montpellier, France, in 1971 and another, called *Witkar*, which was deployed in Amsterdam in 1973 (Shaheen et al., 1999). However, failure breeds experience, which, coupled with the advances in communication technology, enabled several successful programs to be launched in the 1980s. In these programs we may include *Mobility Carsharing* in Switzerland, and *Stattauto* in Germany.

At first it was predicted that carsharing would not work in the US because 'American cities have, with almost no exception, become motor cities – adapted to the owner-driver form of transport' (Fishman and Wabe, 1969). So carsharing programs only appeared later in the 1980s, under the *Mobility Enterprise* program. In contrast to early users in Europe those in the US were motivated more by convenience than by affordability, possibly because driving is very cheap in the US (Lane, 2005). The concept of shared vehicles only started to become popular in the US in the 1990s. Several pilot projects were carried out to achieve a better understanding of how to implement and operate this kind of system. These include *UCR Intellishare* at the University of California at Riverside (Barth and Todd, 2001), *ZEV.NET* at the University of California at Irvine, and *Carlink I* and *II* at the Bay Area Rapid Transit station in Dublin-Pleasanton (Shaheen et al., 2000; Shaheen and Wright, 2001). The projects provided insights on user responses to shared-use vehicles and allowed the assessment of the possibility that these systems could be operated as a business. Hence, a natural progression to the commercialization of the concept in many countries such as the United States, Japan, and Singapore, was expected (Kek et al., 2006). Currently, the largest carsharing company in the World is *Zipcar*, which was founded in 2000. In May 2012, this company had a fleet of 9,000 vehicles and 700,000 members (Wikipedia: Zipcar, 2012).

Carsharing has been observed to have a positive impact on urban mobility, mainly because each car is used more efficiently (Litman, 2000; Schuster et al., 2005). Shared vehicles can have much higher utilization rates than single-user private vehicles because each vehicle spends more time on the road and less time parked, thereby diluting the sunk costs. When cars are being used they are not occupying parking places, so in the medium- to long-run higher vehicle utilization rates should also mean less land needed for parking (Mitchell et al., 2010). The use of carsharing systems has sometimes led to a fall in car ownership rates and thus to lower car use, according to Celsor and Millard-Ball (2007). Martin et al. (2010) conducted a stated-preference survey in North America and concluded also that carsharing members reduced their vehicle holdings significantly, from an average of 0.47 vehicles per household to 0.24 vehicles per household. More recently, Schure et al. (2012) based on a survey conducted in 2010 on 13 buildings in San Francisco concluded that the average vehicle ownership for households that use carsharing systems is 0.47 vehicles/household compared to 1.22 vehicles/household for those that do not. Moreover, a recent study by Sioui et al. (2013) surveyed the users of *Communauto inc.*, a Montreal carsharing company, and concluded that a person who does not own a vehicle and makes a high use of the carsharing systems (more than 1.5 times per week) never reaches the car-use level of a person who owns a vehicle: there was a 30% difference between them. This idea is reinforced by Martin and Shaheen (2011) who found through a survey in US and Canada that the average observed vehicle-kilometers travelled (VKT) by respondents before joining carsharing was 6468 km/year, while the average observed VKT after joining carsharing was 4729 km/year, which is a decrease of 27% (1749 km/year). Furthermore, results of recent survey studies seem to indicate that carsharing systems can have positive environmental effects: for instance, Martin and Shaheen (2011) noted from the VKT estimations presented above that the greenhouse gas (GHG) emissions of the major carsharing organizations in the US and Canada can be statistically significantly reduced by -0.84 t GHG/year/household. While most members increase their emissions; there are compensatingly larger reductions for other members who decrease their emissions. Moreover, Firnkorn and Müller (2011) conducted a survey of a German carsharing company and concluded that the CO2 emissions have decreased by between 312 to 146 kg CO2/year per average user.

In the meantime several studies have been conducted to find out who the users of these systems are. Most of the studies were done through user surveys and have repeatedly demonstrated important tendencies: for instance, it has been shown that many carsharing members are frequent public transportation users and tend to live in medium to high density areas (Cervero, 2003; Shaheen and Rodier, 2005; Burkhardt and Millard-Ball, 2006). The users tend to be in their mid 30s to mid 40s, be highly educated (Brook, 2004; Lane, 2005), belong to a household of less than average size (Brook, 2004; Millard-Ball et al., 2005) and be environmentally aware people (Costain et al., 2012; Efthymiou et al., 2012). Moreover, the accessibility to the stations, in terms of the distance between home/work and the nearest station, is a critical factor to joining carsharing (Zheng et al., 2009; Costain et al., 2012; Efthymiou et al., 2012).

2.3 Demand modeling

One of the most productive streams of research on carsharing has been the study of the characteristics of its users. Most works report on the mean value of population characteristics using a sample of carsharing users. But other studies have used more sophisticated models to better support their conclusions.

Stillwater et al. (2008) compared the use of carsharing vehicles over a period of 16 months with the built environment and demographic factors for an urban US carsharing operator. They used regression analysis to explain the average monthly hours of carsharing use and concluded that the most significant variables were: street width, the provision of a railway service, the percentage of drive-alone commuters, the percentage of households with one vehicle, and the average age of the stations. The percentage of drive-alone commuters, street width, and heavy rail availability were negatively related to carsharing, that is, the higher these factors the lower the demand. The percentage of households with one vehicle, the average age of the stations, and light rail only availability were positively related to carsharing use, meaning that the higher these factors the higher the demand.

In the same year a study by Catalano et al. (2008) was published reporting on a stated-preference survey in Palermo, Italy, with the objective of forecasting the modal split of the urban transportation demand in that city. The respondents could choose from different transportation alternatives, which were private car, public transportation, carsharing, and carpooling. A random utility model was estimated using the survey data. The authors concluded that in a future scenario characterized by active policies to limit private transportation use, the carsharing market could increase up to 10%.

Zheng et al. (2009) studied the potential carsharing market at the University of Wisconsin-Madison performing a stated-preference survey about transportation habits and carsharing preferences, namely travel habits (primary mode of travel and trip purpose), attitudes on transportation and the environment, and familiarity with carsharing, in the university community. With the data obtained from the survey, logistic regression models were developed to predict the willingness to join a carsharing program. This study led to the conclusion that the status in the university (student, staff, etc.) and people’s attitudes have a great impact on the acceptance of carsharing: students are more willing to use carsharing than other faculty members; the same happens with people who are concerned about the environment and the cost of owning and driving a vehicle.

More recently Lorimier and El-Geneidy (2013) studied the factors affecting vehicle usage and availability in the carsharing stations from *Communauto inc.*, a Montreal carsharing company. With this data, they developed a linear regression model to explain vehicle usage, and a logistic regression model to explain vehicle availability (binary response variable). The authors concluded from the results provided by the two models that the size of a carsharing station has a large impact on both variables. Larger stations offered more vehicle options and had a larger catchment basin than smaller stations. Moreover, the seasonal impact on both availability and usage was clear: fewer vehicles were available in the summer, which required an increase in both the number of stations and the number of vehicles in each station. Vehicle age was also considered as a key factor. It increased availability and decreased usage, since members tend to prefer newer vehicles. Having child seats was another factor that corresponded to higher availability and lower usage, probably because of the demographic characteristics of carsharing users in the study region (Lorimier and El-Geneidy, 2013).

A study by Morency et al. (2011) analyzed the carsharing transaction dataset of the same company, *Communauto inc.*, with a view to establishing a typology of carsharing users. This transaction dataset included all trips of all the clients, even those that were cancelled, modified, or not concluded. The main focus of the authors was frequency of use and distribution of distance travelled. With respect to the weekly distance travelled, a cluster-based classification process resulted in two distinctive behaviors with respect to the distance travelled and trip frequency: either urban distances throughout the week, or long distances on just one day of the week.

Motivated by the increasing use of carsharing systems in Europe and the need to understand their effect on urban mobility, Ciari et al. (2013) have developed an activity-based micro-simulation model to estimate travel demand for carsharing, considering that users have different transportation modes available, such as public transportation, car, bicycle, walking and carsharing. The authors opted for this disaggregated model because of the specificity of carsharing with respect to the users' characteristics, which makes it difficult to estimate travel demand using an aggregated model, such as the classical four steps method. The authors followed the round-trip carsharing systems' organization, and so the main features of the modeled system were: carsharing is available to everybody with a driving license (membership was not modeled); agents can pick up, park and drop off cars only at predefined locations (stations); agents have to drop off the car at the same station where it is picked up (round-trip); it was assumed that agents walk to the pick-up point and from the drop-off point; and an unlimited number of cars are available at the stations (no reservation, every agent trying to use the service will find a car) (Ciari et al., 2013). Hence the model did not focused on the carsharing operations themselves but on what the demand would be if a high level of this service was provided for the clients. The model was applied to part of Zurich city center, Switzerland. The aggregate results matched what is happening in reality, given the specifications and the level of detail that was considered. However, the authors stated that the model should be improved to represent the characteristics and the way real carsharing services work, i.e. by imposing constraints on vehicle stocks.

Recently, Morency et al. (2012) took a two-stage approach to study the behavior of carsharing users. In the first stage, the probability of each member being active in a given month was studied using a binary probit model. In the second stage, the probability of an active member using the service multiple times per month (monthly frequency of use) was determined by a random utility-based model. These models were estimated using data from 40 months of *Communauto inc.* operations. The authors concluded that the activity of members in the previous 4 months influences their behavior in the current month, that is, the number of times that users avail themselves of the service in the previous 4 months is directly proportional to the amount of times they use it in the current month. Moreover, some attributes of the users, such as gender and age, have an impact on their behavior: males and people aged between 35 and 44 are more inclined to favor carsharing.

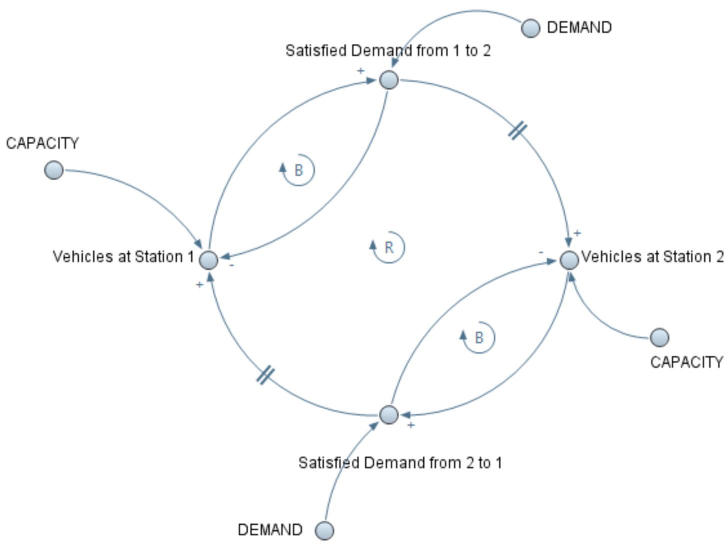
In general, almost all the studies presented, except the one performed by Ciari et al. (2013), are context specific, and local and regional characteristics make standardization more complex. Nevertheless, they do reveal user preferences and provide new models that can be used by other carsharing operators to guide their system's growth. The study by Ciari et al. (2013) is innovative in using simulation to predict demand. However it does not include a representation of the supply side. Furthermore, all the studies are related to the round-trip carsharing. As far as we know, demand estimation has not so far been addressed in the literature for one-way carsharing systems, and it is increasingly important to study it since these systems might be able to capture a higher share of the demand and they are certainly a tendency in recent years.

2.4 Modeling one-way carsharing systems

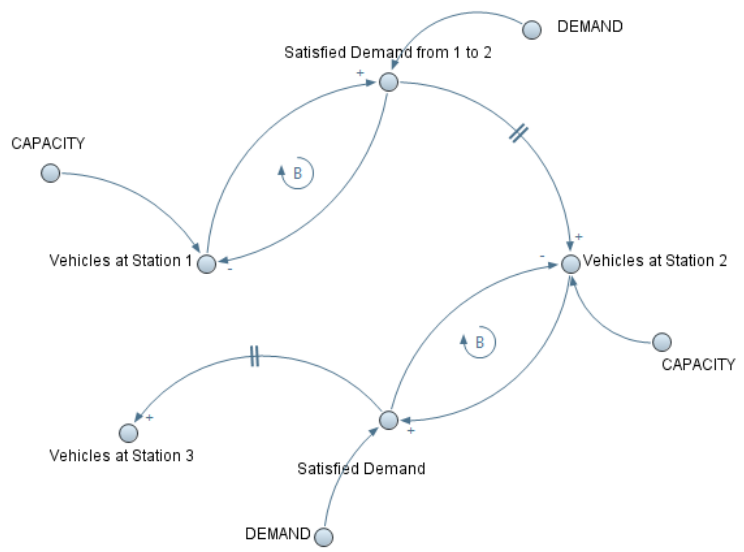
Recent research has been examining one-way carsharing systems. The key issue in them is the dynamically disproportionate distribution of vehicles across the stations, so researchers are currently developing methods to analyze and mitigate the effects of this problem. Comprehensive approaches have aimed at modeling the one-way system as a whole, while other specific techniques have been proposed for balancing the systems.

2.4.1 A comprehensive approach to the vehicle imbalance problem

The problems of one-way carsharing systems are mainly the effect that demand has on the supply characteristics and the effect of supply on demand. To depict this important aspect of one-way carsharing systems we have created the following simplified causal loop diagram (Figure 2.1).



(a) Two station system



(b) More than two stations

Figure 2.1 - Feedback in one-way carsharing systems

In Figure 2.1-a) we can see that when the number of vehicles in station 1 is higher more demand is satisfied and transferred to station 2 with a delay corresponding to the travel time between the stations. If the trips that request a vehicle at station 2 have station 1 as destination a reinforcing loop is formed, where the most important behavior parameters are the demand pattern that controls the vehicle flows, the delay that controls when vehicles will be available at a station, and the capacity of each station.

But hardly any system has just 2 stations and a balanced number of trips between them, thus in Figure 2.1-b) we can see that the loop may be cut open by trips from station 2 to other stations, which will stop feeding station 1 with vehicles, thereby limiting the demand satisfied in station 1.

Papanikolaou (2011) addressed this problem in a recent paper, reporting a system dynamics model to describe the complexity behavior of one-way carsharing systems under non-homogeneous demand patterns. This aggregated simulation model consisted of three stock-flow sub-models: stations, users, and vehicles, and about 120 equations. Papanikolaou's objective was to develop a study tool to understand how these systems evolve over time and to explore organizational solutions to mitigate the feedback loop effect.

After running the model using a synthetic case study area, Papanikolaou concluded that the framework could model delays and capture the essential dynamic behavior of the system, but the model still needs to be validated with data from real systems. Furthermore, the aggregate nature of system dynamics models does not take into account the strong spatial and temporal characteristics of complex urban networks. Another limitation inherent to all continuous forecasting models for system dynamics 'is the simplification of behavior due to the mixing that occurs when aggregating resources in the stocks, that tends to drift the results as simulation time advances sometimes overestimates performance' (Papanikolaou, 2011). The testing of different relocation techniques and the study of random events such as vehicle breakdowns or different reservation schedules are highly compromised by this approach. Besides, it is harder to integrate the effect of other transportation modes in this type of model. The authors are planning to compare this aggregate model to a micro agent-based model where the emergence of the system behavior comes from the decisions of the individual travelers.

2.4.2 The performance of one-way systems

Some authors have been trying to study the performance of these systems by considering different scenarios and using micro models.

Li (2011) developed a discrete-event simulation model to study the performance of one-way carsharing systems under different configurations and customer behaviors. They used different performance measures such as average vehicle utilization, reservation acceptance rate, full parking time, and profit. Configurations include fleet size, number of stations, number of parking spaces, and the distribution of vehicles and parking spaces across stations, while customer behaviors included the time when a customer reserves a vehicle, whether or not they will cancel the reservation, when they will pick up/return the vehicle, what the requirement for parking at pickup/return location is, etc. A reservation is accepted if there is a vehicle available in the origin station for the time the user needs to make the trip and a parking space available in the destination station at the end of the trip. Round trip carsharing was also simulated to compare the behavior of the two systems. The author concluded that concentricity, that is high population density in big cities where origin and destination stations are concentrated at few locations, helps one-way carsharing to perform better, while round trip carsharing performs better for a more dispersed population. Moreover, increasing the number of parking spaces for a one-way system can help improve the reservation acceptance rate and vehicle utilization. The allocation of parking spaces among stations should correspond to the customer demand distribution among stations, so as to achieve the best performance. More recently, Barrios (2012) developed an agent-based simulation model to measure and predict the level of service offered to users of *car2go*, a one-way carsharing system, in Austin, Texas, and San Diego, California. In this simulation model, cars are initially evenly distributed throughout a schematic square city. Users come into the system at a given demand density and have random origins and destinations, searching for the nearest car. If a user is 'created' in a place where there are no cars within walking distance, they cannot travel. Then the simulation model was used to simulate the two cities. Simulation results were compared with the reality of these systems in the two urban areas in terms of accessibility, that is, the proportion of the operating area with an available car within walking distance (0.33 miles). The author concluded that the model reasonably estimates the level of service of a one-way carsharing system. Hence it can be used to make planning level decisions.

These methods could be very useful, since they present advanced simulation tools to evaluate the performance of one-way carsharing systems prior to their implementation, which can help carsharing companies to plan the service. However, they do not include any relocation feature which, as shown in the next section, should be an important leverage for the profitability of one-way carsharing.

2.4.3 Solving the vehicle imbalance through relocation operations

One of the ways that has been suggested to balance vehicle stocks is the operator-based approach that corresponds to the periodic relocation of vehicles among stations by staff members.

In 1999, Barth and Todd developed a queuing based discrete event simulation model that included relocations and a number of input parameters that allowed different scenarios to be evaluated, such as the vehicle-to-trip ratio and payment scheme. Some of the events were customer arrival at a station, vehicle departure from a station, vehicle arrival at a station, relocation start and relocation end. Three ways of deciding when relocations should be performed were presented: 'Static relocation' based on immediate needs in a station; 'Historical predictive relocation', which uses knowledge of expected future demand, looking 20 minutes into the future, and 'Exact predictive relocation' that can be used if perfect knowledge of future demand is available, which is impossible in the real world. The model was applied to a community in Southern California and some measures of effectiveness were calculated, showing that the system is most sensitive to vehicle-to-trip ratio, relocation method used, and charging scheme employed. The authors also concluded that this system can be very competitive with other transportation modes, particularly taxis.

Later, the operator-based approach was tested in the *Honda ICVS* system, which started in March 2002. This system allowed one-way trips, with no reservation required and no return time needing to be specified (Kek et al., 2006). Periodic communication with the backend computer system meant that information from these vehicles prompted the system manager to relocate vehicles between stations when needed. In May 2005 the experimental phase ended and the program started running as a commercial enterprise (Barth et al., 2006). The system was cancelled in 2008 (The Business Times, 2011) because the operator could not keep up the initial service quality as membership grew. All users expected cars to be available but this did not happen, so dissatisfaction and complaints from members increased (The Straits Times, 2008). It still not known if the operator based approach alleviated the company's losses, but its ending is an indication that this system was not profitable.

Kek et al. (2006) developed a discrete event simulation model to help multiple-station carsharing vehicle operators implement an efficient relocation system that could minimize the allocation of resources to vehicles, staff, and parking places, while maintaining certain levels of service. Based on the available resources (vehicles and staff members) and the relocation policy adopted, the model decided which relocation operations the system should implement at each time step. The two possible relocation policies were the shortest time, i.e. moving vehicles to or from a neighboring station in the shortest possible time (including staff movement, if necessary), and inventory balancing, i.e. supplying a station which has a shortage of vehicles with a vehicle from another station which has too many.

The proposed model was tested and validated using real data from the commercial one-way carsharing company mentioned above. The results showed that if the company adopted an inventory-balancing relocation technique, the system could afford a 10% reduction in car park spaces and 25% reduction in staff strength, generating cost savings of approximately 12.8% without lowering the level of service for users. However, this approach required an impractical number of simulation runs to test all the combinations of different parameters. Thus in 2009, Kek et al. introduced an optimization module to the previous simulation tool to overcome this limitation.

The optimizer used the current demand and station configuration with the objective of minimizing the overall cost of the relocation operations. The obtained optimized parameters were the number of people needed to perform the relocations (staff strength), the necessary relocations, and the resulting station status (number of vehicles at the stations at each time step). In phase two these optimized parameters were filtered through a series of heuristics to obtain a set of recommended parameters. On entering the set of operating parameters into the vehicle relocation simulator developed by Kek et al. (2006), phase three evaluated the effectiveness of each combination using three performance indicators: zero-vehicle time (no vehicles are available); full-station time (no parking places available), and number of relocations.

This decision support system was once again tested using operational data provided by *Honda ICVS*. The performance surpassed the results of the previous simulations conducted by Kek et al. (2006). This new three-phase decision support system indicated a 50% reduction in staff costs and an improvement of the performance indicators. However, there is no documented effect on the real application of the model to Honda's system and, as mentioned, the system was cancelled.

Although mathematical programming is an interesting approach to achieving good system configurations for running these systems, it needs a great many variables and constraints in the mathematical programming formulation. Several simplifications were required to reduce the problem size, such as increasing the size of the discrete time steps of the optimization period, and this entailed further limitations to representing accurately what happens in reality.

In 2010, Wang et al. proposed a method to forecast and relocate vehicles in carsharing systems that consisted of three main components: microscopic traffic simulation, forecasting model, and inventory replenishing. The model used to forecast customer demand was an aggregated model at the station level, that is, it forecast the total number of vehicles rented out and returned over time at each station and not the trips for each origin-destination pair. The forecast demand was then fed into the inventory replenishing model to prepare relocations.

With respect to the inventory replenishing model, the stations with more vehicles available than necessary (including safety stock) were defined as overstocked stations thus candidate suppliers, while stations with fewer vehicles available than necessary were defined as understocked stations thus candidate demanders. Once the relocation decision was made (stations and number of vehicles involved, and when to relocate), the understocked stations were replenished from the nearest overstocked stations in terms of the lowest trip cost at that moment of relocation, which was determined by the microscopic traffic simulation model.

The performance of the proposed approach was tested using as case study four possible station locations in Singapore with 12 vehicles each. Experimental results showed that the system improved its efficiency. So the authors concluded that this approach had the potential to improve a carsharing service. The case study was novel in that it improved the realism of travel times and evolved from the computation of a mathematical static optimum pattern of relocation operations planned for the whole day to a policy proposal for real time operation in face of the predicted demand. Even so, it is important to note that it is very small scale in terms of the number of stations, which is smaller than most existing carsharing systems.

Cucu et al. (2010) have studied a forecasting model of one-way carsharing demand in greater detail. The main principle was to understand and exploit customers' preferences so as to anticipate their needs and relocate the vehicles accordingly. To solve the problems of car unavailability at peak periods and medium- and long-term management, and to test new station locations, the authors considered customer preferences related to: the time of departure; the day of the week; the weather conditions, and the traffic conditions associated with their addresses. With this, the maximum vehicle needs for a given period of the day were computed for all stations to distinguish priorities in terms of balancing order, other maintenance operations and to test the implementation of new stations. This method was applied to a small city and the authors concluded that anticipating demand would improve the vehicle availability by balancing vehicle stocks.

Nair and Miller-Hooks (2011) continued exploring optimization methods and proposed a stochastic mixed-integer programming (MIP) model with the objective of generating least-cost vehicle redistribution plans such that a proportion of all near-term demand scenarios is satisfied, recognizing the strong effect of uncertainty on carsharing planning. The model was set up for a fixed short-term planning horizon for which demand is known probabilistically. Relocation operations were performed throughout the day and assumed to be completed before the beginning of the planning period considered. For relocations the operator takes into consideration both vehicles and free parking spaces, that is, if both resources are adequate to satisfy a p-proportion of all possible demand scenarios, no corrective actions are triggered; if not enough vehicles are available this can be remedied by relocating from adjacent stations; and if not enough parking spaces are available, vehicles can be relocated to free up parking spaces in other stations. The model was also applied to *Honda ICVS*. Using computational experiments and simulation, authors showed that when these relocation strategies are used, the system operates at a reliability level that could not be achieved otherwise.

Very recently, Smith et al. (2013) studied how to minimize the number of rebalancing vehicles travelling within a network and the number of rebalancing drivers needed to rebalance vehicle stocks in one-way carsharing systems, considering that the number of waiting customers remains bounded. The authors state that the ‘two objectives are aligned' (Smith et al., 2013), so the optimal rebalancing strategy can be found by solving two different linear programs in a fluid model of the system. In this system, users arrive at one of the stations (origin) and are transported to another station (destination) by driving themselves or by being driven by an employed driver (similar to a taxi) if the system needs to move a driver to the destination station of the particular user. This happens because drivers can also become unbalanced among stations and then they have to be moved to other stations without driving a rebalancing vehicle. The results suggested that in Euclidean network topologies, the number of drivers needed is between 1/4 and 1/3 of the number of vehicles.

2.4.4 Using the users for system balancing

The user-based approach is a system-balancing technique that uses the clients to relocate the vehicles through various incentive mechanisms. This is very intuitive and previous studies have addressed this possibility by modeling its operation.

Uesugi et al. (2007) have proposed grouping or ungrouping parties of people to balance the system. They developed a method for optimizing vehicle assignment to people according to the distribution of parked vehicles, trying to avoid vehicle imbalance. The authors proposed three ways to assign the number of in/out vehicles between pick-up/drop-off stations, depending on the number of vehicles in the stations. In a normal assignment a group of people ride in one vehicle and so they subtract one vehicle from the pick-up station and add it to the return station. In the divided assignment, people from the group ride in vehicles and so the user subtracts vehicles from the pick-up station and adds vehicles to the return station. In the combined assignment groups with the same drop-off station carpool in one vehicle with the combined group, and so the users subtract only one vehicle from the pick-up station and add only one vehicle to the return station. The assignment is limited to the capacity of the vehicles.

In theory, a station that has excess vehicles could decrease their number by assigning a divided ride. Equally, in a station which has few vehicles it would be possible to keep the number of vehicles by assigning a combined trip. The effectiveness of this method was tested through computer simulation. The authors claimed the results showed that it was effective in minimizing the imbalance problem of one-way carsharing systems. But they also stated that incentives would have to be considered to make users behave according to the proposed model.

It should also be noted that the *Intellishare* research team at the University of California at Riverside had already proposed and tried these two user-based relocation methods in 2004. They called them trip splitting and trip joining, and they managed to reduce the number of relocations required (Barth et al., 2004). This method was very similar to the previous one, with the advantage of having a price incentive mechanism to encourage users to sign up to trip splitting and trip joining. When users wanted to travel from a station with a shortage of vehicles to one with an excess they were encouraged to share a ride in a single vehicle (trip joining), thereby minimizing the number of cars moved. Conversely, when they wanted to travel from a station with too many vehicles to one with a shortage they were encouraged to drive separate vehicles (trip splitting), thereby balancing the number of vehicles in the stations.

If these user-based relocation techniques were successful when applied to commercial one-way carsharing companies it would be possible to shift the burden of relocating vehicles to the users. But this strategy has its pitfalls. It may not be a viable option in cities where most travelers value privacy and convenience over minor transportation cost savings. Moreover, trip-joining policies make carsharing similar to carpooling, which has severe sociological barriers associated with riding with strangers, mainly for safety and security reasons (Chan and Shaheen, 2011; Correia and Viegas, 2011). With respect to trip splitting, users may not be willing to be divided and this method can only work in a market where a significant number of trips are made by groups of people rather than by a single driver.

Mitchell et al. (2010) proposed another intuitive principle of dynamic pricing combined with intelligent vehicles that would enable drivers to respond appropriately to pricing. Their idea involved a pricing scheme that could be applied to several urban mobility systems, including carsharing, to make them more efficient for users and companies alike.

This method would take advantage of trip-origin-and-destination choice elasticity combined with price incentives for each specific trip. They considered that people would have the flexibility to walk a block or two to find a vehicle if one is not available right outside their door. Similarly, it might not be a problem for people to park a bit further away from their destination. And if slightly less convenient origins and destinations result in lower-priced trips this could be an incentive to use them, even if more convenient pick-up and return points are available (Mitchell et al., 2010).

Febbraro et al. (2012) proposed a similar method but only taking into consideration the trip destinations. In their system there were no stations, the city was divided into zones and the users could park the vehicle at any parking space inside these zones. A discrete event simulation model was developed to implement this method in which the vehicles are relocated by the users that can opt to end their trips in proposed zones that have a shortage of vehicles or in their desired zones. The zones were determined through a linear integer programming model aiming at minimizing the rejected reservations. If the user is happy to leave the vehicle in the proposed zone they will have a fare discount. The events used in the simulation were: vehicle bookings, booking modifications, booking cancellations, vehicle pick-ups, and vehicle drop-offs. Reservations were made throughout the day using a Poisson distribution and each had a given probability of being modified or cancelled by users. In this model, users were required to establish the departure time, declare their trip origin and destination, and the time at which they will deliver the vehicle. When a vehicle is booked it is guaranteed that it will be available at the beginning of the trip. The authors tested the model for the Restricted Traffic Zone of Turin (Italy), using fifteen scenarios that differ according the probability of accepting the relocation proposed by the system and with different numbers of vehicles available in the system. They concluded that significantly fewer vehicles would be needed for the system to run efficiently using this approach.

Despite the apparent advantages of this option, the authors also recognized that not all trip origins and destinations are elastic to price: for instance, a commuting trip may be more constrained since it is a mandatory trip, usually with very rigid schedules. Other limitations are related to its practical application, since it relies on a very efficient real-time use of information and communication technology that enables people to be aware of price changes. In addition, there must be a willingness to access this information allied to a significant trip-and-station choice elasticity to price. This is yet to be fully tested in real carsharing companies operating on a one-way basis. The price instability may also be a disincentive to using carsharing, which would have a contrary effect.

2.4.5 Full control over where and how to supply vehicles

Other ways of balancing one-way carsharing systems through controlling the supply have been devised. Several authors have proposed trip selection for vehicle allocation in order to achieve a more favorable balance of vehicle stocks, that is, only the trips that help to balance the system should be served. Fan et al. (2008) formulated a mathematical programming model for vehicle fleet management to maximize the profits of one-way carsharing operators. In their model the carsharing operator decides which vehicle reservations should be accepted or refused and how many vehicles should be relocated or held to maximize profit. Thus, if any request was regarded as unprofitable or the system could not accommodate it, it would be declined.

A multistage stochastic linear integer model was formulated that could account for demand variations. A five-day sample network with four carsharing locations was used to test the model and some results were obtained which indicated profit improvement. Limitations of computation time and solver capability, however, meant that the model was not applied to a real network and several unreal conditions were assumed.

A more recent study has addressed the effect of the location of carsharing stations on capturing a trip pattern more favorable to a balanced distribution of the vehicles in the network, thus transferring the system imbalance to the clients by decreasing their possibility of accessing this system. Correia and Antunes (2012) developed three mathematical programming models to balance vehicle stocks through a convenient choice of the location, number and size of stations. The objective was to maximize the profit from operating a one-way carsharing system, considering all the revenues (price paid by clients) and costs involved (vehicle depreciation, vehicle maintenance and parking space maintenance).

The first scheme (model), which was similar to that tested by Fan et al. (2008), assumed that the carsharing organization has total control over trip selection, based on a list of requests made by the clients. The second assumed that all trips requested by the clients would be accepted when they occurred between any pair of stations in the solution. And the third was a hybrid scheme in which there was no obligation to satisfy all trips between stations, but trips could only be rejected if there were no vehicles available at the pick-up station. Each model was applied to the case study city of Lisbon, Portugal, and results showed that the scheme yielding the highest profits was the one where the carsharing operator had full control over trip selection. This was expected since it is the scheme offering the most freedom to maximize profit. The authors concluded that the imbalance situation would lead to severe financial loss in a scenario where all demand should be satisfied, even if the client is charged a very high price. They also found that financial losses could be reduced by making appropriate choices of the stations' configuration (number, location, and size), but profits could only be achieved with full control over trip selection.

The problem with these approaches is once again the limitations of computation time and solver capability, which could not accurately represent the reality of carsharing systems because some simplifications were necessary, such as 10-minute time steps. It was not possible to consider the choice of station location, trip selection schemes and vehicle relocation operations all in the same formulation, which hindered an integrated view of these systems planning. For instance the planning of station locations is intuitively dependent on the existence or non-existence of relocation operations which could mitigate the effects of an uneven trip pattern and so allow the supply to expand, as some of the previous research shows.

2.5 Summary

In Table 2.1 we present a summary of the studies where carsharing has been modeled. For each study we indicate the topic addressed, the modeling approach used and the type of carsharing. The references are in chronological order.

Table 2.1 - Summary of the studies presented

Authors	**Year**	**Topic addressed**	**Modeling Approach**	**Type of carsharing**
Bonsall and Kirby	1979	Testing different scenarios, strategies, locations, scales and prices	Microsimulation	Round-trip
Bonsall	1982	Modeling organized carsharing systems and comparing model predictions with actual performance	Microsimulation	Round-trip
Arnaldi, Cozot, Donikian and Parent	1996	Simulation of carsharing systems	Simulation	Round-trip
Barth and Todd	1999	Operator-based relocation operations	Queuing-based discrete-event simulation	One-way
Barth and Todd	2001	User-based relocation operations	Trip joining	One-way
Barth, Todd and Xue	2004	User-based relocation operations	Simulation	One-way
Kek, Cheu and Chor	2006	Operator-based relocation operations	Discrete-event simulation	One-way
Uesugi, Mukai and Watanabe	2007	User-based relocation operations	Simulation	One-way
Stillwater, Mokhtarian and Shaheen	2008	Environmental and demographic factors that affect the usage of carsharing	Regression analysis	Round-trip
Catalano, Lo Casto and Migliore	2008	Estimation of carsharing demand for carsharing	Random utility model	Not -defined
Fan, Machemehl and Lownes	2008	Trip selection	Optimization	One-way
Zheng et al.	2009	Carsharing market	Regression analysis	Not defined
Kek, Cheu, Meng and Fung	2009	Operator-based relocation operations	Optimization and Discrete-event	One-way

			simulation	
Wang, Chang and Lee	2010	Operator-based relocation operations	Microsimulation and inventory replenishing model	One-way
Cucu, Ion, Ducq and Boussier	2010	Operator-based relocation operations	Optimization	One-way
Febbraro, Sacco and Saeednia	2010	User-based relocation operations	Discrete-event simulation and Optimization	One-way
Morency, Trépanier and Agard	2011	Typology of carsharing users	Cluster analysis	Round-trip
Papanikolaou	2011	Describing the functioning of one-way carsharing systems	System Dynamics	One-way
Li	2011	Performance of a carsharing system	Discrete-event simulation	One-way/Round-trip
Nair and Miller-Hooks	2011	Operator-based relocation operations	Optimization	One-way
Morency, Habib, Grasset and Islam	2012	Behavior of carsharing users	Random utility model	Round-trip
Barrios	2012	Level of service offered to users	Agent-based simulation model	One-way
Correia and Antunes	2012	Trip selection and stations location	Optimization	One-way
Ciari, Schuessler and Axhausen	2013	Estimation of carsharing demand	Activity-based simulation	Round-trip
Lorimier and El-Geneidy	2013	Factors affecting vehicle usage and availability	Regression analysis	Round-trip
Smith, Pavone, Schwager, Frazzoli and Rus	2013	Operator-based relocation operations	Optimization	One-way

From Table 2.1 we can see that most of studies related to carsharing modeling were done after 2000. Moreover, despite the considerable number of studies related to demand modeling for round-trip carsharing, there is a clear predominance of studies about balancing vehicle stocks across stations in one-way carsharing, mainly through relocation operations performed by the company or the users. With respect to the modeling approaches used for studying demand, regression analysis is the most popular technique, while issues related to one-way systems tend to be studied by means of optimization and different types of simulation.

2.6 Suggestions for bridging the gaps found

Carsharing has gained great momentum in the last two decades as an alternative to private vehicle ownership, especially for urban trips. Despite this growth, there are still many questions about its true position among the other modes of transporation and the markets that it should serve. Moreover, these systems operation standards are hard to define. Modeling is increasingly being used to address these issues. Previous research has emphasized demand estimation using techniques ranging from regression analysis to more complex tools such as agent-based simulation models. In general, the statistical methods have helped to improve our understanding of the systems and they have found structural relationships between service characteristics and demand patterns. However, most of them were too context specific and therefore difficult to apply to other realities (Stillwater et al., 2008; Lorimier and El-Geneidy, 2013; Morency et al., 2011; Morency et al., 2012). Moreover, they tend to neglect the supply side and the organizational configurations needed to offer the service, which is directly connected to its economic viability. This is a key aspect for any possible candidate operator of a carsharing service. Advanced demand studies were carried out, like the one by Ciari et al. (2013), who have set up an agent-based model to represent in detail the type of users who are likely to have carsharing as part of their mode choice set, recognizing the fact that carsharing is not likely to be used for commuter trips or by certain traveler groups. However, this study did not consider the supply side, so it is not possible to understand the equilibrium between supply and demand in this system.

The articles reviewed on demand estimation have generally ignored the one-way option, which is understandable if we take into account its youth when compared to the round-trip mode. But more importantly, they tended to disregard the integration of carsharing with traditional transportation modes. Hence it is our belief that a significant effort must be made to develop more general and realistic models to estimate demand, that is, models that can accurately represent the characteristics of carsharing, be valid for different contexts, and apply to one-way carsharing. One of the important questions that still remain to be answered is if carsharing has a greater effect on reducing the use of private vehicles or if, on the contrary, it reduces the number of public transportation users. This is a paramount question for policymakers who may be deciding whether or not to endorse carsharing. Currently there are generous funds available for energy and emissions reduction associated with the transportation sector, particularly in the

European Union, and carsharing systems have been considered candidate recipients for those funds.

We have concluded that most of the literature on the modeling of carsharing systems is concerned specifically with one-way carsharing systems. Operations researchers are devoting increasing attention to its particular problems which we have seen to be mostly linked to the natural imbalance of vehicle stocks caused by the uneven pattern of trips during the course of the day. We have concluded that this is a complex problem with a feedback loop that results from the interaction of demand and supply. In classic transportation systems, such as bus and underground services, the directional capacity is offered to clients irrespective of the existing demand; however, in one-way carsharing, demand can completely change the system's supply in ways that are hard to predict.

Researchers have used complex system modeling tools to address this problem, such as system dynamics to try to translate their behavior and extract better operating principles (Papanikolaou, 2011). However, these tools bring many limitations especially in what concerns to their adherence to reality due to their aggregate nature.

Realizing the need to have a micro-scale approach to the problems of one-way carsharing systems, several researchers have been developing simulation models to study their performance (Li, 2011; Barrios, 2012) and achieve higher profits, but these have not been able to handle the balancing of vehicle stocks. Other researchers have focused on individual techniques to balance those stocks. The objective has been to accomplish an optimum configuration of the systems towards some objective that has varied from the general profit maximization of the operator and the specific minimization of relocation costs. Researchers have mostly used simulation and mathematical programming optimization for this.

Despite the positive results of demonstrating that there are operating principles that can be used to improve these systems' performance, there have been limitations. While simulation requires an impractical number of runs to test all the combinations of the different operational parameters (Kek et al., 2006), optimization requires a large number of variables to integrate several decisions into the same problem in a real case study context (Correia and Antunes, 2012). Several authors tackled this by simplifying the formulations to a level where they start to be unrealistic and the efficiency improvements gained from them may be hard to transfer to real carsharing ventures.

Most of these models have worked with station-based systems, but stationless systems are currently emerging, where the vehicle may be dropped off at any parking space. If this trend develops most of the models devised for studying one-way carsharing systems will be overtaken by a reality that is not compatible with a fixed set of concentrated demand points. Researchers should test the techniques on real case scenarios and use more advanced simulation models to address different aspects of the business, from the most strategic to the operational. We believe that it will be difficult to find optimum solutions for the operational configuration of these systems, so research should head towards developing more detailed simulation models that integrate other modes of transportation and also consider operational issues. This will be at the cost of model size and limited control over the experiments, but the lack of a realistic functioning of the systems is restricting the view of the big picture on how to run carsharing schemes and find their true effect on mobility. A detailed and accurate computation of the effect of carsharing systems should make it possible to bridge a major gap in the literature: there is no measure of the balance of cost and benefits of these systems, largely because of the uncertainty about the effect that they have on users of public and private transportation. A new trend of peer-to-peer systems has appeared in recent years. It has changed the cost of the systems for the operator, who now does not need to buy a whole vehicle fleet. This could greatly change the cost/benefit balance and reduce the risk of managing the systems.

Researchers must continue to closely watch the big commercial round-trip carsharing ventures such as *Zipcar* and *Cambio Car* to observe the management of their operations and the behavior of their clients, and see how any new services provided evolve. The idea is to keep research abreast of the latest tendencies in this market, which may become more relevant in a context of financial crisis where falling household budgets could boost the use of cheaper transportation alternatives. It will be especially interesting to watch the first companies that are adopting one-way trips as their core business, such as *car2go*.

Chapter 3

Comparing Optimal Relocation Operations with Simulated Relocation Policies in One-way Carsharing Systems

3.1 Introduction

Through the last decades, changes have occurred in urban transportation. Despite greater accessibility provided by private transportation, the result has been increases in levels of congestion, pollution, and non-productive time for travelers, particularly in peak hours (Schrank et al., 2010). There are also opportunity costs associated with using urban land for parking spaces instead of other more productive activities. In America, for example, automobiles spend around 90% of their time parked (Hu and Reuscher, 2001). These issues are mitigated by public transportation, but it has other disadvantages, for example, poor service coverage, schedule inflexibility and lack of personalization. In addition, providing public transportation for peak hour demand can result in idle vehicles for much of the day, resulting in inefficiencies and high cost of service.

Strategies are needed to address these issues and simultaneously provide people the mobility they need and desire. One strategy considered is that of carsharing. Carsharing systems involve a small to medium fleet of vehicles, available at several stations, to be used by a relatively large group of members (Shaheen et al., 1999).

The origins of carsharing can be traced back to 1948, when a cooperative known as *Sefage* initiated services in Zurich, Switzerland. In the US, carsharing programs only appeared later in the 1980s, within the *Mobility Enterprise* program (Shaheen et al., 1999). In Asian countries, such as Japan and Singapore, these systems appeared more recently.

Carsharing has been observed to have a positive impact on urban mobility, mainly by using each car more efficiently (Litman, 2000; Schuster et al., 2005). The use of carsharing systems generally leads to a fall in car ownership rates and thus to lower car use, according to Celsor and Millard-Ball (2007). More recently, Schure et al. (2012) conducted a survey in 13 buildings in downtown San Francisco and concluded that the average vehicle ownership for households that use carsharing systems is 0.47 vehicles/household compared to 1.22 vehicles/household for households that do not use carsharing systems. Moreover, a study by Sioui et al. (2013) surveyed the users of *Communauto*, a Montreal carsharing company, and concluded that a person who does not own a vehicle and uses carsharing systems frequently (more than 1.5 times per week) never reaches the car-use level of a person who owns a vehicle: there was a 30% difference between them. This idea is reinforced by Martin and Shaheen (2011) who concluded through a survey in US and Canada that the average observed vehicle-kilometers traveled (VKT) of respondents before joining carsharing was 6468 km/year, while the average observed VKT after joining carsharing was 4729 km/year, which constitutes a decrease of 27% (1749 km/year).

Furthermore, some recent studies concluded that carsharing systems also have positive environmental effects. For instance, Martin and Shaheen (2011) noted from the VKT estimations presented before that greenhouse gas (GHG) emissions of the major carsharing organizations in the US and Canada can be reduced by -0.84 t GHG/year/household. While most members increase their emissions; there are compensatingly larger reductions for other members who decrease their emissions. Moreover, Firnkorn and Müller (2011), through a survey of a German carsharing company, concluded that the CO_2 emissions are decreased between 312 to 146 Kg CO_2/year per average carsharing system user.

With respect to trip configuration, carsharing systems are divided into round-trip (two-way) systems and one-way systems. Round-trip carsharing systems require users to return the cars to the same station from where they departed. This simplifies the task of the operators because they can plan vehicle inventories based on the demand for each station. It is, however, less convenient for the users because they have to pay for the time that vehicles are parked. In one-way carsharing systems, users can pick up a car in a station and leave it at a different one (Shaheen et al., 2006). In theory, therefore, one-way carsharing systems are better suited for more trip purposes than round-trip services that typically are used for leisure, shopping and sporadic trips - short trips in which vehicles are parked a short duration (Barth and Shaheen, 2002). This statement is supported by various studies, including that by Costain et al. (2012), who studied the behavior of a round-trip carsharing company in Toronto, Canada and concluded that trips are mostly related to grocery or other household shopping purposes. A study performed in Greece by Efthymiou et al. (2012) also concluded that the flexibility to return the vehicle to a different station from the one where it was picked up is a critical factor in the decision to join a carsharing service. However, one-way carsharing systems present an operational problem of imbalances in vehicle inventories, or stocks, across the network of stations due to non-uniformity of trip demand between stations. Despite this, a great effort has been made to provide these flexible systems to users in the last years.

Previous research has proposed several approaches to solve this problem, such as: vehicle relocations in order to replenish vehicle stocks where they are needed (Barth and Todd, 1999; Barth et al., 2001; Kek et al., 2006; Kek et al., 2009; Nair and Miller-Hooks, 2011; Jorge et al., 2012); pricing incentive policies for the users to relocate the vehicles themselves (Mitchell et al., 2010; Febbraro et al., 2012); operating strategies designed around accepting or refusing a trip based on its impact on vehicle stock balance (Fan et al., 2008; Correia and Antunes, 2012); and station location selection to achieve a more favorable distribution of vehicles (Correia and Antunes, 2012). Correia and Antunes (2012) proposed a mixed integer programming model to locate one-way carsharing stations to maximize the profit of a carsharing company, considering the revenues (price paid by the clients) and costs (vehicle maintenance, vehicle depreciation, and maintenance of parking spaces), and assuming that all demand between existing stations must be satisfied. In applying their model to a case study in Lisbon, Portugal, tractability issues resulted and the model was only solvable with time discretization of 10-minute steps. The model did not allow integrating relocation operations due to the complexity already reached with the location problem.

In this chapter, the same case study as the one in (Correia and Antunes, 2012) is considered and station location outputs are generated using their model, but now with time discretization of 1-minute. When a 10 minute based model is used, all of the travel times between stations are rounded to the next multiple of 10. So, users are paying for minutes that they are not really using vehicles. Moreover, the vehicles are also considered available only in each multiple of 10 minutes, while the reality is that they could be available earlier. Therefore, a 1 minute based model is always more realistic than a 10 minute based model or a model that considers larger time steps.

A new model is presented to optimize relocation operations on a minute-by-minute basis, given those outputs for station locations brought from the previously referred model. Thus, the two problems, station locations and relocation operations, will not be considered at the same time. The objective function is the same, profit maximization, but in the relocations model, a cost for the relocation operations is also added. The vehicle relocation solutions generated with this approach, optimal solutions, are later compared to those obtained with a simulation model built to evaluate different real-time vehicle relocation policies, realistic solutions. With this comparison, the impacts of relocation operations on the profitability of one-way carsharing systems are then analyzed, and insights into how to design and implement real-time rebalancing systems are gained.

The chapter is structured as follows. In the next section, a new mathematical model is presented to optimize relocation operations, given an existing network of one-way carsharing stations. Then, a simulation model and a specification of several real-time relocation policies are presented. In the following section the case study used for testing the relocation methodologies is described, as well as the data needed and the main results reached. The chapter ends with the main conclusions extracted from the chapter.

3.2 Mathematical model

The objective of the mathematical programming model presented in this section is to optimize vehicle relocation operations between a given network of stations (using a staff of drivers) in order to maximize the profit of a one-way carsharing company. In this model, all demand between existing stations is assumed to be satisfied. The notation used to formulate the model (sets, decision variables, auxiliary variable, and parameters) is the following:

Sets

- $\mathbf{N} = \{1, \dots, \mathrm{i} \dots \mathrm{N}\}$: set of stations;
- $\mathbf{T} = \{1, \dots, \mathrm{t} \dots \mathrm{T}\}$: set of minutes in the operation period;
- $\mathbf{X} = \{1_1, \dots, \mathrm{i}_{\mathrm{t}-1}, \mathrm{i}_\mathrm{t}, \mathrm{i}_{\mathrm{t}+1}, \dots, \mathrm{N}_\mathrm{T}\}$: set of the nodes of a time-space network combining the N stations with the T minutes, where i_t represents station i at minute t;
- $\mathbf{A_1} = \left\{\dots, \left(\mathrm{i}_\mathrm{t}, \mathrm{j}_{\mathrm{t}+\delta_{\mathrm{ij}}^{\mathrm{t}}}\right), \dots\right\}, \mathrm{i}_\mathrm{t} \in \mathbf{X}$: set of arcs over which vehicles move between stations i and $j, \forall i, j \in \boldsymbol{N}, i \neq j$, between minute t and $t + \delta_{ij}^t$, where δ_{ij}^t is the travel time (in number of minutes) between stations i and j when the trip starts at minute t;
- $\mathbf{A_2} = \{\dots, (\mathrm{i}_\mathrm{t}, \mathrm{i}_{\mathrm{t}+1}), \dots\}, \mathrm{i}_\mathrm{t} \in \mathbf{X}$: set of arcs that represent vehicles stocked in station $i, \forall i \in \boldsymbol{N}$, from minute t to minute $t + 1$.

Decision variables

- $R_{i_t j_{t+\delta_{ij}^t}}$: number of vehicles relocated from i to j from minute t to $t + \delta_{ij}^t, \forall \left(i_t, j_{t+\delta_{ij}^t}\right) \in \boldsymbol{A_1}$;
- Z_i: size of station $i, \forall i \in \boldsymbol{N}$, where size refers to the number of parking spaces;

- a_{i_t}: number of available vehicles at station i at the start of minute $t, \forall i_t \in \boldsymbol{X}$.

Auxiliary variables

- $S_{i_t i_{t+1}}$: number of vehicles stocked at each station i from minute t to $t+1, \forall (i_t, i_{t+1}) \in \boldsymbol{A_2}$, this is a dependent variable only used for performance analysis.

Parameters

- $D_{i_t j_{t+\delta_{ij}^t}}$: number of customer trips (not including vehicle relocation trips) from station i to station j from t to $t + \delta_{ij}^t, \forall \left(i_t, i_{t+\delta_{ij}^t}\right) \in \boldsymbol{A_1}$;
- P: carsharing fee per minute driven;
- C_{mv}: cost of maintenance per vehicle per minute driven;
- δ_{ij}^t: travel time, in minutes, between stations i and j when departure time is $t, \forall i_t \in \boldsymbol{X}, j \in \boldsymbol{N}$;
- C_{mp}: cost of maintaining one parking space per day;
- C_v: cost of depreciation per vehicle per day;
- C_r: cost of relocation and maintenance per vehicle per minute driven.

Using the notation above, the mathematical model can be formulated as follows:

$$Max\ \pi = (P - C_{mv}) \times \sum_{i_t j_{t+\delta_{ij}^t} \epsilon \boldsymbol{A_1}} D_{i_t j_{t+\delta_{ij}^t}} \times \delta_{ij}^t - C_{mp} \sum_{i \in \boldsymbol{N}} Z_i - C_v \sum_{i \in \boldsymbol{N}} a_{i_1} - C_r \sum_{i_t j_{t+\delta_{ij}^t} \epsilon \boldsymbol{A_1}} R_{i_t j_{t+\delta_{ij}^t}} \times \delta_{ij}^t \tag{3.1}$$

subject to,

$$S_{i_t i_{t+1}} + \sum_{j \in \boldsymbol{N}} D_{i_t j_{t+\delta_{ij}^t}} + \sum_{j \in \boldsymbol{N}} R_{i_t j_{t+\delta_{ij}^t}} - \sum_{j \epsilon \boldsymbol{N}: t' = t - \delta_{ji}^t} D_{j_{t'} i_t} - \sum_{j \epsilon \boldsymbol{N}: t' = t - \delta_{ji}^t} R_{j_{t'} i_t} - S_{i_{t-1} i_t} = 0 \ \ \forall i_t \in \boldsymbol{X} \tag{3.2}$$

$$a_{i_t} - \sum_{j_t \in \boldsymbol{X}} D_{i_t j_{t+\delta_{ij}^t}} - \sum_{j_t \in \boldsymbol{X}} R_{i_t j_{t+\delta_{ij}^t}} - S_{i_t i_{t+1}} = 0 \ \ \forall i_t \in \boldsymbol{X} \tag{3.3}$$

$$Z_i \geq a_{i_t} \quad \forall i_t \in \boldsymbol{X} \tag{3.4}$$

$$R_{i_t j_{t+\delta_{ij}^t}} \in \mathbb{N}^0 \quad \forall \left(i_t, j_{t+\delta_{ij}^t}\right) \epsilon \boldsymbol{A_1} \tag{3.5}$$

$$S_{i_t i_{t+1}} \in \mathbb{N}^0 \quad \forall (i_t, i_{t+1}) \in \boldsymbol{A_2} \tag{3.6}$$

$$a_{i_t} \in \mathbb{N}^0 \quad \forall i_t \in \boldsymbol{X} \tag{3.7}$$

$$Z_i \in \mathbb{N}^0 \quad \forall i \in \boldsymbol{N} \tag{3.8}$$

The objective function (3.1) is to maximize total daily profit (π) of the one-way carsharing service, taking into consideration the revenues obtained through the trips paid by customers, relocation costs, vehicle maintenance costs, vehicle depreciation costs, and station maintenance costs. Constraints (3.2) ensure the conservation of vehicle flows at each node of the time-space network, and Constraints (3.3) compute the number of vehicles at each station i at the start of time t, assuming that vehicles destined to i at time t arrive before vehicles originating from i at time t depart. Constraints (3.4) guarantee that the size of the station at location i is greater than the number of vehicles present there at each minute t. In practice, size will not be greater than the largest value of a_{i_t} during the period of operation otherwise the objective function would not be optimized. Expressions (3.5)-(3.8) set that the variables must be integer and positive.

3.3 Simulation model

In order to test real-time relocation policies, a discrete-event time-driven simulation model has been built using AnyLogic (xj technologies), which is a simulation environment based on the Java programming language. It is assumed that a trip will be performed only if there is simultaneously a station near the origin of the trip and a station near the trip's destination. The effects of congestion on the road network are captured with different link travel times throughout the day.

In each minute, trips and relocation operations are triggered and the model updates a number of system attributes, including: number of completed minutes driven by customers and by vehicle relocation staff; vehicle availability at each station; total number of vehicles needed; and maximum vehicle stock (that is, number of parked vehicles) at each station, which is used to compute the needed capacity of each station. These updated values are used to compute the objective function. It includes all revenues (price rate paid by customers) and costs (vehicle maintenance, vehicle depreciation, parking space maintenance, and relocation operations). To satisfy all demand, a vehicle is created (the fleet size is correspondingly increased) each time a vehicle is needed in a given station for a trip and there are no vehicles available. Thus the fleet size is an output of the simulation. The period of simulation is between 6 a.m. and midnight which is the same period used in (Correia and Antunes, 2012). At the end of the simulation run, it is possible to obtain the total profit and the total number of parking spaces needed in each station.

3.3.1 Relocation Policies

Two real-time relocation policies (1.0 and 2.0) were tested in the simulation. For each one, it is determined for each minute of the day at each station s if the status of s is that of supplier (with an excess number of vehicles) or demander (with a shortage of vehicles). For policy 1.0, a station s at time t is classified as a supplier if, on a previous day of operations, the number of customer trips destined for that station at instant $t + x$ exceeds or equals the number of customer trips that depart that station at the same period. Note that only customer trips, and not repositioning trips, are included in this calculation. Each station that is not designated as a supplier is classified as a demander. In this policy, x is varied between 5 and 20 minutes in 5 minutes increments to determine the supplier and the demander stations. If s is classified as a supplier, its supply is equal to the number of extra vehicles (those not needed for serving customer demand) at s at time t, multiplied by a relocation percentage that is a parameter. If s is classified as a demander, its demand for vehicles is set equal to the number of additional vehicles needed to serve demand at time $t + x$. For relocation policy 2.0, the process is the same, but x is set equal to 1 minute to determine the set of supplier stations and the associated supplies are determined as described for policy 1.0. The demander stations and their demand are determined as in relocation policy 1.0.

A schematic representation of these policies is shown in Figure 3.1.

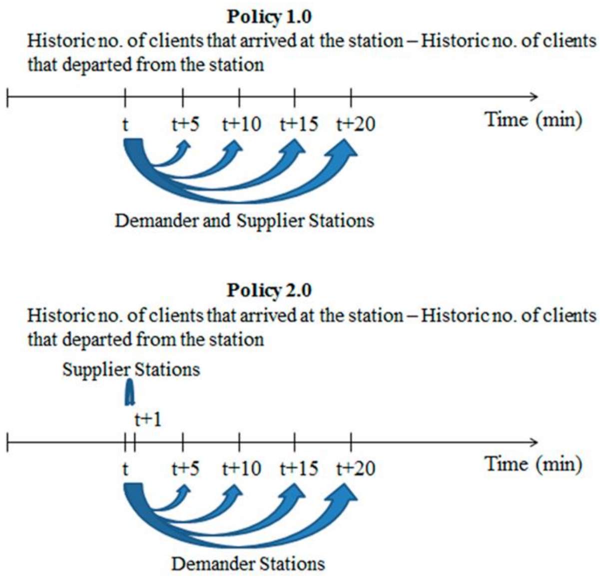


Figure 3.1 - Policies 1.0 and 2.0 schematic representation

For each time t, given these calculated values of vehicle supply or demand at each station, the relocation of vehicles between stations is determined by solving a classic transportation problem. The objective is to find the minimum cost distribution of vehicles from m origin nodes (representing supplier stations) to n destination nodes (representing demander stations), with costs equal to total travel time. An artificial supply node and an artificial demand node are added to the network, with all supply and demand concentrated at the respective artificial nodes. The artificial supply node is connected to the supply nodes, which are linked to the demand nodes, and finally the demand nodes are linked to the artificial demand node (as shown Figure 3.2). For each arc, the following three parameters are defined: cost of the arc (travel time); lower bound on arc flow (minimum number of vehicles); and upper bound on arc flow (maximum number of vehicles). On each arc from the artificial supply node to a supply node i, the lower and upper bounds on flow equal the supply at i and travel time on the arc is 0. For each arc between a supply node at station i and a demand node j, the lower bound on flow is zero and the upper bound is the minimum of the supply of vehicles at i and the number of vehicles demanded at j. On each arc between a demand node j and the artificial demand node, the lower and upper flow bounds equal the demand at j and travel time on the arc is 0. When there is imbalance between total supply and total demand either, one extra supply node or one extra demand node is created.

In the simulation, an optimal relocation is determined using a minimum cost network flow algorithm that is available in the simulation programming language Java (Lau, 2007).

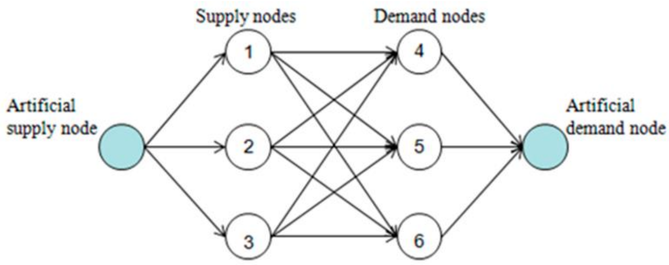


Figure 3.2 - Minimum cost flow algorithm scheme

As it is referred above, for each simulation run, two tuning parameters, the relocation percentage and x, are defined. The relocation percentage multiplied by the supply (of vehicles) at a supplier station represents the value of the supply input to the transportation algorithm. x represents the time period used for the minute-by-minute calculation for each station to determine its status as either a supplier or demander of vehicles.

Using relocation policies 1.0 and 2.0 as a starting point, three variants of these two policies were developed for each of them. The first is that each supplier station is required to keep at least one vehicle at that station at all time steps, that is, its supply is equal to the number of extra vehicles minus 1 at time t, multiplied by the relocation percentage (policies 1.A and 2.A). The second is that the distribution of vehicles at each station at the start of the day is set to that generated by the mathematical model defined in the previous section (policies 1.B and 2.B). And the third is the same as the second with priority given to stations with the greatest demand for vehicles (policies 1.C and 2.C). In practice this is done through reducing artificially the travel time to those stations that need a higher number of vehicles, thus making them more attractive as a destination for the vehicles according to the assignment method explained before. Travel times to a demander station are reduced as a function of the relative magnitude of demand at that station. For example, if demand at station *s* equals or exceeds 10% of the total demand for vehicles at all demander stations, travel times between supplier stations and station *s* are decreased by 10% (which is done by multiplying travel times by 0.9).

A schematic representation of the methodology that is used in this chapter is presented in Figure 3.3.

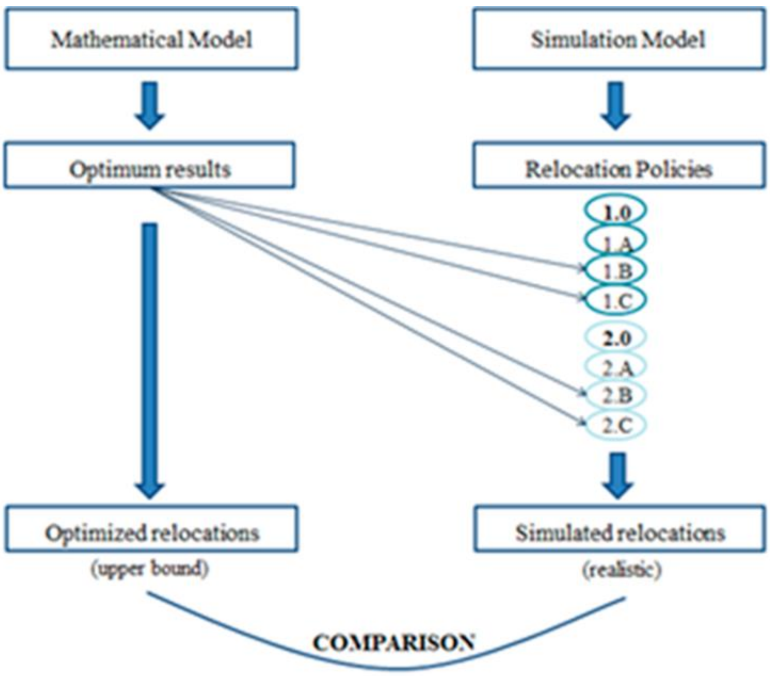


Figure 3.3 - Schematic representation of the methodology used

3.4 Lisbon case study

The case study used in this chapter is the same as in (Correia and Antunes, 2012). It is the municipality of Lisbon, the capital city of Portugal. Lisbon has been facing several mobility problems, such as traffic congestion and parking shortages due to the increase in car ownership and the proliferation of urban expansion areas in the periphery not served by public transportation. Moreover, public transportation, even with the improvements that have been achieved, was not able to restrain the growth in the use of private transportation for commuter trips. For these reasons, the municipality of Lisbon is a good example where different alternative transportation modes, such as carsharing, may be implemented.

3.4.1 Data

The data needed are the following: a carsharing trip matrix, a set of candidate sites for locating stations, driving travel times, and costs of operating the system. The trip matrix was obtained through a geo-coded survey conducted in the mid-1990s and updated in 2004 in the Lisbon Metropolitan Area (LMA). The survey data contains very detailed information on the mobility patterns of LMA, including origins and destinations, time of the day and transportation mode used for each trip. This survey was filtered through some criteria, such as age of the travelers, trip time, trip distance, time of the day in which the trip is performed, and transportation mode used, in order to consider only the trips that can be served by this system, resulting in 1777 trips. The candidate station locations were defined by considering a grid of squared cells (with sides of length 1000m) over Lisbon, and associating one location with the center of each cell. The result was a total of 75 possible station locations. This is obviously a simplification. To implement a carsharing system in a city, a detailed study of appropriate locations would be necessary. Travel times were computed using the transportation modeling software VISUM (PTV), considering the Lisbon network and the mobility survey referred above, and were expressed in minutes. The carsharing system is available 18 hours per day, between 6:00 a.m. and 12:00 a.m. The morning and afternoon peaks correspond to the periods between 8:00 a.m. and 10 a.m. and 6:00 p.m. and 8 p.m., respectively. To compute the costs related to the vehicles, it is considered an 'average' car, whose initial cost is 20,000 €, and that this car is mainly driven in a city. The costs of running the system were calculated as realistic as possible:

- C_{m1} (cost of maintaining a vehicle): 0.007 euros per minute. This cost was calculated using a tool available on the internet that was developed by a German company, INTERFILE (2012), and includes insurance, fees and taxes, fuel, maintenance and wear of the vehicle;
- C_v (cost of depreciation per vehicle): 17 euros per day, calculated using the same tool referred above (INTERFILE, 2012) and considering that the vehicles are used during 3 years. It was also considered that the company needed fully financing for the purchase of the vehicles with an interest rate of 12% and vehicles' residual value equal to 5000 €;

- C_r (cost of relocating a vehicle): 0.2 euros per minute, since the average hourly wage in Portugal is 12 euros per hour;
- C_{m2} (cost of maintaining a parking space): 2 euros per day, this cost is smaller than the parking fee in a low price area in Lisbon, considering that the city authorities would be able to give support to these types of initiatives.

The carsharing price per minute, P, was considered to be 0.3 euros per minute, which is based on the rates of *car2go* (2012).

The station location model (Correia and Antunes, 2012) was run for three scenarios, with a minute-by-minute discretization of time (note that this model does not include vehicle relocations). The three networks used in this work are the three found in (Correia and Antunes, 2012), as well as the trip matrix used. In the first, the number of stations was constrained to be just 10 (considered a small network). In the second scenario, the stations were freely located to maximize profit (any number, any location). In the third scenario, stations were located to satisfy all demand in the city (where there is demand, there is a station). The results, including station locations, number of stations, and associated profits, are presented in Figure 3.4.

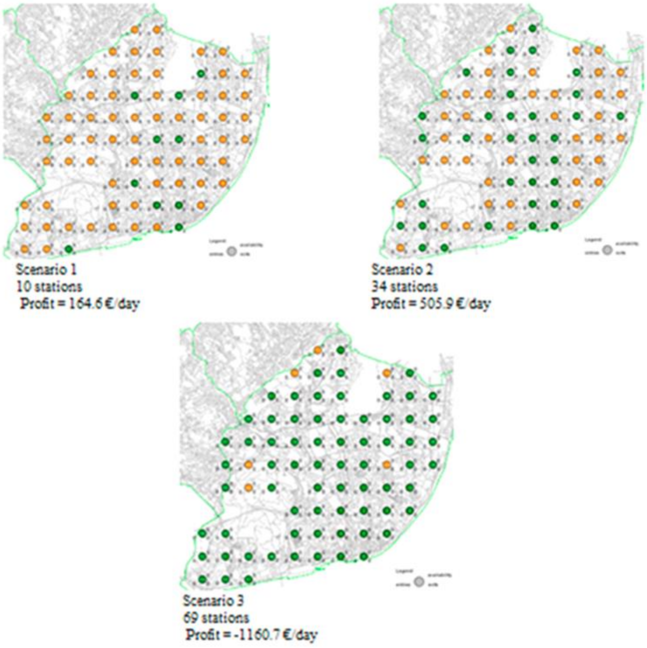


Figure 3.4 - Location model solutions

3.4.2 Results

The optimum relocation operations were determined using model (3.1)-(3.8), and all relocation policies were simulated with all possible parameters' combinations, for each of the three station location solutions (scenarios) generated with the approach of (Correia and Antunes, 2012). The value of *x* was varied between 5 and 20 minutes in 5 minutes increments, as it is referred in Section 3.3. This range was selected because most travel times are between these two values. The relocation percentage was varied between 0% (no relocations) and 100% (all available vehicles in the supplier stations can be relocated) in 10% increments. For policies 1.C and 2.C, simulation results were generated for the following combinations of parameters: 0.1/0.9 (more that 10% of demand in a station, 10% decreasing of travel time), 0.3/0.7, 0.5/0.5, 0.7/0.3, and 0.9/0.1. In the end, the number of simulation runs was 1920.

For all the scenarios, the mathematical model was run in an i7 processor @ 3.40 GHz, 16 Gb RAM computer under a Windows 7 64 bit operation system using Xpress, an optimization tool that uses branch-and-cut algorithms for solving MIP problems (FICO, 2008). The solutions found were always optimal. Xpress took about 206min to reach the optimal solution for scenario 1, 5min for scenario 2, and 8.3s for scenario 3. The time that the model took to run is reasonable even for the bigger scenario with 69 stations located. The factor that influences how quickly the solutions are achieved is the number of stations doubtless.

With respect to the simulation model, there was the need to run it many more times than the optimization routine, but each time the model took only few seconds to run.

In Table 3.1, the best simulation results for each relocation policy are shown.

Table 3.1 - Results for the different relocation policies

Station network (scenarios)	Indicators	Optimization of the station locations	Best results for each policy							
			1.0	2.0	1.A	1.B	1.C	2.A	2.B	2.C
69 (full demand attended)	x (min)	--	5	10	15	5	10	10	10	10
	Best relocation %	--	50	90	100	60	80	100	40	90
	Vehicles	390	264	273	262	264	257	267	318	222
	Parking spaces	739	533	490	550	412	409	480	415	334
	Time driven (min)	23711	23711	23711	23711	23711	23711	23711	23711	23711
	Time of relocations (min)	0	4008	2921	4800	4346	5169	2967	2661	9051
	Demand proportion/Travel time decreasing	--	--	--	--	--	0.7/0.3 - 0.9/0.1	--	--	0.1/0.9
	Profit (€/day)	-1160.7	591.7	742.1	433.3	766.1	726.5	854.9	179.1	695.1
34 (free optimum)	x (min)	--	5	5	5	5	15	5	5	5
	Best relocation %	--	0	0	10	0	10	0	0	0
	Vehicles	121	121	121	121	126	125	121	126	126
	Parking spaces	241	241	241	240	195	195	241	195	195
	Time driven (min)	10392	10392	10392	10392	10392	10392	10392	10392	10392
	Time of relocations (min)	0	0	0	4	0	54	0	0	0
	Demand proportion/Travel time decreasing	--	--	--	--	--	0.1/0.9 - 0.3/0.7	--	--	all equal
	Profit (€/day)	505.9	505.9	505.9	507.1	512.9(*)	519.1(**)	505.9	512.9(*)	512.9(*)
10 (small network)	x (min)	--	5	5	5	5	5	5	5	5
	Best relocation %	--	0	0	0	0	0	0	0	0
	Vehicles	22	22	22	22	22	22	22	22	22
	Parking spaces	42	42	42	42	29	29	42	29	29
	Time driven (min)	2125	2125	2125	2125	2125	2125	2125	2125	2125
	Time of relocations (min)	0	0	0	0	0	0	0	0	0
	Demand proportion/Travel time decreasing	--	--	--	--	--	all equal	--	--	all equal
	Objective (€/day)	164.6	164.6	164.6	164.6	190.6(*)	190.6(*)	164.6	190.6(*)	190.6(*)

(*) no relocations occur, profit achieved only by bringing the initial availability from optimization
(**) this profit is achieved using relocations and bringing the initial availability from optimization

Analyzing Table 3.1 and comparing to the solution with no relocations, policy 1.0, achieves better results only for the 69 station scenario, increasing from -1160.7€/day (losses) to 591.7€/day (profit). This profit is achieved by setting the x parameter equal to 5 minutes and the relocation percentage equal to 50%. Similar results to policy 1.0

are evident for policy 2.0, but policy 2.0 achieves a greater profit (742.1€/day), with the relocation percentage set to 90%, and x equal to 10 minutes.

Policy 1.A achieves better results (a profit of 433.3€/day) when compared to the solution with no relocations only for the 69 station scenario, using a relocation percentage equal to 100% and x equal to 15 minutes. This profit, however, is lower than the profits reached by using policies 1.0 and 2.0.

For policy 1.B, it is possible to improve profits for all scenarios compared to the model with no relocations; however, for the 34 station and 10 station scenarios, profit increases are achieved by using the initial availability of vehicles at each station brought from model (3.1)-(3.8). Profit is 766.1€/day for the 69 station scenario, using a relocation percentage equal to 60% and an x equal to 5 minutes. For the scenarios with 34 stations and 10 stations, however, the increase in profit is very low.

With respect to policy 1.C, results are better than the no relocation solution for the 69 station scenario. The best result, 726.5€/day, is achieved for two fraction-of-demand, fraction-of travel time scenarios, (0.7/0.3) and (0.9/0.1), a relocation percentage equal to 80%, and x equal to 10 minutes. For the 34 station scenario, the profit is 519.1€/day, which is similar to that obtained with no relocations (512.9€/day).

For policy 2.A, results are similar to those for policy 1.A, but with greater profit (854.9€/day), using a relocation percentage equal to 100% and x equal to 10 minutes. The results for policies 2.B and 2.C are similar to those obtained for 1.B and 1.C.

Policy 2.0 is better than policy 1.0 for the 69 station scenario; policy 1.A is worse than policy 2.A; and policies 1.B and 1.C are better than policies 2.B and 2.C. For the network with the optimum number of stations located (34 stations), policy 1.C is better than policy 2.C, while policies 1.A and 1.B are similar in effectiveness to policies 2.A and 2.B. Finally, for the 10 station scenario, the best profit is reached when no relocations occur and the initial availability of vehicles at each station is brought from model (3.1)-(3.8). The small network tailored to the demand data makes it difficult to improve profit with relocations.

Although only the best results are presented in Table 3.1, it is important to note that with variations in the relocation percentage and x parameters, the objective function values fluctuate greatly. This can be seen in Figure 3.5 for the 69 station scenario and policy 2.A. With x equal to 10 minutes, variations in the relocation percentage result in variations in the objective function value from -1037.1€/day to 854.9€/day. These parameters must be appropriately calibrated for each city and travel pattern scenario to produce the best results.

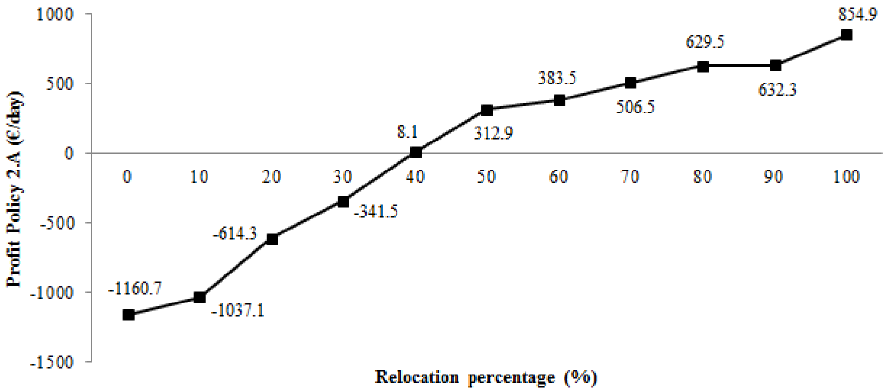


Figure 3.5 - Evolution of profit for the best relocation policy found with 69 stations located and parameter x equal to 10 min

As a general conclusion, with relocations, improvements in profit are achieved through a combination of a reduction in the number of vehicles and/or in the number of parking spaces. These reductions offset the corresponding increases in staff costs and vehicle maintenance costs resulting from the relocations. For the 69 station scenario, the greatest profit is reached with policy 2.A, which allows a reduction of 31.5% in the number of vehicles and a reduction of 35.0% in the number of parking spaces relative to the scenario with no relocations. The time spent with vehicle relocations in this case is 2967 minutes/day (about 50 hours/day). However, policy 2.C allows the greatest reduction in the number of vehicles (43.1%) and in the number of parking spaces (54.8%), but requires about a 3-fold increase in relocation time (9051 minutes/day). This illustrates that minimizing vehicles and parking spaces does not necessarily maximize profit.

In Table 3.2, for each of the three network scenarios, results are compared for the solutions to the station location model without relocations (Correia and Antunes, 2012), the solutions applying the relocation optimization model (3.1)-(3.8), and the best performing simulated relocation policy.

Table 3.2 - Results for the different problems

Models	69 stations		34 stations		10 stations	
	Profit (€/day)	Improvements (€/day)	Profit (€/day)	Improvements (€/day)	Profit (€/day)	Improvements (€/day)
Optimization of station locations	-1160.7	--	505.9	--	164.6	--
Optimization of relocation operations	3865.7	5026.4	1768.1	1262.2	322.0	157.4
Simulation with the best relocation policy	854.9	2015.6	519.1	13.2	190.6	26

Results for the simulated relocation policies are far from the optimal relocation solutions, showing that it is difficult to design effective real-time strategies based on fixed rules. A case in point is the 34 station scenario in which the optimized relocations contribute to an improvement in profit of about 1262€/day, while the real-time relocation policies improve profit only to about 13€/day.

Nevertheless, it is important to observe that the policies evaluated in this work were able to make profitable the 69 station scenario that serves all demand in the city. Relocation policies, then, can help carsharing companies to provide sustainable services to greater numbers of people in expanded geographic areas.

3.5 Conclusions

The most convenient carsharing systems for users are one-way systems; however as detailed in the literature, these systems require vehicle repositioning to ensure that vehicles are located where they are needed (Mitchell et al., 2010; Nair and Miller-Hooks, 2011; Febbraro et al., 2012). Several approaches have been proposed to try to solve this problem, such as an operator-based approach (Kek et al., 2006; Kek et al., 2009) and a station-location approach (Correia and Antunes, 2012). With the operator-based approach, the stock of vehicles at stations is adjusted by relocating vehicles to locations where they are needed.

In this chapter we present two independent tools that can be combined: a mathematical model for optimal vehicle relocation, and a discrete-event time-driven simulation model with several real-time relocation policies integrated. Kek et al. (2006) and Kek et al. (2009) developed also an optimization model and a simulation model, but in their work only the optimization model allows determining the relocation operations. The simulation model is just used to evaluate the performance of the systems when the relocation operations determined by the optimization model are performed. Nair and Miller-Hooks (2011) developed a stochastic mixed-integer programming model to optimize vehicle relocations, which has the advantage of considering demand uncertainty. However, they did not develop a simulation model and a way of determining relocation operations in real time. Barth and Todd (1999) presented a queuing based discrete event simulation model and three ways of deciding when relocations should be performed, one of which, called 'Historical predictive relocation', is similar to what is proposed in the relocation policies presented here. Although, there is a higher number of policies and combination of parameters tested in this work than in (Barth and Todd, 1999). Moreover, Barth and Todd (1999) did not develop an optimization model and ways of combining both optimization and simulation. With respect to Barth et al. (2001), an aggregated approach was developed. They only studied a measure to determine if the whole system needs relocations or not, while in this chapter, each station is treated individually.

The developed optimization model was applied to the case study first introduced by Correia and Antunes (2012). Using the alternative networks of stations that were obtained for the city of Lisbon, the relocation approaches developed in this research were evaluated and compared.

The optimized relocation decisions for these networks indicated significant potential improvements in system profit. For instance, the solution covering all demand for the entire city (containing 69 stations) has an estimated daily loss of 1160 €, but when operations are expanded to include optimal relocation decisions, this estimated daily loss is transformed into an estimated daily profit of about 3800 €. There are also significant economic improvements in the other networks (containing 34 and 10 stations).

Optimal solutions to the relocation model provide upper bounds on the economic gains achievable with relocations, because inputs to the optimization model require a priori knowledge of the full pattern of daily trip demands. To evaluate the impacts of real-time relocation operations in this research, relocation policies were devised and executed in a simulation model. For the largest network of stations these simulated, real-time relocation strategies, are estimated to improve profitability significantly, reaching a profit of about 855 €/day with the best relocation policy. This is far from the optimum; however it is implemented real-time making it more likely to be achieved in the real operation when vehicles are not reserved one day in advance. For the smaller networks, the correspondingly smaller improvement is explained by the fact that the station locations in these networks were specifically chosen to reduce the need for repositioning by using the model in (Correia and Antunes, 2012). By integrating results of the relocation optimization model with the relocation policies (for example, using in the simulation the optimization's initial vehicle availability at each station), improved results are achieved for the relocation policies.

The main conclusion that is drawn from this work is that relocation operations should be considered when setting up station-based one-way carsharing systems. An important effort must be made into studying more deeply what was defined in this chapter as real-time relocation policies to be implemented in the day-to-day operation of these systems, thus allowing the sustainability of full network coverage of this service in a city. The fact that by introducing relocation policies it was possible to transform the worst profitable network (69 stations) into the most profitable encourages research into expanding the methods to estimate when and how many vehicles should be relocated between stations (Jorge and Correia, 2013).

In regard to the transferability of both models (mathematical model and simulation model) to another city, it is important to refer that mathematical models always have a computation time that is dependent on the problem dimension. Thus, as the city size increases, that is, the number of carsharing stations', the computation time should also increases due to the increasing number of decision variables. Regarding the simulation model, this problem is non-existent. Therefore, it can be applied to any city independently of its dimension.

Moreover, the results presented in this chapter are very sensitive to changes in travel demand. So, the simulation model that was built in this work should be improved in future projects to increase the realism of the day-to-day operation of such transportation system, including stochastic trip variability and travel time.

Chapter 4

Trip Pricing of One-way Station-based Carsharing Networks with Zone and Time of Day Price Variations

4.1 Introduction

Carsharing systems involve a small to medium fleet of vehicles available at several stations or parking places spread across a city, which can be used by a relatively large group of members (Shaheen et al., 1999). These systems appeared in 1948, in Europe (Shaheen et al., 1999), as an alternative to private vehicle and public transportation. They allow users to have access to a fleet of vehicles, with the flexibility and accessibility associated to owning a private vehicle, without the costs of owning one. Vehicles in these systems also have a higher utilization rate when compared to those privately owned (Litman, 2000; Schuster et al., 2005; U.S. Department of

Transportation, 2001). At the same time, they can contribute to mitigating negative externalities associated with cars, such as reducing the amount of pollutant emissions, especially when using an eco-fleet of vehicles. When compared to traditional public transportation systems, such as bus and metro, carsharing systems can contribute to expanding service coverage, and have more schedule flexibility, among other advantages.

In the 1980's, successful programs were launched in Europe and carsharing was expanded to the United States, gaining popularity in this country only in the 1990's (Shaheen et al., 1999). Currently, carsharing is implemented all over the world, which motivated several studies based on its performance and contribution to the accessibility of urban activities (Celsor and Millard Ball, 2007; Firnkorn and Müller, 2011; Martin and Shaheen, 2011; Schure et al., 2012; Sioui et al., 2013).

Regarding the operating model, carsharing systems can be classified into round-trip systems, in which users have to return the vehicles to the same station where they were picked up, and one-way systems that give users the flexibility to return the vehicles to a different station from the one where they picked up the vehicle (Shaheen et al., 2006). Moreover, a particular type of one-way carsharing has appeared recently, the so-called free-floating carsharing, in which vehicles may be picked up and left in parking spaces spread across a city (Ciari et al., 2014; Schmoller et al., 2014).

Round-trip carsharing is generally used for short trips, for example shopping, leisure and sporadic trips (Barth and Shaheen, 2002; Costain et al., 2012); while one-way carsharing can be used for wider trip purposes, even for commuting (Balac and Ciari, 2014; Ciari et al., 2014). However there is a major drawback to one-way carsharing: the vehicle stocks often become imbalanced in stations, constituting a problem for the service operator (Jorge and Correia, 2013). This happens because the demand for vehicles varies throughout the day and per origin-destination pair of stations, creating a tendency for more vehicles to accumulate at stations where they are not needed, and therefore lack in other demanding stations. This situation can even lead to a parking shortage for users wanting to park their vehicle at a saturated station. The management of parking space reservation policies to cope with this problem has been addressed in a previous study by Kaspi et al. (2014). Several approaches have been proposed in the literature to address the imbalance problem. The most extensively studied method is to relocate vehicles (Barth and Todd, 1999; Barth and Todd, 2001; Kek et al., 2006; Kek et al., 2009; Nair and Miller-Hooks, 2011; Krumke et al., 2013; Jorge et al., 2014; Nourinejad and Roorda, 2014; Repoux et al., 2014). There are also other alternatives: accepting or refusing a trip based on its impact on vehicle stock balance (Fan et al., 2008; Correia and Antunes, 2012); station location selection to achieve a more favorable distribution of vehicles (Correia and Antunes, 2012); price incentives for grouping parties of people if they are travelling from a station with a shortage of vehicles, and ungrouping parties of people otherwise (Barth et al., 2004; Uesugi et al., 2007); price incentive policies for the users to accept choosing another drop-off station (Febbraro et al., 2012; Weikl and Bogenberger, 2012; Pfrommer et al., 2014); and trip pricing, that is, changing the price of the trips charged to the clients taking into account their contribution in stock balancing (Mitchell et al., 2010; Zhou, 2012).

The focus of this work is this last approach: trip pricing. Pricing has been used to solve several problems related to transportation, namely congestion (Wie and Tobin, 1998; Wang et al., 2011; Chung et al., 2012), high occupancy/toll lanes management (Lou et al., 2011), and airline seat management (You, 1999; Atasoy et al., 2012). With respect to carsharing, trip pricing has been referred in many scientific publications as a way to solve vehicle imbalances (Mitchell et al., 2010; Febbraro et al., 2012; Weikl and Bogenberger, 2012; Pfrommer et al., 2014; Zhou, 2012). To the best of our knowledge, no one has ever proposed a method for setting these prices and proven its usefulness for profit maximization and reducing vehicle imbalance. Hence, the main objective of this chapter is to create such a method and investigate if it is possible to increase the profit of a one-way carsharing company by varying the price charged to clients. A methodological approach is developed to reach this objective, which is mainly constituted by two components: (i) a mixed-integer non-linear programming (MINLP) model that, having the trips made throughout an entire day and the price elasticity of demand, determines which prices to charge at a given period of time for profit maximization; and (ii) an iterated local search (ILS) meta-heuristic to solve the problem. Furthermore, for simplification purposes the stations are grouped into zones, which are determined through clustering analysis on a theoretical relocation vector obtained for profit maximization. This methodological approach is tested for the case study of the city of Lisbon, in Portugal.

The main contributions of this chapter are:

- developing a method to implement variable trip pricing in one-way carsharing;
- testing the method with a real case study; and
- drawing conclusions on the usefulness of applying trip pricing as a way to balance this type of system and obtain a higher profit.

The chapter is structured as follows. In the next section, we present the notation and method used to address this problem. In section 4.3, the solution algorithm is presented. This is followed by the case study to which the method is applied. Afterward, the computational experiments on the case-study are presented, followed by the main results in Section 4.6. Finally, the chapter finishes with the main conclusions withdrawn from this study and some possibilities of future developments. Acronyms used in this chapter are summarized in Table 4.1.

Table 4.1 - Acronyms used in the chapter

Abbreviation	Complete form
CBD	Central business district
ILP	Integer linear programming
ILS	Iterated local search
LSO	Local search operator
MINLP	Mixed-integer non-linear programming
MIP	Mixed integer programming
OD	Origin-destination
PO	Perturbation operator
TI	Time interval
TPPOCS	Trip pricing problem for one-way carsharing systems
VRPOCS	Vehicles relocation problem for one-way carsharing systems

4.2 Notation and method

In this section, as a basis for the method of setting the trip prices, we first introduce the model proposed and applied by Jorge et al. (2014) in which optimal relocation operations are found for a set of stations in a one-way carsharing system. This model provides a desired vector of relocated vehicles between each pair of stations, which constitutes the perfect solution for the vehicle imbalance problem, providing a reference to the mitigation of the vehicle imbalance problem through trip pricing. A new model is adapted from the previous one incorporating price variations per pair of zones and period of the day, substituting the reference static price by a new set of decision variables and introducing price elasticity of demand. Relocation operations are naturally excluded from the new model. Given the dependence of demand with respect to price, this new model becomes non-linear. Consequently, there is the need to resort to a solution method to determine the prices charged for each OD pair of zones per time interval (TI). Notations used in the chapter are summarized in Table 4.2.

Table 4.2 - A summary of the notation used

Notations	Explanations
π	Daily profit of the one-way carsharing company when relocation operations are used
θ	Daily profit of the one-way carsharing company when trip pricing is used
δ_{kj}^{t}	Travel time, in time instants, between stations k and j when departure time is $t, \forall k_t \in \boldsymbol{X}, j \in \boldsymbol{K}'$
E	Price elasticity of demand
$P0$	The current carsharing price for all OD pairs of stations at any time instant per time step driven
C_{mv}	The maintenance cost of each vehicle per time step driven

C_{mp}	The cost of maintaining one parking space per day
C_v	The cost of depreciation of one vehicle per day
C_r	The cost of relocation per vehicle per time step driven
o	Number of observations in the cluster analysis
u	Number of clusters desired
$P0_{zw}^{i}$	The current carsharing price per time step driven between zones z and w when departure time interval is $i, \forall z, w \in \boldsymbol{Z'}, i \in \boldsymbol{I'}$ (all prices set to P0)
$D0_{k_t j_{t+\delta_{kj}^t}}$	Number of customer trips from station k to station j from instant t to instant $t+\delta_{kj}^t, \forall \left(k_t, j_{t+\delta_{kj}^t}\right) \in \boldsymbol{A_1}$ for the reference price
p_{min}	Minimum price charged allowed per time step driven
p_{max}	Maximum price charged allowed per time step driven
$time$	Longest allowed processing time for the heuristic algorithm and the *local search* operator (LSO)
$step$	The smallest price change than can be performed during the local search
$(P_{zw}^{i})_{down}$	Potential new lower price considered by the LSO and calculated by lowering the initial price P_{zw}^{i}
$(P_{zw}^{i})_{up}$	Potential new higher price considered by the LSO and calculated by increasing the initial price P_{zw}^{i}
n	The size of the set of prices in the trip pricing table that may be changed using the *perturbation* operator (PO)
d	The maximum allowed value of price change
Δp	The price change during the perturbation, which belongs to the interval $[-d; d]$
$\boldsymbol{K'} = \{1, \dots, k \dots K\}$	The set of stations
$\boldsymbol{T'} = \{1, \dots, t \dots T\}$	The set of time instants in the operation period
$\boldsymbol{Z'} = \{1, \dots, z \dots Z\}$	The set of zones
$\boldsymbol{I'} = \{1, \dots, i \dots I\}$	The set of time intervals in the operation period
tb_i	The beginning instant of time interval $i, \forall\, i \in I'$
te_i	The end instant of time interval $i, \forall\, i \in I'$
$\boldsymbol{X} = \{1_1, \dots, k_{t-1}, k_t, k_{t+1}, \dots, K_T\}$	The set of the nodes of a time-space network combining the K stations with the T time instants, where k_t represents station k at time instant t
$\boldsymbol{A_1} = \left\{\dots, \left(k_t, j_{t+\delta_{kj}^t}\right), \dots\right\}, k_t \in \boldsymbol{X}$	The set of arcs over which vehicles move between stations k and $j, \forall k, j \in \boldsymbol{K'}, k \neq j$, between time instant t and $t+\delta_{kj}^t$
$\boldsymbol{A_2} = \{\dots, (k_t, k_{t+1}), \dots\}, k_t \in \boldsymbol{X}$	The set of arcs that represent vehicles stocked in station $k, \forall k \in \boldsymbol{K'}$, from time instant t to time instant $t+1$
C_{ls}	The changing candidate set of prices for the LSO

C_p	The changing candidate set of prices for the PO
$R_{k_t j_{t+\delta_{kj}^t}}$	Decision variables on the number of vehicles relocated from k to j from time instant t to $t+\delta_{kj}^t, \forall \left(k_t, j_{t+\delta_{kj}^t}\right) \in \boldsymbol{A_1}$
$R^0_{k_t j_{t+\delta_{kj}^t}}$	Number of vehicles relocated from k to j from time instant t to $t+\delta_{kj}^t, \forall \left(k_t, j_{t+\delta_{kj}^t}\right) \in \boldsymbol{A_1}$ when the cost of relocations is 0.
$\alpha^0_{k_t}$	Number of vehicles relocated to station k at time instant t when relocation costs are 0, , $\forall k_t \in \boldsymbol{X}$
$\beta^0_{k_t}$	Number of vehicles relocated from station k at time instant t when relocation costs are 0, , $\forall k_t \in \boldsymbol{X}$
$\epsilon^0_{k_t}$	Difference of the number of relocated vehicles to/from station k at time instant t when relocation costs are 0, $\forall k_t \in \boldsymbol{X}$
$\omega^0_{k_i}$	Difference of the number of relocated vehicles to/from station k during time interval i when relocation costs are 0, $\forall k \in \boldsymbol{K'}$, $\forall i \in \boldsymbol{I'}$
Z_k	Decision variables on the size of station $k, \forall k \in \boldsymbol{K'}$, where size refers to the number of parking spaces
a_{k_t}	Decision variables on the number of available vehicles at station k at time instant $t, \forall k_t \in \boldsymbol{X}$
$D_{k_t j_{t+\delta_{kj}^t}}$	Decision variables on the number of customer trips from station k to station j from time instant t to $t+\delta_{kj}^t, \forall \left(k_t, j_{t+\delta_{kj}^t}\right) \in \boldsymbol{A_1}$ after the price is varied
P^i_{zw}	Decision variables on the carsharing price per time step driven between zones z and w when departure time period is $i, \forall z, w \in \boldsymbol{Z'}, i \in \boldsymbol{I'}$
$\bar{P}$	The best (optimal) trip pricing table
$V_{k_t k_{t+1}}$	Auxiliary variable on the number of vehicles stocked at each station k from time instant t to $t+1, \forall (k_t, k_{t+1}) \in \boldsymbol{A_2}$
$P(p_{min}, p_{max})$	Trip pricing table with all elements greater than $Pmin$ and lesser than $Pmax$
$\mathcal{P}(p_{min}, p_{max})$	Set of all feasible pricing tables for price interval $[p_{\min}, p_{\max}]$
$P_{initial}$	The initial trip pricing table
P^*	The current best known trip pricing table found during the ILS algorithm run
P'	The perturbed trip pricing table obtained from the application of the PO during the ILS algorithm run

P'^{*}	The local optimum in the environment of the perturbed pricing table P' during the ILS algorithm run
P_{best}	Best pricing table found in this work

4.2.1 The Vehicles Relocation Problem for One-way Carsharing Systems (VRPOCS)

Jorge et al. (2014) proposed an integer linear programming (ILP) model for the optimal relocation movements between a set of stations in a city in order to maximize the daily profit of a one-way carsharing company. We denote this as the Vehicle Relocation Problem for One-way Carsharing Systems (VRPOCS). These movements are considered to be performed by a staff of drivers and all demand between existing stations has to be satisfied.

Using the notation in Table 4.2, the model is formulated as follows:

$$Max\ \pi = (P0 - C_{mv}) \times \sum_{k_t j_{t+\delta_{kj}^t} \epsilon \boldsymbol{A_1}} D0_{k_t j_{t+\delta_{kj}^t}} \times \delta_{kj}^t - C_{mp} \sum_{k \in \boldsymbol{K'}} Z_k - C_v \sum_{k \in \boldsymbol{K'}} a_{k_1} - C_r \sum_{k_t j_{t+\delta_{kj}^t} \epsilon \boldsymbol{A_1}} R_{k_t j_{t+\delta_{kj}^t}} \times \delta_{kj}^t \tag{4.1}$$

subject to,

$$V_{k_t k_{t+1}} + \sum_{j_t \in \boldsymbol{X}} D0_{k_t j_{t+\delta_{kj}^t}} + \sum_{j_t \in \boldsymbol{X}} R_{k_t j_{t+\delta_{kj}^t}} - \sum_{j \epsilon \boldsymbol{K'}: t'=t-\delta_{jk}^t} D0_{j_{t'} k_t} - \sum_{j \epsilon \boldsymbol{K'}: t'=t-\delta_{jk}^t} R_{j_{t'} k_t} - V_{k_{t-1} k_t} = 0 \ \ \forall k_t \in \boldsymbol{X} \tag{4.2}$$

$$a_{k_t} - \sum_{j_t \in \boldsymbol{X}} D0_{k_t j_{t+\delta_{kj}^t}} - \sum_{j_t \in \boldsymbol{X}} R_{k_t j_{t+\delta_{kj}^t}} - V_{k_t k_{t+1}} = 0 \quad \forall k_t \in \boldsymbol{X} \tag{4.3}$$

$$Z_k \geq a_{k_t} \quad \forall k_t \in \boldsymbol{X} \tag{4.4}$$

$$R_{k_t j_{t+\delta_{kj}^t}} \in \mathbb{N}^0 \quad \forall \left(k_t, j_{t+\delta_{kj}^t}\right) \epsilon \boldsymbol{A_1} \tag{4.5}$$

$$V_{k_t k_{t+1}} \in \mathbb{N}^0 \quad \forall (k_t, k_{t+1}) \in \boldsymbol{A_2} \tag{4.6}$$

$$a_{k_t} \in \mathbb{N}^0 \quad \forall k_t \in \boldsymbol{X} \tag{4.7}$$

$$Z_k \in \mathbb{N}^0 \quad \forall k \in \boldsymbol{K'} \tag{4.8}$$

The objective function (4.1) is to maximize the total daily profit (π) of the one-way carsharing service, taking into consideration the revenues obtained through the trips paid by clients, vehicle maintenance costs, vehicle depreciation costs, station maintenance costs, and relocation costs. Constraints (4.2) ensure the conservation of vehicle flows at each node of the time-space network. Constraints (4.3) compute the number of vehicles at each station k at the start of time instant t, assuming that vehicles destined to arrive at station k at time instant t arrive before vehicles leave from the same station at time instant t. Constraints (4.4) guarantee that the size of the station at location k is greater than the number of vehicles located there at each time instant t. In practice, size will not be greater than the largest value of a_{k_t} during the period of operation because this would penalize the objective function. Expressions (4.5)-(4.8) set that the variables must be integer and positive.

4.2.2 Grouping stations through k-means clustering

Running the VRPOCS model for null relocation operations costs ($C_r = 0$) yields an ideal vector of relocation flows, which we will call $R^0_{k_t j_{t+\delta^t_{kj}}}$. With this vector it is possible to compute the ideal number of relocated vehicle entries and exits at each station.

The vehicle entries are given by:

$$\alpha^0_{k_t} = \sum_{\mathrm{j}\epsilon\mathbf{K'}:t'=\mathrm{t}-\delta^{\mathrm{t}}_{\mathrm{jk}}} \mathrm{R}_{j_{t'}\mathrm{k_t}} \qquad \forall(t', \mathrm{k_t})\epsilon\mathbf{A_1} \tag{4.9}$$

The vehicle exits are given by:

$$\beta^0_{k_t} = \sum_{j_t \in \boldsymbol{X}} R_{k_t j_{t+\delta^t_{kj}}} \ \forall \left(k_t, j_{t+\delta^t_{kj}}\right) \epsilon \boldsymbol{A_1} \tag{4.10}$$

The difference between both vectors $\alpha^0_{k_t} - \beta^0_{k_t}$ yields a new vector $\epsilon^0_{k_t}$ that will be positive or negative whether station i is a supplier ($\epsilon^0_{k_t}$>0) or a demander of vehicles ($\epsilon^0_{k_t}$<0).

The values of the vector $\epsilon^0_{k_t}$ can be aggregated for each time interval. We call the set of time intervals in which the day is divided the $\mathbf{I'} = \{1, \ldots, \mathrm{i} \ldots \mathrm{I}\}$ set. Hence it is possible to compute the vector for the relocation balance at each time interval i as:

$$\omega^0_{k_i} = \sum_{t=tb_i}^{te_i} \epsilon^0_{k_t}, \forall k \in \boldsymbol{K'}, \forall i \in \boldsymbol{I'} \tag{4.11}$$

In order to obtain zones of stations that are similar in their vehicle needs or in their ability to provide vehicles at a given interval, the *K-means* clustering algorithm is applied. *K-means* partitions o observations into u clusters. Considering o observations, it consists of firstly choosing u centroids, where u is the number of clusters desired. Each observation o will then be assigned to the closest centroid, and each group of observations assigned to a centroid will be a cluster. The centroid of each cluster is then updated based on the observations assigned to the cluster. We use vector $\omega_{k_i}^0$ as a measure of similarity between the stations in each time interval i, hence the number of u centroids is the number of desired zones (set $\boldsymbol{Z'}$) for which prices will vary, and the number of observations o is the number of stations (set $\boldsymbol{K'}$). It is well known that this clustering process does not lead to a global optimum, since the process is dependent on the choice of the u first observations (Ji and Geroliminis, 2012); nevertheless, this is not the major concern of the method developed herein.

The clustering process described is meant to produce the same number of zones for any of the time intervals and does not require continuity, that is, stations in each zone do not need to be contiguous. A station may belong to a cluster and later to another, which permits any station having different prices from its neighbor along the day.

4.2.3 The trip pricing problem for one-way carsharing systems (TPPOCS)

The mixed-integer non-linear programming (MINLP) model proposed in this section derives from the VRPOCS. This problem is defined as follows: 'given a set of carsharing stations operating in one-way mode for which an OD matrix is known for a given price, the TPPOCS aims at finding new prices between groups of stations such that the profit of running the system is maximized while satisfying all demand for the new prices'.

Demand, in this model, varies according to a simple elastic behavior. The new demand $\left(D_{k_t j_{t+\delta_{kj}^t}}\right)$ results from applying the price elasticity E to a reference demand $\left(D0_{k_t j_{t+\delta_{kj}^t}}\right)$ that exists for price $P0$. The expression is the following:

$$E = \frac{\dfrac{\mathrm{D}_{\mathrm{k_t j}_{\mathrm{t}+\delta_{\mathrm{kj}}^{\mathrm{t}}}} - \mathrm{D0}_{\mathrm{k_t j}_{\mathrm{t}+\delta_{\mathrm{kj}}^{\mathrm{t}}}}}{\mathrm{D0}_{\mathrm{k_t j}_{\mathrm{t}+\delta_{\mathrm{kj}}^{\mathrm{t}}}}}}{\dfrac{\mathrm{P}_{\mathrm{zw}}^{\mathrm{i}} - \mathrm{P0}_{\mathrm{zw}}^{\mathrm{i}}}{\mathrm{P0}_{\mathrm{zw}}^{\mathrm{i}}}} \tag{4.12}$$

We are assuming the elasticity to be the same for any interval of price variation which may be unrealistic for great variations of price. However, one does not expect to change prices beyond a realistic interval around the current price *P0*.

Using the notation presented in Table 4.2 and the elasticity defined in equation (4.12), the MINLP model is formulated as follows:

$$Max\ \theta = \sum_{\substack{k_t j_{t+\delta_{kj}^t} \in \boldsymbol{A_1} \\ z,w \in \boldsymbol{Z'} \\ i \in \boldsymbol{I'}}} (P_{zw}^i - C_{mv}) \times D_{k_t j_{t+\delta_{kj}^t}} \times \delta_{kj}^t - C_{mp} \sum_{k \in \boldsymbol{K'}} Z_k - C_v \sum_{k \in \boldsymbol{K'}} a_{k_1} \tag{4.13}$$

subject to,

$$D_{k_t j_{t+\delta_{kj}^t}} \geq D0_{k_t j_{t+\delta_{kj}^t}} + \frac{E \times D0_{k_t j_{t+\delta_{kj}^t}} \times (P_{zw}^i - P0_{zw}^i)}{P0_{zw}^i} - 0.5 \text{ }, \forall \left(k_t, j_{t+\delta_{kj}^t}\right) \epsilon A_1, z, w \in \boldsymbol{Z'}, i \in \boldsymbol{I'} \quad (4.14)$$

$$D_{k_t j_{t+\delta_{kj}^t}} \leq D0_{k_t j_{t+\delta_{kj}^t}} + \frac{E \times D0_{k_t j_{t+\delta_{kj}^t}} \times (P_{zw}^i - P0_{zw}^i)}{P0_{zw}^i} + 0.5 \text{ }, \forall \left(k_t, j_{t+\delta_{kj}^t}\right) \epsilon A_1, z, w \in \boldsymbol{Z'}, i \in \boldsymbol{I'} \quad (4.15)$$

$$D0_{k_t j_{t+\delta_{kj}^t}} + \frac{E \times D0_{k_t j_{t+\delta_{kj}^t}} \times (P_{zw}^i - P0_{zw}^i)}{P0_{zw}^i} \geq 0 \quad (4.16)$$

$$V_{k_t k_{t+1}} + \sum_{j \in \boldsymbol{K'}} D_{k_t j_{t+\delta_{kj}^t}} - \sum_{j \epsilon \boldsymbol{K'}: t'=t-\delta_{jk}^t} D_{j_{t'} k_t} - V_{k_{t-1} k_t} = 0 \text{ }, \forall k_t \in \boldsymbol{X} \quad (4.17)$$

$$a_{k_t} - \sum_{j_t \in \boldsymbol{X}} D_{k_t j_{t+\delta_{kj}^t}} - V_{k_t k_{t+1}} = 0 \text{ }, \forall k_t \in \boldsymbol{X} \quad (4.18)$$

$$Z_k \geq a_{k_t} \text{ }, \forall k_t \in \boldsymbol{X} \quad (4.19)$$

$$D_{k_t j_{t+\delta_{kj}^t}} \in \mathbb{N}^0 \text{ }, \forall \left(k_t, j_{t+\delta_{kj}^t}\right) \epsilon \boldsymbol{A_1} \quad (4.20)$$

$$P_{zw}^i \in \mathbb{R}^0, \quad \forall z, w \in \boldsymbol{Z'}, i \in \boldsymbol{I'} \quad (4.21)$$

$$V_{k_t k_{t+1}} \in \mathbb{N}^0 \text{ }, \forall (k_t, k_{t+1}) \in \boldsymbol{A_2} \quad (4.22)$$

$$a_{k_t} \in \mathbb{N}^0 \text{ }, \forall k_t \in \boldsymbol{X} \quad (4.23)$$

$$Z_k \in \mathbb{N}^0 \text{ }, \forall k \in \boldsymbol{K'} \quad (4.24)$$

The objective function (4.13) maximizes the total daily profit (θ) of the one-way carsharing service, taking into consideration the revenues obtained through the trips paid by the clients, vehicle maintenance costs, vehicle depreciation costs, and station maintenance costs. Notice that in this model no relocations are considered. Constraints (4.14) and (4.15) compute the demand that resulted from considering the change of price. Given that this demand is a continuous function of price, we use two inequalities to ensure that D will be integer. Constraints (4.16) ensure that the demand resulting from the application of the price elasticity to the reference demand is positive. Constraints (4.17), and (4.18) are the same as constraints (4.2), and (4.3) from the VRPOCS model but excluding the variables related to the vehicle relocation operations. Constraints (4.19) are the same as constraints (4.4). Expressions (4.20)-(4.24) set the variables domain.

The decision variables of the model are: the number of vehicles in each station at the beginning of the day, the demand for each OD pair of stations at each time step, and the prices charged for each OD pair of zones per time interval. As it is possible to observe, the objective function (4.13) is non-linear because demand multiplies by the price, and is non-concave, which makes this a MINLP problem not easily solvable by traditional branch and cut algorithms. To solve this type of problems for both concave and non-concave formulations, some MINLP solver software solutions are available but these typically have difficulties managing real size problem instances (Bussieck and Vigerske, 2014). The size of the search space of our problem is much greater than the size of the problems these software solutions are able to solve. For only 5 zones and 6 time periods, if prices vary from 0 to 0.70 €/min, with 0.01 increments, the number of possible solutions for this problem would be $|\mathcal{P}| = 71^{5.5.6} = 4.88 \cdot 10^{277}$. Therefore, in the next section we present a solution algorithm for reaching a good solution to this problem.

4.3 Solution algorithm

4.3.1 Iterated local search (ILS)

The goal of the solution algorithm presented in this section is finding the prices P_{zw}^{i} for which the daily profit θ of the TPPOCS will be as high as possible. A solution of this problem is a set of trip pricing tables denoted $P\ [|I|][|Z|][|Z|]\ (p_{min}, p_{max})$, or in short $P\ (p_{min}, p_{max})$, where $|I|$ is the number of time intervals, $|Z|$ is the number of zones and p_{min} and p_{max} are the minimum and maximum allowed prices, respectively. Pricing table $P\ (p_{min}, p_{max})$ contains $(|I| \cdot |Z| \cdot |Z|)$ individual elements and each element P_{zw}^{i} corresponds to the price charged per time step driven for trips from any station in zone z to any station in zone w starting during time interval i. The set of feasible solutions $\mathcal{P}(p_{\min}, p_{\max})$ is defined as the set of all possible trip pricing tables of appropriate dimensions $(|I| \times |Z| \times |Z|)$ and whose elements are at a given price interval.

The optimal pricing table $\bar{P}$ is such a trip pricing table for which the daily profit (θ) of a carsharing company is optimal. More formally, the goal of the optimization algorithm is to find $\bar{P}$ for which the following equation is satisfied:

$$\text{Max}\ \theta(\overline{\text{P}})\ \geq \text{Max}\ \theta\ (P), \qquad \forall P\ (p_{min}, p_{max})\ \in \mathcal{P}(p_{\text{min}}, p_{\text{max}}). \tag{4.25}$$

For each trip pricing table $P(p_{min}, p_{max})$ generated by the solution algorithm, the TPPOCS mathematical model is executed as a classical mixed integer programming (MIP) problem where prices are given. In that manner, the TPPOCS model finds the best possible profit that can be achieved using a fixed trip pricing table suggested by the solution algorithm. The best possible profit value is then provided back to the algorithm, in essence rendering the model as an evaluator for the solutions suggested by the algorithm.

During the previous decades, various meta-heuristic techniques have accomplished great success solving this type of problems. They are general problem-independent algorithmic frameworks that can be applied to various optimization problems. While they give no guarantee on optimality, if implemented properly, they can provide solutions that are good enough for practical use. For many problems, they are yielding state-of-the-art results (Lourenço et al., 2003; Luke, 2013).

In this work, we applied the *iterated local search* (ILS) (Stützle and Hoos, 1999; Lourenço *et al.*, 2001; Lourenço *et al.*, 2003; Luke, 2013) to solve the mixed-integer non-linear TPPOCS. It is a simple, but effective meta-heuristic that successively applies *local search* (LSO) and *perturbation* operators (PO) in an attempt to focus on exploring proximities of known good solutions while avoiding being stuck in local optima. It was successfully implemented for classical combinatorial optimization problems, such as travelling salesman problem (Stützle and Hoos, 1999; Katayama and Narihisa, 1999) or the quadratic assignment problem (Stützle, 2006), as well as more specific types of problems, such as scheduling and graph partitioning (Lourenço *et. al.,* 2003; Carlier, 1982; Martin and Otto, 1995).

The following sections contain the implementation details of the ILS meta-heuristic for solving the TPPOCS. First, the general structure of the meta-heuristic is presented. Secondly, the algorithm to generate initial solutions is elaborated. Finally, the implementation details of the LSO and PO are given.

4.3.2 Algorithm Structure

The ILS algorithm is based on two operators (Lourenço *et al.*, 2001; Lourenço *et al.*, 2003; Luke, 2013):

1. *local search* operator (LSO); and
2. *perturbation* operator (PO).

The pseudo-code of the algorithm we use is given in Table 4.3.

The local search looks for the best solution in a restricted neighborhood of the initial solution. Given an initial solution $P_{initial}$, it enumerates all of the solutions from its neighborhood and returns the best as the result, called *local optimum* and denoted P^*. The quality of the local optima depends on the way the neighborhood structure is defined as well as the initial solution choice.

While local optima are as good as, or better than the initial solution, in general, there is no warranty on their quality in the context of all possible solutions. Local search results are often globally suboptimal (Lourenço et al., 2003; Luke, 2013), and to extend the search beyond the initial neighborhood, ILS uses the PO. The PO takes the current local optimum and modifies it into a perturbed solution, denoted P'. The intensity of the modification should be low enough to prevent the algorithm from losing focus and degrading to random restart local search, but at the same time high enough to ensure local search does not converge to the same solution during the next iteration (Lourenço et al., 2003).

Table 4.3 - Pseudo-code of the implemented *iterated local search* (ITS) meta-heuristic algorithm

*Procedure Iterated Local Search (**time**)*

Generate initial solution $P_{initial}$

P^* = *local search*($P_{initial}$)

*repeat until **time** expired*

    P' = *perturb*(P^*)

    P'^* = *localSearch*(P')

    if the profit for P'^* *is greater than the profit for* P^* *then*

        $P^* = P'^*$

Various options are available while deciding on the end condition for the algorithm and the LSO. In the numerical experiments, we decided to use the time limit as the end condition, which can be set as a parameter. Furthermore, different solution acceptance criteria can be chosen for the PO: starting each perturbation from the best so far, from the current local search result or some other solution found during the algorithm run history. Algorithm runtimes for our problem numerical experiments, as described in Section 4.5, are very long, therefore, we decided to focus the search as much as possible, always using the best known solution as the perturbation starting point. In the

ILS literature, such acceptance criterion is usually called the *best* acceptance criterion (Lourenço et al., 2003).

4.3.3 Initial solutions

Initial solutions $P_{initial}$ are randomly generated trip pricing tables with each element $P_{zw}^{i} \in P_{initial}$ in the given interval $[p_{min}; p_{max}]$. They are obtained using a random number generator that generates numbers with approximately uniform distribution in the specified interval. Preliminary tests have shown that the quality of initial solutions significantly varies depending on the choice of the price interval $[p_{min}; p_{max}]$. Further analysis of the influence of these parameters is given in Section 4.5.

4.3.4 Local search

The LSO used in our approach is explained in the pseudo-code in Table 4.4. It is a simple method that iteratively increases and then decreases trip pricing table elements as long as these changes improve profit. The procedure has two parameters: *step* and *time*. The *step* parameter defines the smallest change in price that can be performed during the search and the *time* parameter defines the longest allowed duration of the search. The interval in which the local search can modify the solutions is p_{min} and p_{max}. The price interval should be selected as a reasonable interval for the problem in hands.

The order in which table elements are being modified is randomized to promote discovery of features for which the order of price changes matters, thus the operator is non-deterministic. For each considered element of the table, the operator first tries to increase the price by adding $step$ to the initial price. If the modification caused a better profit, further increases will be performed until p_{max} is reached or price increases are no longer improving the profit (or the time expires). The analogous procedure is done for price decreases. After benefits of both increasing and decreasing the price have been examined, the algorithm updates the trip pricing table accordingly so that the new value gives the highest profit gain or retains the old value if price changes caused a profit drop. After all of the trip pricing table elements have been considered for modification, the operator will start again, but visiting the elements in a new randomly generated sequence.

The aforementioned procedure runs until on entire pass through the table has been done without making any improvements or until the allowed time has elapsed. By systematically exploring the effect of price variations and combining contributions of many small price changes, the LSO can yield significant solution improvements, as it will be shown in the numerical application.

Table 4.4 - Pseudo-code of the *local search* operator (LSO) algorithm

*Procedure local search (**step**, **time**)*
*Repeat until **time** expires*
Initialize random list of table elements C_{ls}
For each $P_{zw}^{i} \in C_{ls}$
$(P_{zw}^{i})_{down} = P_{zw}^{i}$,
$(P_{zw}^{i})_{up} = P_{zw}^{i}$
Repeat while profit is increased, $(P_{zw}^{i})_{down} > P_{min}$ *and **time** is not expired*
$(P_{zw}^{i})_{down} = (P_{zw}^{i})_{down} - \boldsymbol{step}$
*Repeat while profit is increased **and*** $(P_{zw}^{i})_{up} < P_{max}$ *and **time** is not expired*
$(P_{zw}^{i})_{up} = (P_{zw}^{i})_{up} + \boldsymbol{step}$
Update P_{zw}^{i} *to the element of* $\{P_{zw}^{i}, (P_{zw}^{i})_{up}, (P_{zw}^{i})_{down}\}$ *for which the profit is maximal*

4.3.5 Perturbation

The PO, presented in Table 4.5, introduces random price changes in a small subset of the price table elements. The operator has two parameters: maximum number of elements to change (n) and the maximum allowed change (d). First, n elements from a price table $P\ (p_{min}, p_{max})$ are randomly selected into the perturbation modification candidate set $C_p \subseteq P\ (p_{min}, p_{max})$. Then, for each element $P_{z,w}^{i} \in C_p$, the new price is calculated by adding a random value $\Delta p \in [-d, d]$ to the previous value. The interval, in which the perturbation can change the prices, varies between p_{min}, and p_{max}. If the price after adding Δp is lower than p_{min}, it is updated to p_{min}, and likewise, if it is greater than p_{max}, it is updated to p_{max}.

The set C_p is called the modification candidate set, since there is no guarantee that all of its members will be changed. Due to the definition of the interval from which Δp values are selected, it is possible that for some elements Δp will be equal to zero, keeping table elements unchanged. This behavior is intentional to ensure greater variability of the perturbation effects on a candidate solution.

It should be noted that *local search* (LSO) and *perturbation* (PO) operators are structurally related in such a way that it is unlikely for the local search to cancel the effects of perturbation. If *step* is greater than 0.01 €/min, the local search can return back to the previous local optimum only if all of the changes caused by the perturbation are multiples of search *step* value. Probability for such event to occur drops very quickly as d grows in comparison to *step* and $n > 1$. Nevertheless, finding a balanced perturbation intensity is still very important to ensure that it is not too strong, as shown in the numerical application.

Table 4.5 - Pseudo-code of the *perturbation* operator (PO) algorithm

*Procedure **perturb** ($\boldsymbol{n}$, $\boldsymbol{d}$)*
Initialize set P_c containing $\boldsymbol{n}$ random table elements
For each table element $P^i_{z,w} \in C_p$
Set Δp to a random value in interval $[-\boldsymbol{d}, \boldsymbol{d}]$
Modify table element: $P^i_{z,w} = P^i_{z,w} + \Delta p$

4.4 The case study of Lisbon (Portugal)

The case study used in this work is the municipality of Lisbon, in Portugal. This municipality has been dealing with several mobility problems, such as traffic congestion and parking shortage associated to the increase in car ownership and the consequent high use of private transportation. Public transportation has been upgraded; however, it has not been able to reduce the use of private transportation for commuter trips. There is the need to manage mobility in a smart way by, for instance, transportation alternatives such as carsharing.

The data needed to study the trip pricing methodology is: a set of stations, a carsharing trip matrix, a reference price, the price elasticity of carsharing demand, driving travel times between the set of stations, and costs of operating the system. The possible station locations were defined by considering a grid of squared cells (with sides of length 1000m) over Lisbon, and associating one location with the center of each cell, which resulted in a set of $K = 75$ possible station locations. This is obviously a simplification, but it serves the purpose of the application. The trip matrix was based on a geo-coded survey updated in 2004 in the Lisbon Metropolitan Area. Several data are available in the survey, namely trip origins and destinations, time of departure, and transportation mode used for each trip. Thus, it had to be filtered through some criteria, such as: age of the travelers, trip time, trip distance, time of the day, and transportation mode used, in order to consider only the trips that are potentially served by carsharing, resulting in 1777 trips.

As far as we know, there are no studies in the literature specifically addressing the calculation of carsharing price elasticity of demand. Therefore, we decided to use a value of $E = -1.5$, which is the price elasticity of vanpooling demand found by (York and Fabricatore, 2001), because it is the most similar transportation mode to carsharing for which there is available information. Travel times were computed using the transportation modeling software VISUM (PTV), considering the Lisbon network and the car trip matrix for the entire region, being expressed in minutes. We consider that the carsharing system is available 18 hours per day, between 6:00 a.m. and 12:00 a.m.

To compute the costs related to the vehicles, we take as reference an 'average' car mainly driven in the city that costs 20,000€ initially, thus yielding the following parameter values:

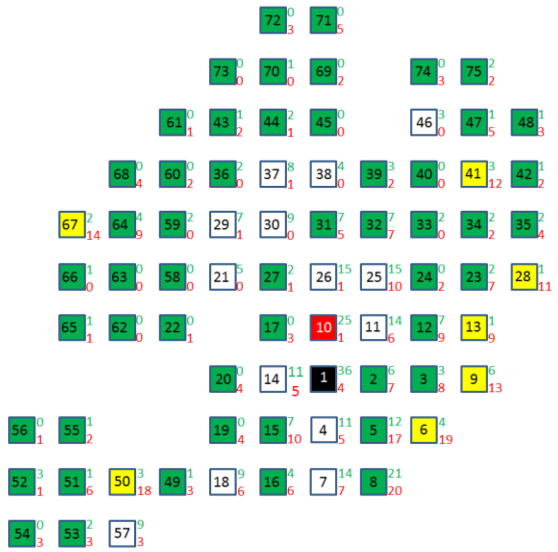
- C_{mv} (cost of maintaining a vehicle): 0.007 euros per minute. This cost was calculated using INTERFILE (INTERFILE, 2012), a tool available on the internet that was developed by a German company, and includes insurance, fees, taxes, fuel, maintenance and wear of the vehicle;
- C_v (cost of depreciation per vehicle): 17 euros per day, calculated using the same tool referred above (INTERFILE, 2012) and expecting 3 years of use in the system. It was also considered that the company needed fully financing for the purchase of the vehicles with an interest rate of 12% and vehicles' residual value equal to 5000€;
- C_{mp} (cost of maintaining a parking space): 2 euros per day, this cost is smaller than the parking fee in a low price area in Lisbon, considering that the city authorities would be able to give support to these types of initiatives.

The base carsharing price per minute, $P0$, was considered to be 0.3 euros per minute, which is based on the rates of *car2go* (car2go, 2014). Note that there is no linkage between this price and the demand that is going to be used for the computational experiments since carsharing is not being offered in this city at the moment.

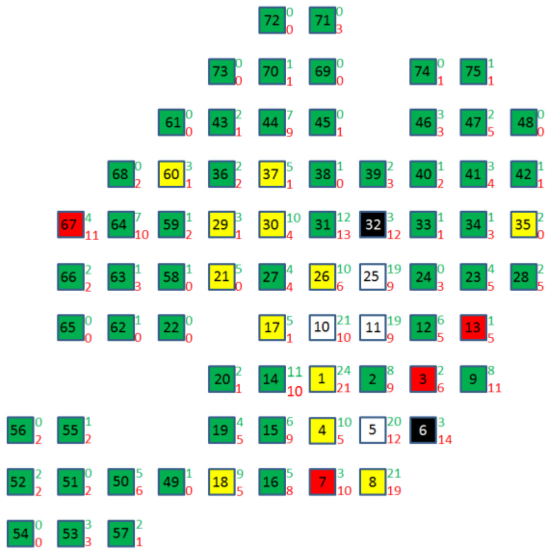
With these data the VRPOCS was implemented with a time step of one minute and solved using Xpress 7.7, an optimization tool that uses branch-and-cut algorithms for solving MIP problems (FICO, 2014). The model was first run with no relocations operations resulting in a daily deficit of 1160.7 €, which proves the need for balancing strategies. Secondly the VRPOCS was run with null costs of vehicle relocation. This solution produced the relocations balance vector $\epsilon_{k_t}^0$. Time was then divided into 6 intervals for computing the time interval relocation balance ($\omega_{k_i}^0$): 6:00a.m. to 8:59a.m., 9:00a.m. to 11:59a.m., 12.00p.m. to 2:59p.m., 3:00p.m to 5:59p.m., 6:00p.m. to 8:59p.m, and finally from 9:00p.m. to 00:00a.m.

Stations were grouped into 5 zones using the clustering algorithm described previously ($u = 5$) applied with vector $\omega_{k_i}^0$. Five seems to be a reasonable number to capture the different trip patterns between the stations and maintain computation tractability. Results of the clustering algorithm application are presented in Figure 4.1, where, for analysis purposes, we numbered each cluster in each interval according to its typical behavior along the day. It is possible to see that the belonging of each station to each of the 5 zones varies with the 6 time interval relocation patterns, that is, a station may belong to a zone in the first time interval and to another zone in the following one. We also present in Figure 4.1 the number of trips entering (upper right side of the station) and exiting (lower right side of the station) each station according to the demand vector $D0_{k_t j_{t+\delta_{kj}^t}}$ (no relocated vehicles are considered in these numbers).

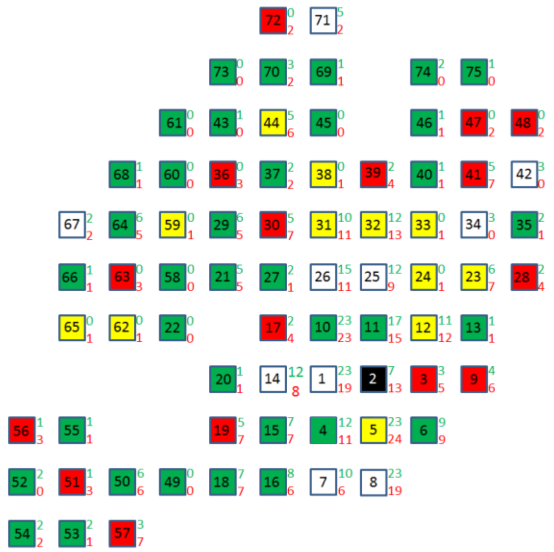
Stations included in zones 1 and 4 are mostly located in the central business district (CBD); however, zone 4 also includes several stations located in the periphery at lunch time. Therefore, these have a higher number of trip destinations in the morning against more trip origins in the afternoon but zone 4 seems to be including lunch time commuters too. These zones contain in general only a few stations along the day. Zone 2 includes stations located in the CBD and in the periphery, their number varying greatly along the day. Despite that variation the trip pattern remains the same with more trip arrivals than trip departures throughout the day. It makes sense, for this reason, that zone 2 is providing more vehicles than the ones that it requests. Zone 3 contains the highest number of stations for most of the time intervals, with special emphasis to the beginning and the end of the day. The stations included in this zone are mainly located in the periphery, but there are also some of them located in the CBD. This mixed behavior makes the difference between relocated vehicle arrivals and relocated vehicle departures to be not significant. Finally, zone 5 is mostly a mixed zone.



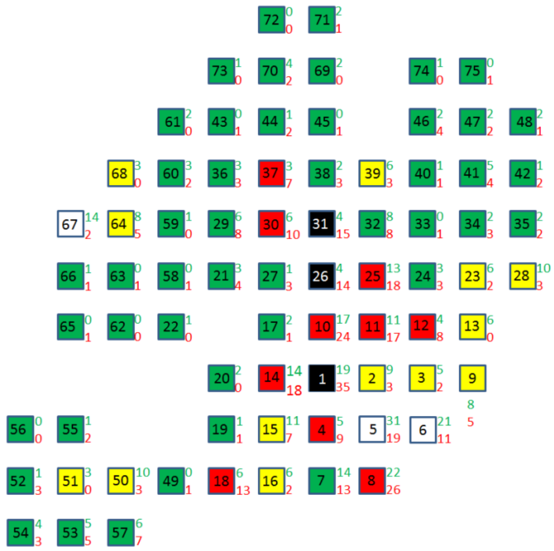
TI 1 (6:00a.m.-8:59a.m.)



TI 2 (9:00a.m.-11:59a.m.)



TI 3 (12.00p.m.-2:59p.m.)



TI 4 (3:00p.m.-5:59p.m.)

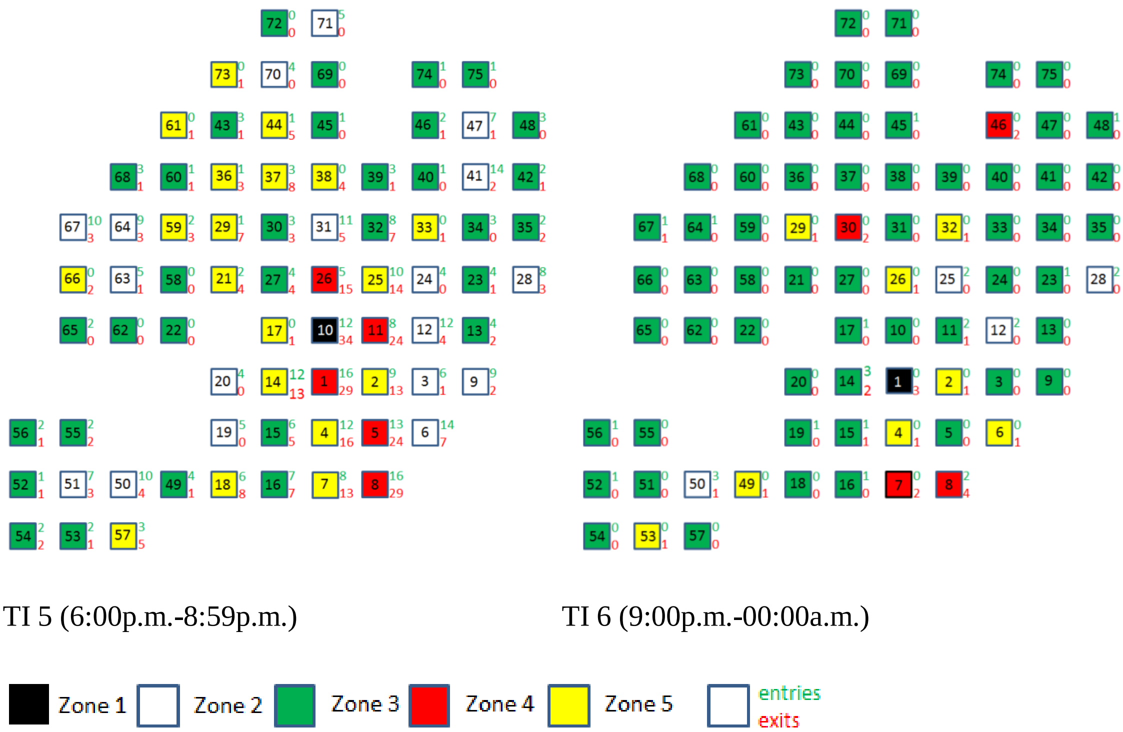


Figure 4.1 - Stations grouped in zones and number of trip entries and exits at each station in each time interval

4.5 Computational experiments

The TPPOCS mathematical model was also implemented using Xpress 7.7 with the same data that was used in the VRPOCS model. The ILS meta-heuristic was implemented in Java 1.8 programming language and Xpress Java Application Programming Interface to gain access to the model. All experiments were performed on two identical computers equipped with a 2.4 GHz Intel Core i7-4700HQ processor and 16 GB of RAM and using Java 1.8.0_11-b12 runtime environment under Windows 8.1 operating system.

A single run of the TPPOCS model takes around 30 seconds and approximately one minute when 8 instances of the model are running simultaneously. Most of the algorithm runtime is therefore spent evaluating the candidate solutions – our benchmarks have shown that, in the best case, only around 430 evaluations could be performed during one hour, using all of the eight logical processor cores in parallel. This fact strongly influenced the tuning process of the algorithm as well as the algorithm design itself. As hinted in Section 4.3, to obtain good solutions as quickly as possible, strong intensification is performed through detailed local search and the use of the *best* perturbation acceptance policy (Lourenço et al., 2003). The strong intensification is introduced to facilitate the discovery of profit increasing features as soon as possible. In the remainder of this section, an overview of the tuning process is given and the best results the algorithm has found are presented in the next Section.

4.5.1 Parameter tuning

Meta-heuristic methods usually come with a set of parameters that need to be set up to some values. They can significantly influence the heuristic performance and, while quick setup based on implementer's intuition might work, experimental evaluation of the influence of the parameters is usually performed to ensure the parameters are adapted to the problem instances to be solved and improve the algorithm results (Birattari, 2005).

The parameter tuning applied to this problem was done in three stages:

1. Initial solution generator tuning,

2. Local search tuning,
3. Perturbation tuning.

Initial solution generator tuning consisted of determining price bounds p_{min} and p_{max} for the initial solutions. Initial solution tuning rationale is based on the assumption that good initial solutions will enable the local search to find better results more quickly. In total, 105 different intervals were explored: each interval with p_{min} and p_{max} being a multiple of 0.05 €/min in the range [0.00 ; 0.70] €/min, with 50 solutions generated in each of these intervals. The results proved that the average daily profit for the initial solutions varied greatly depending on the price interval.

The worst discovered profit was measured for the interval [0 ; 0.05] €/min, (average deficit of 16,714.2 €/day) and the best profit, zero, was achieved for any interval with p_{min} and p_{max} above 0.5 €/min. While at first this might seem like a good result, it should be pointed out that the simulated carsharing demand adapts to price. In cases when unreasonably high prices are applied, the demand drops to zero by force of the elasticity. Zero demand causes the model to shut down the service, interpreted as a zero profit result.

To take this into account, both profit and demand were considered for the initial trip pricing tables. The scatter plot of a subset of explored initial intervals can be seen on Figure 4.2, with average profit on x-axis and average demand on y-axis. The Pareto non-dominated set of (*profit*, *demand*) pairs displayed by grey dots on the chart was selected as a set of candidate intervals (Powell, 1964; Powell, 1977). The highlighted interval [0.35 ; 0.40] €/min has the lowest average deficit (deficit of 32.48 €/day) while also retaining high average demand (1579 trips that corresponds to 89 % of the demand with the reference price). Configurations with higher profit do exist, but for them, the demand drops to near zero, as can be seen in the example of the interval [0.45; 0.65] €/min, indistinguishable from the zero demand interval [0.5 ; 0.7] €/min. Having near-zero demand in the system is clearly not the desired result. Therefore, the values of $p_{min} = 0.35\ €/min$ and $p_{max} = 0.40\ €/min$ are selected for initial randomly generated solutions.

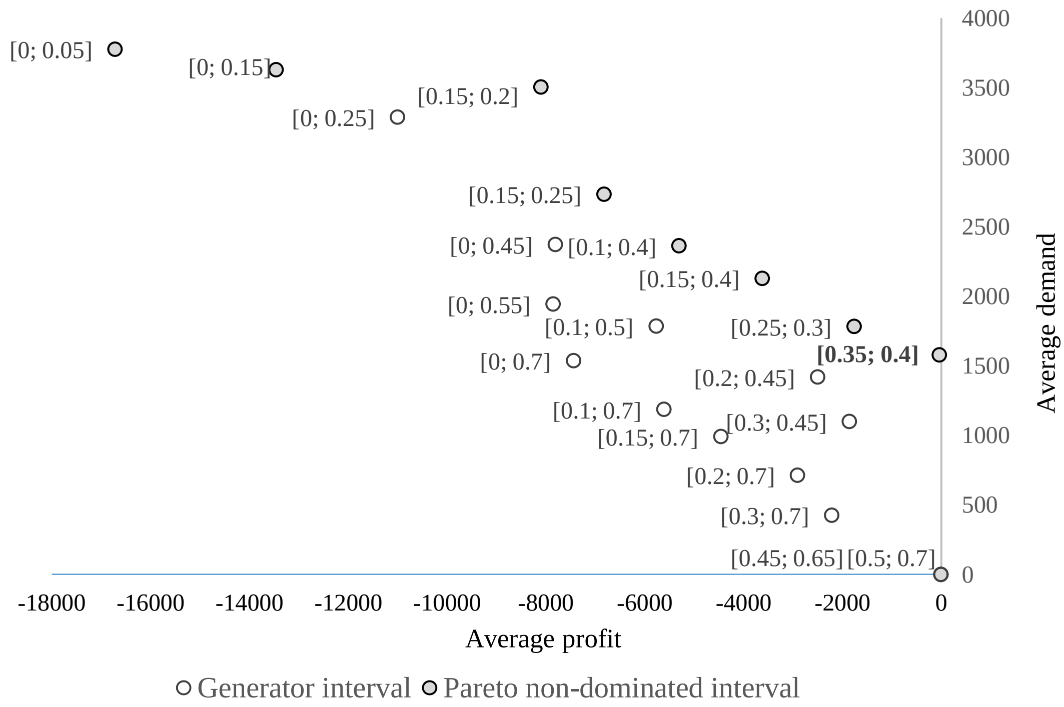


Figure 4.2 - Initial solution generator configurations

The local search tuning consisted of determining the best search $step$ parameter. Five initial solutions with price intervals set up according to the values given above were randomly selected and for each of them, local search with $step$ equal to 0.01€, 0.02€, 0.05€ and 0.10€ was applied. The experiment was repeated five times, resulting in 100 test runs with each local search being limited to run for 4 hours. It is assumed that a better functioning local search will provide good results faster in the environment of the ILS. The results of the experiments are displayed in Table 4.6, showing average, median, minimum, maximum and sample standard deviation of the profits obtained with local search results. As can be seen in this table, the best results were in general achieved using a $step$ of 0.02 €.

Table 4.6 - Local search parameter exploration

$Step$ (€)	Profit (€/day)				
	Average	Median	Min	Max	Sample standard deviation
0.01	1164.8	1224.5	732.7	1561.0	206.7
0.02	1307.7	1338.0	763.2	1727.1	245.4
0.05	1262.0	1302.7	940.4	1455.8	140.1
0.10	1164.2	1118.1	830.8	1589.4	193.7

Perturbation tuning consisted of trying to identify which pair of changed set size and intensity (n, d) works best with the LSO configured as in previous stage. A total of 8 different configurations were run 5 times to determine which perturbation parameters best fit the balance of diversification and intensification as described in Section 4.3. The results of the experiments are shown in Table 4.7 with average, median, minimum, maximum and sample standard deviation of the profits obtained with different perturbation settings. As preliminary tests have shown, the model is very sensitive to price changes. Best average profits are achieved with low perturbation intensities $(n = 2,\ d = 0.02)$ and $(n = 5,\ d = 0.02)$, which have almost equal average profit. If perturbation is more pronounced, average profits get lower. This can be explained by the fact that the local search is unable to find good solutions before another intensive round of perturbation reduces the profit of the current local optimum.

Table 4.7 - Perturbation parameter exploration

n	d (€)	Profit (€/day)				
		Average	Median	Min	Max	Sample standard deviation
2	0.02	1782.7	1827.1	1624.7	1846.7	91.4
2	0.05	1660.5	1730.1	1190.1	1905.5	273.5
5	0.02	1767.3	1796.8	1554.6	1954.5	172.6
5	0.05	1628.8	1720.1	1349.8	1790.8	185.3
10	0.02	1674.2	1783.4	1187.9	2068.1	357.7
10	0.05	1560.5	1561.6	1427.3	1721.4	110.1
20	0.02	1696.5	1761.2	1456.3	1885.8	172.2
20	0.05	1618.3	1646.4	1469.6	1743.3	124.7

It is interesting to note that higher perturbation settings can yield very good results. In fact, the best result found during our experiments was found with a rather high perturbation setting $(n = 10,\ d = 0.02)$. As standard deviation values indicate, while good average profits are obtained using low perturbation settings, they also lead to results of approximately equal quality. Conversely, higher perturbation means more variability of the output solutions quality.

Choosing appropriate perturbation settings can be done based on the planned algorithm run duration. For short runs, it is important to keep both n and d low to ensure search intensification. For longer runs, however, setting the perturbation to higher levels might be beneficial. With long algorithm runs (in our preliminary experiments, 12 hours or longer) the search progress tends to become stuck in a very good solution local search can no longer further improve. Higher perturbation rates might help the algorithm to change the high profit solutions sufficiently to diversify the search around very high profit solutions and in that manner, preventing stagnation.

To conclude the algorithm parameter analysis, in Table 4.8, we provide recommended heuristic parameters for solving the TPPOCS using Lisbon as case study. The time limits in the table are valid for equipment with similar performance to our experimental setup (around 1440 model evaluations available in 12 hours). While these parameters could work well for similar trip patterns, travel times and price elasticity, they are problem instance specific and may differ for other cities, clustering methods and zone dimensions.

Table 4.8 - Recommended meta-heuristic parameters

	Initial solution		$step$ (€)	d	n
	P_{min} (€)	P_{max} (€)			
Short runs (< 12h)	0.35	0.40	0.02	0.02	2
Long runs (>12h)	0.35	0.40	0.02	0.02	10

4.6 Results

The best trip pricing table found in our experiments, denoted P_{best}, is presented in Table 4.9. Using this pricing table, the system is able to achieve a profit of 2068.1 €/day. Compared to the deficit of 1160.7 €/day that results from not having any balancing strategy implemented and having to satisfy all reference demand (1777 trips) it is clear that variable pricing can lead to significant profit increases. For the best trip pricing table found, demand satisfied is equal to 1471 trips per day, which represents a loss of 306 trips in relation to the reference demand (17.7 % demand reduction). We should, however, note that this demand is not rejected per se, it is the case that some travelers will find the price too high to use the carsharing service. The average price charged is 0.39€/min, with all the prices in the interval [0.35 ; 0.46] €/min, that is, all prices charged are higher than the reference carsharing price ($P0$), which is 0.30€/min.

Table 4.9 - Best found trip prices for each origin-destination pair of zones and time interval

TI 1 (6:00a.m.-8:59a.m.)					
Zones	1	2	3	4	5
1	0.36	0.44	0.38	0.40	0.38
2	0.38	0.39	0.39	0.38	0.39
3	0.46	0.37	0.38	0.44	0.38
4	0.35	0.41	0.36	0.38	0.39
5	0.39	0.45	0.35	0.41	0.39

TI 2 (9:00a.m.-11:59a.m.)					
Zones	1	2	3	4	5
1	0.35	0.43	0.38	0.41	0.40
2	0.39	0.39	0.39	0.39	0.39
3	0.38	0.38	0.39	0.38	0.39
4	0.39	0.40	0.39	0.41	0.40
5	0.38	0.39	0.38	0.36	0.38

TI 3 (12.00p.m.-2:59p.m.)					
Zones	1	2	3	4	5
1	0.40	0.39	0.39	0.40	0.41
2	0.38	0.39	0.38	0.39	0.39
3	0.39	0.39	0.39	0.39	0.39
4	0.38	0.40	0.38	0.39	0.39
5	0.39	0.39	0.39	0.39	0.39

TI 4 (3:00p.m.-5:59p.m.)					
Zones	1	2	3	4	5
1	0.39	0.43	0.39	0.39	0.38
2	0.38	0.38	0.38	0.38	0.39
3	0.39	0.39	0.38	0.38	0.39
4	0.39	0.39	0.39	0.37	0.46
5	0.39	0.39	0.38	0.38	0.35

TI 5 (6:00p.m.-8:59p.m.)					
Zones	1	2	3	4	5
1	0.39	0.38	0.39	0.38	0.45
2	0.39	0.38	0.38	0.38	0.39
3	0.36	0.39	0.40	0.38	0.38
4	0.38	0.40	0.39	0.39	0.38
5	0.39	0.38	0.41	0.38	0.39

TI 6 (9:00p.m.-00:00a.m.)					
Zones	1	2	3	4	5
1	0.39	0.36	0.38	0.38	0.36
2	0.40	0.39	0.40	0.35	0.40
3	0.38	0.36	0.39	0.38	0.39
4	0.35	0.35	0.38	0.36	0.36
5	0.39	0.38	0.40	0.38	0.38

In grey we indicate the OD pairs of zones in which there is a decrease in the demand due to the increase of price

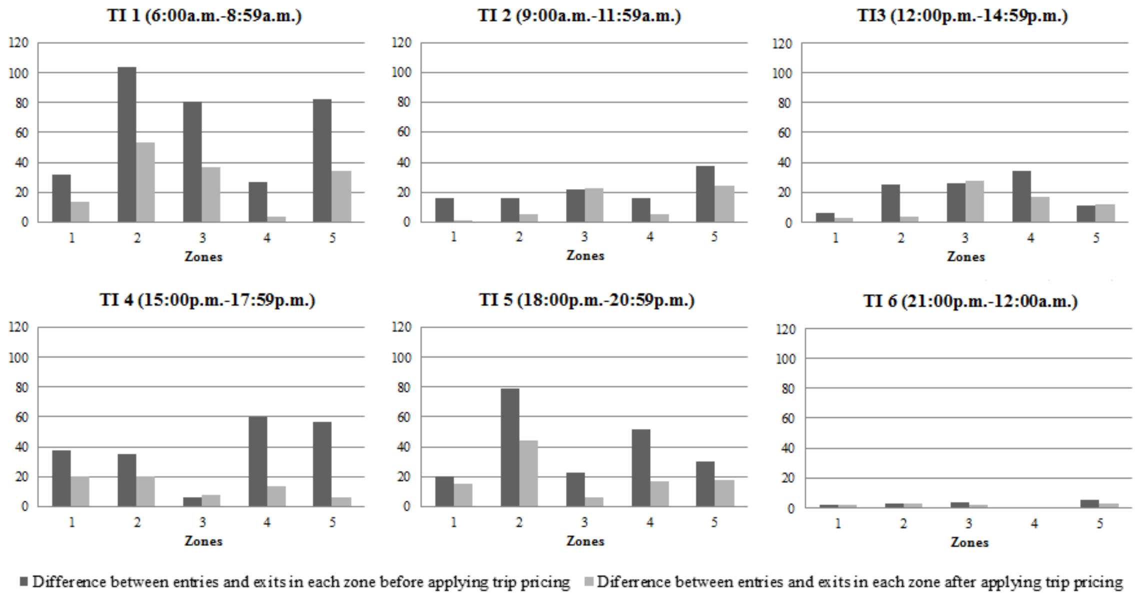


Figure 4.3 - Difference between trip entries and exits for each zone and time interval (TI), before and after applying trip pricing

Figure 4.3 presents: the difference between the vehicles entering and exiting in each station before applying trip pricing and having no relocations; and the difference between entries and exists with the trip pricing. Before applying trip pricing, time intervals 1 and 5 have great entry-exit imbalance, since they correspond mostly to the morning and afternoon rush hours. Analyzing Figure 4.3, it can be seen that in these periods of the day, the effect of trip pricing is more notorious for all zones balance, whilst in time intervals 2, 3 and 4, this effect is not so obvious. Furthermore, in these three intervals, zone 3 seems unchanged. This may happen because this zone encompasses more stations and therefore, more variability in trip patterns.

Most of the OD pairs of zones that present a significant demand decrease correspond to a price charged equal or higher than 0.40 €/min. Noting that we decided to round the demand vector $D_{k_t j_{t+\delta_{kj}^t}}$ to 0 instead of 1 when the result of applying the elasticity leads to a value of 0.5. We should also refer that the elasticity is being applied to the unit price per trip and not to the total price of a trip, thus, we are not considering that longer trips may present different results from shorter ones.

With the results of the model and the algorithm, it is possible to do a more detailed analysis on what happens in each time interval for each zone and trip direction (entering or exiting the zone). For the case of the early morning (6:00a.m. to 8:59a.m.), there are mainly demand reductions through price increases for: the trips that depart from zones 3 and 5, which are located in the periphery and thereby present many more trip origins than destinations in this period; and the trips that arrive at zone 2, which is located in the center and therefore, it has many more trips arriving to it (about 70% of the trips) than those beginning there. This occurs because people tend to travel from residential areas to the CBD in the morning. Moreover, this is the interval that presents the higher prices for all OD pairs of zones, which confirms that it is the most imbalanced one.

The following periods, 2 and 3 (9:00a.m. to 11:59a.m. and 12:00p.m. to 14:59p.m., respectively), are mostly intermediate periods of the day in which most of the prices charged are below or equal to the average price charged for the entire day (0.39 €/min). However, despite there not being a great difference between number of departures and arrivals, when this happens, the prices charged act to reduce the demand in the most imbalanced directions.

Time interval 4 (15:00p.m. to 17:59p.m.) is also an intermediate more balanced time interval. It is noticeable its proximity to the afternoon peak hour, having already some return home trips. The prices charged in this time interval also reflect this fact, being higher than the average for some OD pairs of zones. The model acts in decreasing the demand that departs from zones 1 and 4 located in the center, since these outbound trips are more than 50% of the total trips for these two zones, and decreases the demand that arrives at zone 5 located at the periphery. Zone 5 presents more trip destinations than origins (about 68%/32%). For the OD pair 4-5, the price charged is equal to 0.46 €/min, which is the highest price charged in the pricing table.

The afternoon peak period (18:00p.m. to 20:59p.m.) shows a greater imbalance of vehicles across all the stations. Therefore, the demand reductions, due to the price increase, are more pronounced in this period. As an example, they exist for both directions in zone 4. In this period, zone 4, located in the city center, shows a higher number of trip origins than trip destinations due to work-home trips. Thus, a decrease in the demand with this zone as destination was not expected. However, trip arrivals are also decreased as expected and the effect of reductions in both ways results in a more balanced zone at a scale that is manageable by the whole network. This time interval sets a price of 0.45 €/min for OD pair 1-5 (the second highest price), which was expected, since it is a very imbalanced movement at this time of the day with trips from the center to the periphery.

Finally, the end of the day, which corresponds to time interval 6 (21:00p.m. to 12:00p.m.) has few trips (only 11). For this reason, there is no need to reduce the demand significantly, and at the same time, price reductions for demand increase are apparently not beneficial either.

The improvement in the profitability of the company is not only due to the decrease of the demand for some OD pairs of zones and time intervals, but it is also due to the price increase itself in many OD pairs where the increase is not enough to produce an expected demand reduction, but sufficient to have an impact on increasing the profits. This occurs even though we have considered in the case study that demand is elastic to price variations, elasticity is greater than 1 in module, which should point for a reduction in profit from price increase in a linear model. The special complex nature of interdependence of supply and demand in carsharing systems is leading to a benefit of running the system for a lower number of trips, yet one that is more balanced.

The zoning that was determined by computing a theoretical desired relocation vector is able to divide the stations in sets for which the price variations yield a higher profit. Despite the fact that by using the meta-heuristic we are not guaranteed to find the optimal solution, we are however, able to demonstrate through its application to the case study that an increase in prices can actually lead to a higher profit, one that not only avoids losses (system closure will generate 0 profit) but that is able to generate positive and significant profits. We may conclude through the global results presented in Table 4.10 that vehicles' balance and profit are directly related, because having a more balanced system, despite resulting in less revenues, allows having fewer vehicles in the fleet and less parking spaces at the stations which means less operating costs.

Table 4.10 - Global results with and without trip pricing

	Profit related to the trips (€/day)	Costs of vehicle maintenance (€/day)	Costs of vehicle depreciation (€/day)	Fleet of vehicles	Costs of parking spaces maintenance (€/day)	Number of parking spaces
No balancing strategy	7113.3	166.0	6630	390	1478	739
Trip pricing	7576.4	138.3	4352	256	1018	509

4.7 Conclusions

There are two main types of carsharing operating models: the round-trip carsharing, in which the users have to pick up and return the car to the same station, and the one-way carsharing that allows users to pick up a vehicle in a station and drop it off at another. The latter has been associated with more trip purposes when compared to round-trip carsharing – for example, one way carsharing could also be used for commuting (Balac and Ciari, 2014). However, it also brings up a problem of the vehicle stock imbalance and a need to find efficient ways to balance vehicle stocks across stations. Several ways for increasing this balance have been proposed in the literature, and some empirical studies have suggested the use of variable trip pricing (Mitchell et al., 2010). This method consists of varying the price charged to the clients based on the stock of vehicles located at the origin and destination stations. Though never proven, the conjecture is that by changing demand through pricing, carsharing systems could provide higher levels of profit.

In this chapter, we have proposed a model that considers demand as a function of price and searches for the prices that maximize the profit of the daily operation of a carsharing company. Because this model is non-linear and the objective function is non-concave, we use ILS as a meta-heuristic to solve the problem (Stutzle and Hoos, 1999; Lourenço *et al.*, 2001; Lourenço *et al.*, 2003; Luke, 2013). For setting the prices, stations were grouped into zones and time was divided into time intervals. In this manner, trip prices varied between each OD pair of zones according to the time interval in which the trip begins. This methodological approach was numerically tested for the case study of the municipality of Lisbon, in Portugal.

The case study application shows that the use of price variation as a strategy to balance vehicle stocks across one-way carsharing stations works in a satisfactory way. When no vehicle balancing mechanism is applied, the carsharing company has a deficit of 1160.7 €/day. Using the trip pricing approach, the profit for the best price combination found through the use of the ILS is 2068.1 €/day, which corresponds to an increase of 3228.8 €/day in a system that has 75 stations and serves 1471 trips. It is important to note that the prices charged to the clients for every OD pair of zones increased in comparison to the reference price, which leads to a demand reduction. However, the increase in price happens through a generalized reduction in the imbalanced demand served by carsharing.

Through the analysis of the results we concluded that, in most cases, the OD pairs of zones that have the higher increases in price, therefore a decrease in demand, are the ones with a greater difference between trip origins and trip destinations. This shows that the solution algorithm (meta-heuristic), despite not being an exact method, is able to capture the essential behavior of the system related to the trip imbalance across zones and time intervals, improving its performance.

The main conclusion that is drawn from this study is that trip pricing can be considered as an option to balance vehicle stocks in one-way carsharing systems. Concerning the generalizability of the method, it should be possible to apply it to different regions, however it must be stated that the solution algorithm computation time is dependent on the problem dimension.

The developed meta-heuristic is an approximate method, providing solutions that are not guaranteed to be optimal. However, this is not necessarily the goal of this work. Our objective was to provide a method that could compute good solutions for the problem and, at the same time, assess if the trip pricing approach is able to mitigate vehicle imbalances in one-way carsharing systems.

Regarding further developments, we suggest to enhance the solution method proposed in this chapter. Studying different principles to determine the zones could also be relevant for profit maximization. Moreover, the computation of the demand variation with price, which was performed in a very simple way in this study, should also be improved, because it is a key aspect to the realism of the results.

Chapter 5

Assessing the Viability of Enabling a Round-trip Carsharing System to Accept One-way Trips: Application to Logan Airport in Boston

5.1 Introduction

Two main urban transportation modes have been used in the past few decades: private vehicle and public transportation. When the use of private vehicles started to become common, greater accessibility and flexibility in industrialized countries was achieved; however, several externalities resulted, including loss of time, pollution, congestion, and unrecoverable costs associated with the vehicle itself (Mitchell et al., 2010). Traditional public transportation modes like bus and rail may help solve these issues. However, public transportation has drawbacks, such as poor service coverage, schedule inflexibility and lack of personalization due to high investment costs.

Therefore, there is the need to find alternatives that are both sustainable and also guarantee that people have transport that enables them to carry out their activities. One of those alternatives is carsharing services. Carsharing systems involve a small to medium fleet of vehicles available at several stations to be used by a relatively large group of members (Shaheen et al., 1999). It appeared in 1948, in Europe, with a cooperative known as *Sefage*, which initiated services in Zurich, Switzerland. Later, in the 1980s, it came to the US within the *Mobility Enterprise* program (Shaheen et al., 1999). Currently, one of the world's largest carsharing companies is *Zipcar*, which was founded in January 2000. It has more than 850,000 members and about 10,000 vehicles spread across the USA, Canada, UK, Spain, and Austria (Zipcar(a), 2014). In March 2014, *Zipcar* started to offer one-way trips in Boston, USA (ZipcarOneWay, 2014).

Some studies (Litman, 2000; Schuster et al., 2005) have shown that carsharing has a positive impact on urban mobility, through a more efficient use of automobiles, mainly by reducing the time that each car is waiting to be used. The use of carsharing systems has also quite often allowed car ownership rates to decline (Schure et al., 2012; Klincevicius et al., 2014) and thus lowered car usage (Celsor and Millard-Ball, 2007; Martin and Shaheen, 2011; Sioui et al., 2013). Furthermore, some recent studies concluded that carsharing systems should have positive environmental effects by allowing the reduction of greenhouse gas emissions (Martin and Shaheen, 2011, Firnkorn and Müller, 2011).

Considering the operating model, carsharing systems can be classified into: round-trip systems, in which users have to return a car to the station where it was picked up; one-way systems, in which users may pick up a car from one station and return it to another (Shaheen et al., 2006). Recently, a particular case of one-way carsharing appeared in which the vehicles are scattered around parking spots within a city, the so-called free-floating carsharing (Ciari et al., 2014; Schmoller et al., 2014). From the user perspective, round-trip services may not be attractive if a trip requires spending a long time parked at a location other than the vehicle's home location. Hence, this type of carsharing is mostly used for short trips when vehicles are parked for a short duration (Balac and Ciari, 2014; Barth and Shaheen, 2002; Costain et al., 2012), typically for leisure, shopping and sporadic trips; whereas one-way carsharing can be used for all other trip purposes, even commuting (Balac and Ciari, 2014; Ciari et al., 2014). Therefore, one-way carsharing systems are suitable for more trip purposes than round-trip services. Schmoller et al. (2014) concluded this through a study on two German cities, Munich and Berlin. In the one-way systems that are implemented in these cities, the highest number of bookings occurs on Fridays and Saturdays, which indicates that the system is used for shopping and social-recreational activities. However, during the week, peaks of demand correspond to the typical rush hours, that is, commuter traffic. This was also concluded by (Balac and Ciari, 2014), who found that peaks of demand for one-way carsharing occur in the morning rush hour, around noon, and in the afternoon rush hour, while for round-trip carsharing peaks of demand happen outside rush hours. Balac and Ciari (Balac and Ciari, 2014) did, however, conclude that the introduction of one-way carsharing does not cause a significant decline in round-trip carsharing demand, showing that the services are complementary.

Despite being an advantage for users, one-way carsharing operators often face the complexity of managing fleet imbalances since incoming and outgoing trips are rarely balanced at each station at any given time and clients may not find vehicles or parking spots available when they need them. Moreover, one-way carsharing may compete with public transportation, walking and cycling as well as with the car, as concluded by Ciari et al. (2014); this might be less beneficial than round-trip carsharing in terms of transportation sustainability. Balac and Ciari (2014) showed that car and walking are the modes more likely to be replaced by one-way carsharing. With respect to the car, this replacement is good and more sustainable. But the replacement of walking is harmful because it might lead to more car usage.

We can therefore conclude that a combination of round-trip and one-way carsharing could be better for the operator and the clients, considering that the decision to offer one-way trips is limited to special services, at least for a transition period. A carsharing system that operates as a one-way system can easily be used for round-trips; however, the opposite is rarely possible because the daily management of the system would have to be changed. The hypothesis discussed in this chapter is that one-way carsharing services can sometimes be beneficial for both the users, who do not need to pay for the time the vehicle is parked, and the operator, which will be able to expand its market. When carsharing is operated only as a round-trip service, clients will choose other transportation modes for long-stay durations at the destination. One such mode is the taxi, which has door-to-door capability and only charges for the effective distance of the trip. Therefore, allowing a one-way service for some trips could be particularly interesting in cities where carsharing prices are significantly lower than the cost of a taxi or a private vehicle (if parking charges are included). Alfian et al. (2014) studied this possibility using a simulation tool to test several types of carsharing services, specifically those that offer both round-trip and one-way. They concluded that those services need to be cheaper than the taxi price for intermediate length trips. The goal of our work is to develop a methodology for testing if a round-trip carsharing system can provide a one-way service for very specific OD pairs, for which the round-trip service is usually not appropriate because it involves vehicles being parked for a long time.

A mathematical programming model is proposed that maximizes the expected daily profit from accepting or rejecting one-way trips between a specific high demand generator site in a city and the existing round-trip stations.

The model is applied to the case study of trips between the round-trip carsharing stations in Boston's *Zipcar* network and Logan International Airport. It is relevant to note that Boston is a city where carsharing costs significantly less than other transportation modes, such as private cars and taxis, especially for longer trips.

Therefore, the main contributions of this chapter are:

- assessing the possibility of combining both round-trip and one-way carsharing services in a network that was created originally for a round-trip service;
- developing an integer programming model that provides such assessment by selecting trips for a specific high demand generator site to help maximize the daily profit of the company;
- applying the model to a case study, the United States city of Boston, in MA, using realistic data obtained from a survey performed in 2010 (Logan Airport Air Passenger Ground-Access Survey, 2010);
- performing a sensitivity analysis of the model's performance by varying several parameters and by introducing relocation operations between the existing network and the high demand generator site, which have been used in one-way services around the world; and
- providing insights on how this transition between one-way and round-trip should be put into practice.

The chapter is structured as follows. Section 5.2 presents the mathematical model. The model is then applied to the Boston case study. The main results of the model are presented in Section 5.4. The chapter finishes with the main conclusions drawn from this study and some possibilities of future work.

5.2 Mathematical model

A mathematical programming model is proposed whose objective is to select the one-way trips that should maximize the expected daily profit of a carsharing company currently operating in a round-trip mode.

Two assumptions were considered for this model: the capacity, that is, the number of parking spots in each round-trip station is not increased, and the fleet of vehicles is limited to the number of vehicles currently operating in the round-trip service.

It is important to note that there may be a different number of vehicles available in each station at the end of each day. Moreover, we performed a sensitivity analysis of the model's performance, including the repositioning of vehicles between the existing round-trip stations and the station that it is created in the high demand generator site. The formulation presented below includes relocations. Even though they are only included for sensitivity analysis purposes, it is easier to explain the original model for this situation.

The notation used to formulate the model (sets, data and decision variables) is as follows:

<u>Sets</u>

- $\boldsymbol{S} = \{1, \dots, i \dots I\}$: set of stations, where I is the number of stations including the high demand generator site.
- $\boldsymbol{T}' = \{1, \dots, t \dots T\}$: set of time steps in the operation period, where T is

the last optimization time step.

Data

- δ_{ij}^{t}: Travel time, in time steps, between stations i and j when departure time is $t, i, j \in \boldsymbol{S}, t \in \boldsymbol{T}'$.
- N: Total number of vehicles in the fleet.
- HTT: The longest travel time between any pair of stations during the whole day.
- $D_{i_t j_{t+\delta_{ij}^{t}}}$: One-way carsharing demand from i to j from time t to time $t + \delta_{ij}^{t}, i, j \in \boldsymbol{S}, i \neq j, t \in \boldsymbol{T}', t + \delta_{ij}^{t} \leq T + HTT$.
- U_{i_1}: Number of unavailable vehicles at station i at the beginning of the optimization period (t=*1*), $\forall i \in \boldsymbol{S}$, given that the round-trip service already exists and when the one-way service starts its operation,vehicles may be being used for the round-trip service, and therefore out of the stations.
- Z_{i_t}: Number of vehicles that arrive at i at time t, $i \in \boldsymbol{S} \backslash \{I\}, t \in \boldsymbol{T}'$ for the round-trip service.
- W_{i_t}: Number of vehicles that depart from i at time t, $i \in \boldsymbol{S} \backslash \{I\}, t \in \boldsymbol{T}'$ for the round-trip service.
- P_{ij}: Taxi fare per trip from station i to j.

- m: Percentage of the taxi price charged to the clients of the one-way carsharing system.
- Cmp: Daily cost of a parking spot in the high demand generator site.
- Cv: Cost of vehicle maintenance per time step driven in the one-way trips.
- Cf: Cost of fuel per time step driven.
- Cr: Cost of relocating a vehicle per time step driven.
- Cap_i: Capacity of station $i, i \in \boldsymbol{S} \backslash \{I\}$ in number of parking spots.

<u>Decision Variables</u>

- $x_{i_t j_{t+\delta_{ij}^t}}$: Number of trips accepted from i to j from time t to time $t + \delta_{ij}^t$, $i, j \in \boldsymbol{S}, i \neq j, t \in \boldsymbol{T'}, t + \delta_{ij}^t \leq T + HTT$.
- $r_{i_t j_{t+\delta_{ij}^t}}$: Number of vehicles relocated from i to j from time t to time $t + \delta_{ij}^t$, $i, j \in \boldsymbol{S}, i \neq j, t \in \boldsymbol{T'}, t + \delta_{ij}^t \leq T + HTT$.
- a_{i_t}: Number of vehicles available at station i at time , $i \in \boldsymbol{S}, t \in \boldsymbol{T'} \backslash \{1\}$.
- a_{I_1}: Number of vehicles available at site I at the beginning of the operation period (t=*1*).
- c_I: Capacity of the station at the high demand generator, I, in number of parking spots.

Using the notation above, the mathematical model can be formulated as follows:

$$\begin{aligned} Max\ \pi = & \sum_{\substack{i,j\in \boldsymbol{S} \\ i\neq j}} \sum_{\substack{t\in \boldsymbol{T'} \\ t+\delta_{ij}^t \leq T+HTT}} x_{i_t j_{t+\delta_{ij}^t}} \times \left(P_{ij} \times m\right) - Cmp \times c_I \\ & -(Cf + Cv) \times \sum_{\substack{i,j\in \boldsymbol{S} \\ i\neq j}} \sum_{\substack{t\in \boldsymbol{T'} \\ t+\delta_{ij}^t \leq T+HTT}} x_{i_t j_{t+\delta_{ij}}} \times \delta_{ij}^t \\ & -(Cr + Cf) \times \sum_{\substack{i,j\in \boldsymbol{S} \\ i\neq j}} \sum_{\substack{t\in \boldsymbol{T'} \\ t+\delta_{ij}^t \leq T+HTT}} r_{i_t j_{t+\delta_{ij}^t}} \times \delta_{ij}^t \end{aligned} \tag{5.1}$$

subject to,

$$\sum_{i\in \boldsymbol{S}} a_{i_t} + \sum_{i\in \boldsymbol{S}} U_{i_t} = N, t = 1 \tag{5.2}$$

$$a_{i_1} = Cap_i - U_{i_1}, \forall\ i \in \boldsymbol{S}\backslash\{I\} \tag{5.3}$$

$$\begin{aligned} a_{i_t} = a_{i_{t-1}} - & \sum_{\substack{j\in \boldsymbol{S} \\ i\neq j \\ t+\delta_{ij}^t \leq T+HTT}} x_{i_{t-1} j_{t-1+\delta_{ij}^t}} + \sum_{\substack{j\in \boldsymbol{S} \\ i\neq j \\ t-\delta_{ij}^t \geq 1}} x_{j_{t-\delta_{ij}^t} i_t} \\ & - \sum_{\substack{j\in \boldsymbol{S} \\ i\neq j \\ t+\delta_{ij}^t \leq T+HTT}} r_{i_{t-1} j_{t-1+\delta_{ij}^t}} + \sum_{\substack{j\in \boldsymbol{S} \\ i\neq j \\ t-\delta_{ij}^t \geq 1}} r_{j_{t-\delta_{ij}^t} i_t} - W_{i_{t-1}} + Z_{i_t}, \\ & \forall\ i \in \boldsymbol{S}, t \in \boldsymbol{T'}\backslash\{1\} \end{aligned} \tag{5.4}$$

$$x_{i_t j_{t+\delta_{ij}^t}} \leq D_{i_t j_{t+\delta_{ij}^t}}, \qquad \forall i,j\ \in \boldsymbol{S}, i\neq j, t\in \boldsymbol{T'}, t+\delta_{ij}^t \leq T+HTT \tag{5.5}$$

$$\sum_{\substack{j \in \boldsymbol{S} \\ i \neq j \\ t+\delta_{ij}^{t} \leq T+HTT}} x_{i_t j_{t+\delta_{ij}^{t}}} + \sum_{\substack{j \in \boldsymbol{S} \\ i \neq j \\ t+\delta_{ij}^{t} \leq T+HTT}} r_{i_t j_{t+\delta_{ij}^{t}}} + W_{i_t} \leq a_{i_t}, \qquad \forall i \in \boldsymbol{S}, t \in \boldsymbol{T}', t+\delta_{ij}^{t} \leq T+HTT \tag{5.6}$$

$$a_{i_t} \leq Cap_i, \qquad \forall i \in \boldsymbol{S} \backslash \{I\}, t \in \boldsymbol{T}' \tag{5.7}$$

$$a_{I_t} \leq c_I, \qquad \forall t \in \boldsymbol{T}' \tag{5.8}$$

$$x_{i_t j_{t+\delta_{ij}^{t}}} \in N^0, \qquad \forall i,j \in \boldsymbol{S}, t \in \boldsymbol{T}', t+\delta_{ij}^{t} \leq T+HTT \tag{5.9}$$

$$r_{i_t j_{t+\delta_{ij}^{t}}} \in N^0, \qquad \forall i,j \in \boldsymbol{S}, t \in \boldsymbol{T}', t+\delta_{ij}^{t} \leq T+HTT \tag{5.10}$$

$$a_{i_t} \in N^0, \qquad \forall i \in \boldsymbol{S}, t \in \boldsymbol{T}' \tag{5.11}$$

$$c_I \in N^0 \tag{5.12}$$

The objective function (5.1) of the mathematical model maximizes the total daily profit (π) of the one-way trips, taking into consideration the revenue from the trips paid by the clients (assuming that the price of each trip is $P_{ij} \times m$), the cost of maintaining the vehicles used for the one-way service, the parking costs of the station at site I, and the vehicle relocation costs, when applicable. Constraint (5.2) guarantees that the total number of vehicles in the system is not greater than the current fleet at $t = 1$ and computes the initial availability of vehicles (a_{I_1}) at the station at site I. Constraints (5.3) compute the initial availability of vehicles in each existing station, given that their capacities and the number of unavailable vehicles are inputs. Constraints (5.4) ensure the conservation of vehicle flows at each node (i_t) of the time-space network for $1 < t \leq T$. Constraints (5.5) guarantee that the number of trips between stations i and j at time t will not exceed the existing demand. Constraints (5.6) ensure that the number of vehicles leaving each station i at each time t does not exceed the availability of vehicles in each station i at each time t. Constraints (5.7) guarantee that the capacity of station i will not be greater than the current capacity of i in the case of the existing round-trip carsharing stations. Constraints (5.8) ensure that the capacity of the station in the high demand generator at site I is greater than the number of vehicles present there at any time t. In practice, capacity will not be greater than the highest value of a_{I_t} for the operation period, because this would penalize the objective function. Expressions (5.9)-(5.12) set the domain of the decision variables. The parameter HTT is used to allow all the trips to be performed, even those that leave the station at the end of the operating period (T), because the system is open 24 hours and therefore clients can pick up the vehicles on one day and return them on subsequent days. Despite the fact that we are only optimizing one typical day of operations, due to computational limitations, the model can be used for any day of operation. It assumes that, at the start of each day, which corresponds to the end of the previous day, there are a number of unavailable vehicles at each station that are already being used by the round-trip or the one-way services.

When no relocation operations are included in the model, the variable $r_{i_t j_{t+\delta_{ij}}}$ is taken out from the constraints and the relocation costs are eliminated from the objective function (5.1).

5.3 Applying the model to the Logan Airport case study

The model is applied to the trips between existing round-trip carsharing stations in Boston and Logan International Airport, which is close to the city center. Currently, there are 391 stations spread across the city with a fleet of about 1200 vehicles for use by clients (Zipcar(b), 2014). Most of the stations are within the city center; however, some of the suburbs are also served by *Zipcar* (Figure 5.1).

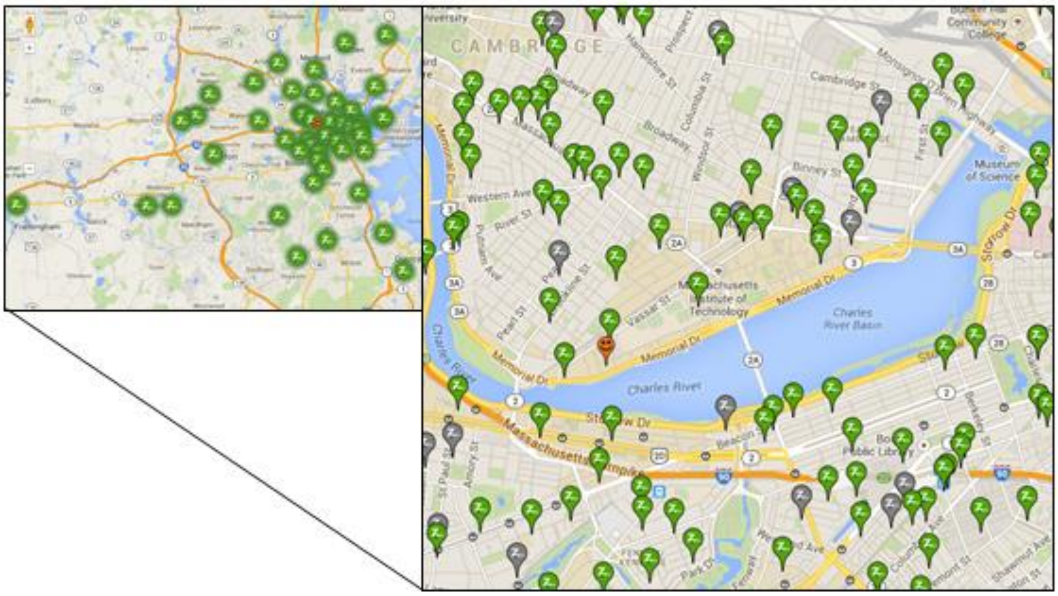


Figure 5.1 - Visualization of the Boston *Zipcar* network (Zipcar(b), 2014)

Considering the round-trip service already offered in this city, i.e. the stations' location and their capacity (number of parking spots) obtained from the *Zipcar* website (Zipcar(b), 2014), the data needed to apply the model are: the number of available vehicles in each station at each time, due to running the round-trip service, for three different days in May and June 2014 (information that was also collected from (Zipcar(b), 2014)); the potential trip demand matrix for the one-way carsharing service; the driving travel times from the existing stations to Logan Airport and vice-versa; the cost of running the one-way system.

The potential trip demand matrix uses data from a survey performed in 2010 by Logan Airport (Logan Airport Air Passenger Ground-Access Survey, 2010), and flight data (Flightstats, 2013). In spring 2013, an average of 39,424 passengers enplaned daily at Logan Airport according to information provided by the airport authorities. Taking this into account, together with the number of passengers enplaning and arriving at Logan Airport in 2012, taken from the DB1B database (Bureau of Transportation, 2013), it was possible to estimate the average number of passengers arriving each day at that airport in spring 2013, which resulted in 39,699 trips. Data from the Logan Airport Survey (Logan Airport Air Passenger Ground-Access Survey, 2010) were used to assign enplaning passengers to the origin station and arriving passengers to the destination station. This survey provides data about the number of passengers by origin (zip code), the transportation mode used to travel to the airport (private vehicle, taxi, rental vehicle, and public transportation), and the type of passenger: resident business; resident leisure; non-resident business, and non-resident leisure.

First, considering the current stations in the Boston *Zipcar* service (Zipcar(b), 2014), only 36% of the total number of passengers surveyed can be captured by the one-way carsharing service; the others come from or are going to zip code areas with no *Zipcar* stations. These passengers correspond to a total of 14,193 enplaning passengers and 14,292 arriving passengers. Of these, it was assumed that only trips that currently use private vehicles, taxis or rental vehicles can be captured by carsharing. Moreover, demand may differ for the two trip purposes (business or leisure). While it can be expected that only a small percentage of business trips would transfer to carsharing, because companies usually pay for these trips, higher adoption rates can be expected with respect to leisure trips, since the main objective of these travelers is to choose the cheapest travel option. Therefore, we considered that only 15% of business passengers would be willing to choose carsharing while probably 100% of the non-business passengers would not mind taking this option. Moreover, vehicle occupation rates were considered diferentely, depending on the type of trip: for business trips we considered 1.0 person per vehicle, since business passengers usually travel alone, and for non-business trips we considered the vehicle occupation rate of 2.0. Given this, 2 non-business passengers correspond to one trip. The application of these criteria resulted in a potential trip demand matrix with a total of 5,474 trips. This is the upper bound for the demand scenarios that were tested.

The 5,474 trips were distributed by each zip code area according to the survey data. Knowing that there is more than one station in each zip code area, we decided to assign the trips to each station in each zip code according to the capacity (number of parking spots) that each station has at present for the round-trip service, that is, the more parking spots currently assigned to that station, the more trips starting from or ending at it.

Flight data (Flightstats, 2013) were used to assign a departure time to each trip from a station or from the airport. Flight schedule data (departures and arrivals to Logan Airport) were considered for one week in April 2013, with respect to their departure and arrival time and type of airplane used for each flight. The type of airplane provides information on the number of seats on each flight and the Consulting Bureau of Transportation (2013) provides details of airplane load factors for domestic and international flight departures and arrivals for the year 2012, which were: 0.8493, 0.7346, 0.8723 and 0.7491, respectively. This information was combined to give an estimation of the number of passengers on each flight at each time of the day. Hence, the probabilities of enplaning trips happening at a given time of the day are estimated by dividing the number of enplaning trips occurring at each time by the total number of enplaning trips in the whole day. Equally, with respect to the arriving trips, the process is the same.

The process explained above provided aggregated information, such as: the number of trips departing from each station in a whole day; the number of trips arriving at each station in a whole day; the probability of enplaning trips occurring at each time in the 24 hours, and the probability of arriving trips happening at each time in the 24 hours. However, we needed to distribute the trips by pair of stations and time of the day at which each occurs. The Monte Carlo simulation method was used for this, computing the cumulative probabilities and randomly generating a time when each enplaning and arriving trip will occur. Therefore, the Monte Carlo simulation is only used to generate the potential demand matrix, which is an input to the optimization model. We note, however, that this process may have a significant influence on the optimization results due to its randomness, hence this will be tested.

With the process described above we obtained the distribution of the trips according the flight departure and arrival times, however, it is necessary to note that people need to arrive to the airport some time before the flight departure and are only able to leave the airport some time after the flight arrival. Thus, to match the airplane trips with the carsharing trips and lacking better information, we considered that passengers going on a domestic flight begin their trip 2 hours before boarding, and for international flights, they begin 3 hours before boarding. With respect to the arrivals, it is assumed that passengers are able to pick a car from the airport one hour after the airplane's arrival, for domestic and international flights alike.

The day was divided into time steps of 20 minutes, which allows the necessary precision for the most frequent travel times in the city. The proposed model takes the effects of congestion into account, although data limitation issues meant that we used the same driving travel times for the whole day, which were computed using the Google Maps application (GoogleMaps, 2014) and expressed in time steps of 20 minutes.

The Honda Civic Ex Sedan 1.6 that is currently in use in the *Zipcar* fleet was the reference for computing vehicle costs. It has an initial cost of USD 20,815.0 (autos, 2013). The cost of running the system was calculated as realistically as possible according to:

- Cf (cost of fuel): USD 0.442 per time step driven (20 min), taking an average speed of 10 miles/hour, a price per gallon of USD 3.668 (BostonGasPrices, 2014), which is according to today's cost, and assuming that the cars are mainly driven in the city (consumption of 28 miles per gallon according to *autos* (2013));
- Cr (cost of relocating a vehicle): USD 4.323 per time step driven (20 min), since the average hourly wage of a taxi driver in Boston, MA, is USD 12.97 (Bureau of Labor Statistics, 2013);
- Cmp (cost of maintaining a parking space): USD 29 per day, which is the fee for parking in the terminal area of Logan International Airport (Massport, 2014);
- Cv (cost of one vehicle, which includes maintenance and repairs): USD 0.034 per time step driven, calculated for a city car (autos, 2013).

The price charged to clients of the one-way carsharing service varies according to the location of the origin and destination stations and is given by multiplying an experimental parameter (m percentage) by the taxi price charged to each pair of OD stations (P_{ij}), which includes the initial fare, Massport fee, tolls and distance travelled fare (Taxifarefinder, 2013; Itoataxi, 2013). The m percentage is always lower than 1 (100%).

5.4 Results

Considering that the matrix produced in the previous section is the upper bound of the demand (potential demand) that can be reached by the one-way service, 6 demand scenarios were tested based on different percentages of potential demand that may be captured by carsharing (demand scenario): 1%, 5%, 10%, 30%, 50%, and 100%. These scenarios were considered in order to observe the effects of the captured demand on the profit of the company, even when it is very low, as happens with the 1% and 5% scenarios. The following parameters were varied for each of the demand scenarios in order to perform a sensitivity analysis: percentage of the taxi price (m), airport parking cost (Cmp), and allowing or preventing vehicle relocations between existing stations and Logan Airport (vector $r_{i_{t-1}j_{t-1+\delta_{ij}}}$).

The tests were performed using round-trip data for May 27 (Tuesday), June 10 (Tuesday) and 11 (Wednesday), 2014. We used more than one day so as to test the sensitivity of the model to different days and thus different availabilities of vehicles in each station. The initial availability $(a(i,1))$ of vehicles at each existing station varies for each day. Moreover, the model was also run assuming only the one-way service in order to see how the round-trip service (the priority one) constrains the new service.

The model was run 5 times for each demand scenario and combination of parameters, and the average results were computed to account for the randomness inherent to the use of the Monte Carlo simulation in the determination of the potential trip demand matrix.

A summary of the testing methodology is shown in Figure 5.2.

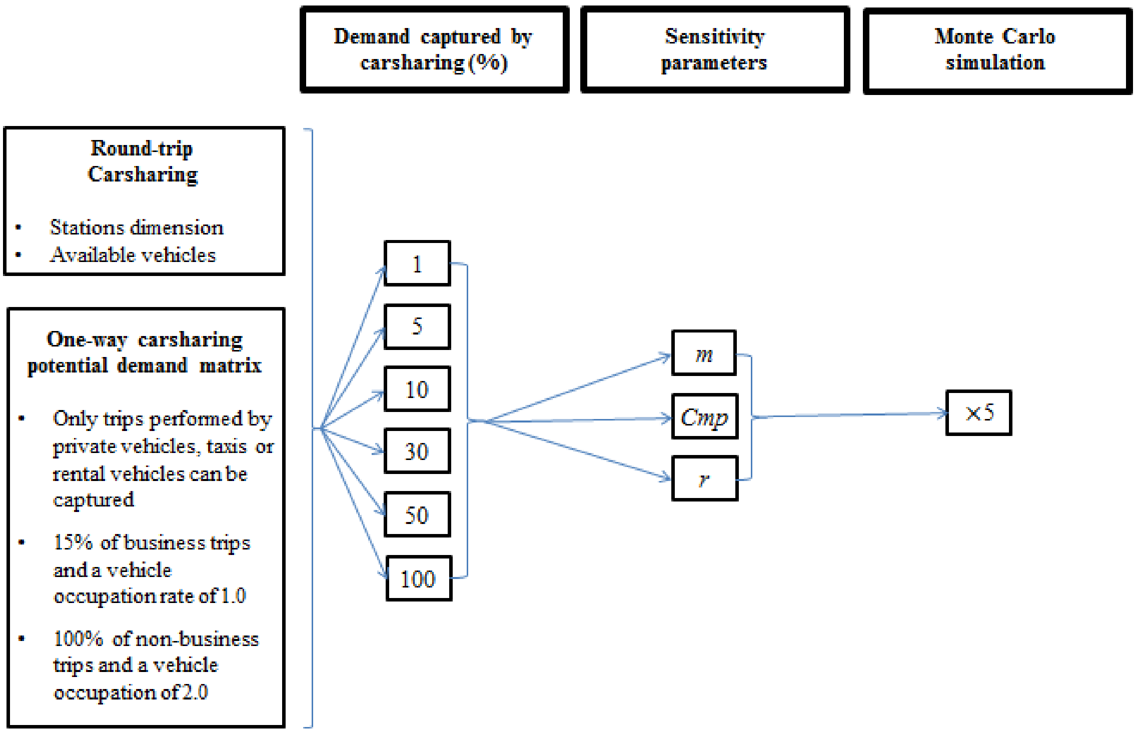


Figure 5.2 - Methodology used to obtain the results

The mathematical model (5.1)-(5.12) was run for all the possible combinations of these experimental factors (a total of 360 runs) in an i5 processor @ 2.50 GHz, 4 Gb RAM computer under a Windows 7 64 bit operating system. The model was built using Xpress 7.7, an optimization tool that uses branch-and-cut algorithms for solving MIP problems (FICO, 2014). The model always reached optimum solutions for every run, taking a minimum of 0.5s and a maximum of 308.8s as running time.

5.4.1 Sensitivity analysis

The following variables were used as performance indicators for the experiments: the percentage of trips effectively served by the one-way carsharing system for the demand scenario considered; the total number of trips performed; the total number of time steps driven by the clients (time steps of 20 minutes); the number of parking spots that were needed at the airport (airport station capacity); the daily profit obtained by the company; the percentage of relocations related to the demand effectively satisfied for each demand scenario; the total number of relocated vehicles; the total number of time steps of vehicle relocation.

It is important at this point to explain that in this chapter we define three levels of demand: the potential demand that corresponds to a total upper bound demand (5,474 trips); the demand scenario that is basically a percentage of the upper bound; the demand effectively satisfied by carsharing that will result from applying the model (it will of course be a percentage of the previous one).

The following is the base combination of parameters considered for sensitivity analysis purposes:

- 60% of the taxi price (m = 0.6) charged to the clients, since it seems to be the most reasonable one in terms of profit for carsharing, competitiveness with the private vehicle and the taxi, and sufficiently greater than the public transportation price in order to not capture that demand;

- the cost of maintaining a parking space in the airport is taken to be USD 29 per day, which is the price currently charged to private drivers (Massport, 2014);
- no relocations are considered, since they present additional operational complexity to the operator, who may not be willing to use them.

The price charged to the clients is then varied, decreasing to 40% of the taxi price per trip and increasing to 80%, while the other parameters remain the same. The cost of maintaining a parking space in the airport is also varied, decreasing to USD 20 per day and then increasing to USD 40 per day, keeping the other parameters the same as the base combination. Finally, relocation operations are added to the base combination of parameters.

Table 5.1 presents all the experimental configurations, as well as the average results for 5 replications of demand estimation, applied to the data of May 27, 2014.

Table 5.1 - Average results for 5 demand estimation replications

Experimental configuration				Results							
Potential demand that can be captured (% of total demand)	m	Cmp	Relocations	Demand effectively captured (% of the potential demand)	Total n. of trips done using one-way carsharing service per day	Total n. of time steps driven per day	N. of parking spaces needed at the airport	Profit per day (USD)	Relocations (%)	Total n. of relocations	Total n. of reloc. time steps per day
1	**0.6**	**29**	**no**	**0.36**	**20**	**24**	**4**	**315.6**	**--**	**--**	**--**
	0.4	29	no	0.34	19	23	3	174.0	-	--	--

	0.8	29	no	0.60	33	37	10	492.9	-	--	--
	0.6	20	no	0.60	33	37	10	383.2	-	--	--
	0.6	40	no	0.35	19	23	3	278.4	-	--	--
	0.6	29	yes	0.97	53	60	3	653.3	64.48	34	37
5	**0.6**	**29**	**no**	**2.43**	**133**	**141**	**11**	**1890.5**	**--**	**--**	**--**
	0.4	29	no	2.37	130	139	10	1134.1	-	--	--
	0.8	29	no	3.24	177	187	28	3058.1	-	--	--
	0.6	20	no	2.94	161	170	26	2053.3	-	--	--
	0.6	40	no	2.39	131	139	10	1770.5	-	--	--
	0.6	29	yes	4.60	249	268	8	3210.8	43.93	110	119
10	**0.6**	**29**	**no**	**4.68**	**256**	**281**	**21**	**3826.3**	**--**	**--**	**--**
	0.4	29	no	4.55	249	274	19	2316.0	-	--	--
	0.8	29	no	5.07	278	302	32	5402.9	-	--	--
	0.6	20	no	5.09	278	303	32	4072.2	-	--	--
	0.6	40	no	4.60	252	276	19	3605.3	-	--	--
	0.6	29	yes	8.90	487	534	12	6708.9	44.87	218	239
30	**0.6**	**29**	**no**	**13.91**	**762**	**838**	**49**	**11524.5**	**--**	**--**	**--**
	0.4	29	no	13.56	742	818	44	7095.1	-	--	--
	0.8	29	no	14.34	785	861	61	16037.3	-	--	--
	0.6	20	no	14.30	785	861	61	12032.2	-	--	--
	0.6	40	no	13.77	754	830	46	10997.8	-	--	--
	0.6	29	yes	27.99	1532	1674	34	21158.3	46.34	710	775
50	**0.6**	**29**	**no**	**24.30**	**1330**	**1454**	**74**	**20334.1**	**--**	**--**	**--**
	0.4	29	no	23.82	1304	1428	67	12648.9	-	--	--
	0.8	29	no	24.58	1346	1469	81	28088.8	-	--	--
	0.6	20	no	24.61	1347	1471	82	21034.6	-	--	--
	0.6	40	no	23.97	1312	1436	69	19549.6	-	--	--
	0.6	29	yes	47.26	2585	2830	51	36018.5	45.52	1177	1293
100	**0.6**	**29**	**no**	**46.20**	**2529**	**2767**	**88**	**40166.1**	**--**	**--**	**--**
	0.4	29	no	45.51	2491	2730	78	25523.2	-	--	--
	0.8	29	no	46.55	2548	2787	96	54860.1	-	--	--
	0.6	20	no	46.68	2555	2794	100	40984.3	-	--	--
	0.6	40	no	45.80	2507	2746	82	39220.4	-	--	--
	0.6	29	yes	93.50	5118	5593	96	69972.6	49.76	2547	2779

The base combination of parameters is shown in bold.

Besides the average of the results for the 5 replications, the standard deviation and the coefficient of variation were also computed (not shown in the table). The coefficient of variation was mostly lower than 0.2 for scenarios with 10% or less of potential demand captured by carsharing and 0.0 for scenarios with more than 10% of demand captured by carsharing. The maximum value of the coefficient of variation was 0.2 for the first 3 scenarios and 0.1 for the rest. The number of parking spots needed at the airport had the highest coefficient of variation, which means that this output has the highest sensitivity to the demand variations.

Analyzing Table 5.1, the most important aspect to notice is that all demand scenarios and combinations of parameters resulted in a profit for the one-way trips to and from Logan Airport. This happens even for 1% demand scenario. With the base combination of parameters, the profit obtained varies between USD 315.6 and USD 40,166.1 per day. However, it should be noted that scenarios with more than 10% of demand are probably not that realistic and have only been studied for sensitivity purposes.

As the price charged to the client increases, the profit, as expected, also increases (Figure 5.3). For example, for the 1% demand scenario, it varies from USD 174.0/day (when 40% of the taxi price was charged) to USD 492.9/day (when 80% of the taxi price was charged). The profit is inversely proportional to the cost of parking at the airport, so as the cost decreases, the profit increases (Figure 5.3). Considering the 10% demand scenario, the profit obtained varies from USD 3605.3/day for a parking cost of USD 40/spot×day to USD 4072.2/day for a parking cost of USD 20/spot×day.

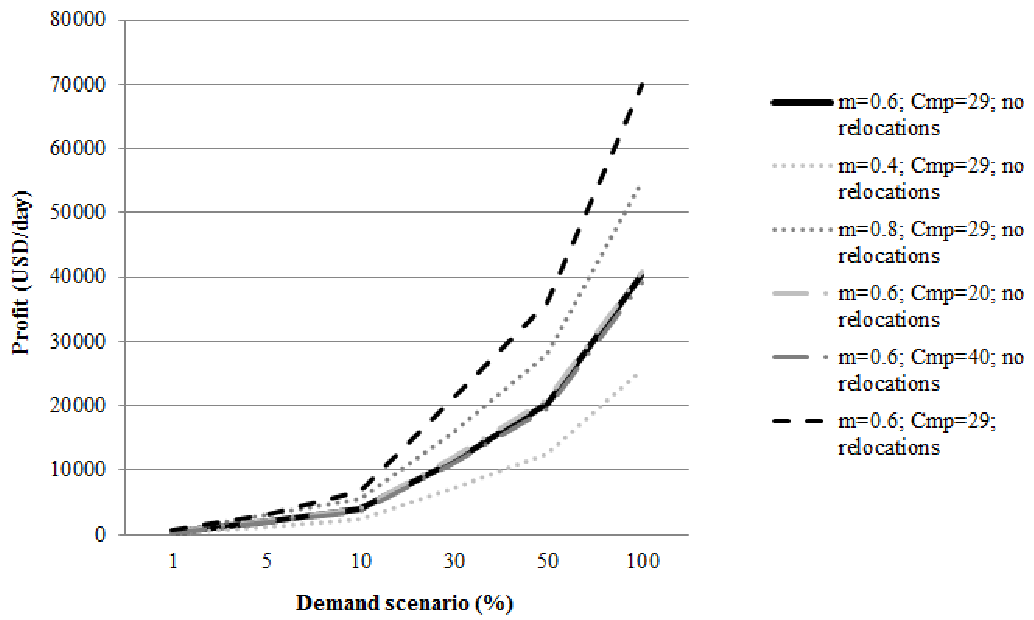


Figure 5.3 - Profit obtained for each demand scenario

It can also be concluded from Table 5.1 that if the price charged to the clients or the cost of maintaining a parking space in the airport is varied, the changes in the demand that is effectively satisfied by the one-way carsharing for each demand scenario are not as great as using relocation operations. Moreover, for the variations considered in this study, changing parking costs for the company at the airport produces effects on the demand effectively captured by carsharing similar to changes in the price charged to the clients, taking into consideration their inverse proportionality.

The primary axis in Figure 5.4 represents the percentage of demand effectively satisfied for the 6 demand scenarios considered and each of the 6 parameter configurations. It is possible to see that the effect of relocation operations on the one-way system is very significant, since they allow at least 90% of all the demand to be satisfied for each of the 6 demand scenarios. This occurs because relocating vehicles repositions them where they are needed and the whole system has enough vehicles for all the one-way trips if they are positioned in the desired stations at each time step, something that does not happen naturally without relocation operations. Although, as shown in the secondary axis through the number of potential trips in each demand scenario, this is much more relevant for the 100% demand where the maximum potential demand (5,474 trips) can almost be satisfied.

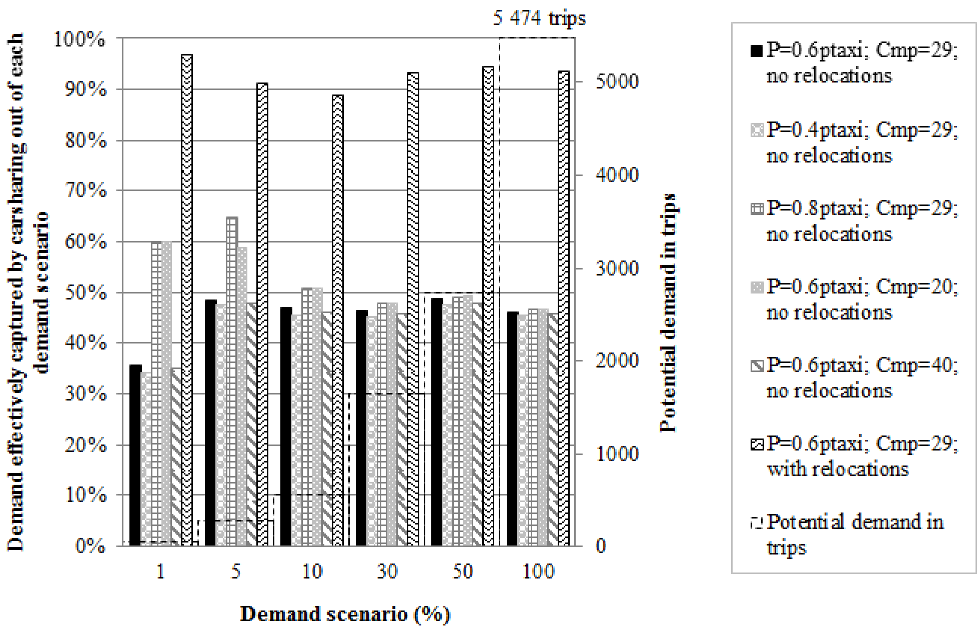


Figure 5.4 - Demand effectively satisfied for each demand scenario

With respect to the number of parking spots needed at the airport, this increases as the price charged increases, because there are more trips being served. It is important to note that we are not considering demand elasticity relative to price and that generally as price increases, demand decreases. However, we always considered lower prices for carsharing than the taxi and private vehicle prices. Therefore, we think that it is reasonable to consider that even if the price rises, the number of trips could still increase because some of the previously unprofitable trips would be more attractive to the system. When the cost of parking at the airport falls, there are more trips being served as happens when the price charged to the clients increases, and the capacity of the airport station also increases. Furthermore, as already mentioned, the results of changing parking costs at the airport or changing the price charged to the clients are similar for the combinations of parameters considered in this chapter. As an example, Figure 5.5 shows a great parallelism between the lines related to the combination of parameters with the highest price charged to the clients and the lowest cost of parking at the Airport. When relocations are added, it is possible to have a smaller station at the airport for all the demand scenarios considered except the 100% scenario, varying between 3 spots for the 1% scenario and 96 spots for the 100% scenario.

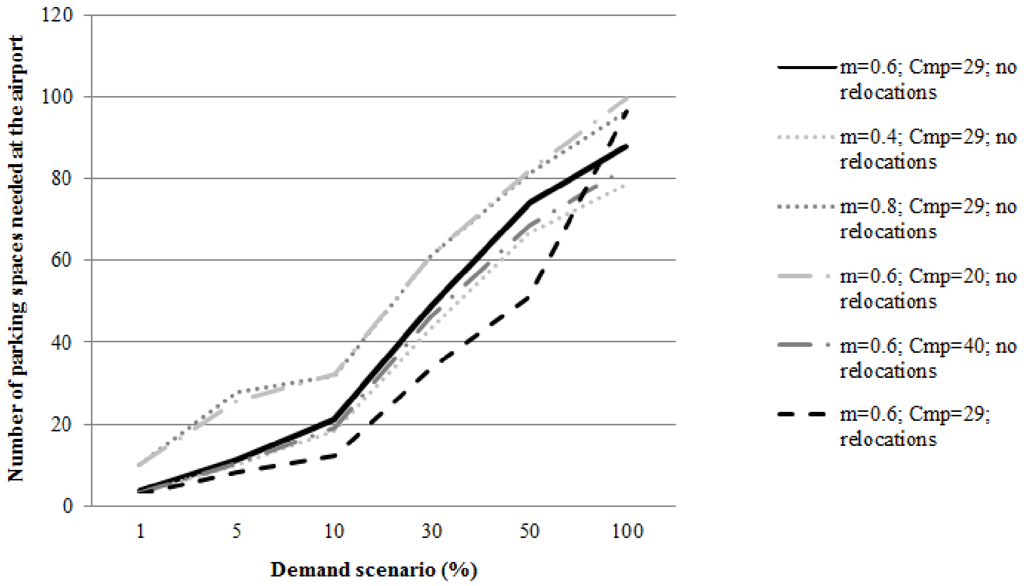


Figure 5.5 - Number of parking spots needed at the airport for each demand scenario

Analyzing the scenario that involves relocation operations, we find that this has the best results in terms of profit, demand effectively captured by carsharing, and capacity of the airport station - except for the 100% scenario - as noted previously. Nonetheless, the number of relocations is nearly half the one-way trips satisfied and even more for the 1% scenario, as shown in Table 5.1. This could be difficult for the company to manage. The complexity of managing relocation operations is not discussed in detail in this chapter. For a better insight on this problem, see Chapter 3. This is the reason why relocation operations are only an add-on to the base combination of parameters and are not included in all the other tests performed.

Analyzing the departures and arrivals of trips over a whole day for each station in the city, it is possible to assess which stations should be open to the one-way carsharing service. If no relocations are considered, these are the stations that have a potential demand (departures plus arrivals) higher than the average potential demand for all the stations (14 trips), and that at the same time have more than one vehicle assigned to them. When there is only one vehicle available, this is mostly used for the round-trip service, which leaves no vehicle available for the one-way service. Note that this model does not consider trip rejection for the round-trips. Moreover, it is concluded that the price charged to the clients has no influence on the location of the stations that should be open to the one-way carsharing service towards the airport. This is because the bigger stations are closer to the airport (for instance, in Boston, Cambridge, Somerville, Dorchester, Jamaica Plain, and Brookline). Thus, the trips from/to these stations are cheaper, but they are the ones most likely to be performed because they are from/to stations with more available vehicles.

Looking at the stations located in the Boston suburbs, revenue from the trips where they are the origin or destination would be higher, but at the moment they have few vehicles for the round-trip service, and not enough for one-way trips. This effect can be seen by running the model without considering the round-trips. The number of trips performed using the one-way carsharing service in that case increases, as well as the number of time steps driven, as expected. For instance, for the base combination of parameters and the 5% demand scenario, there are 25 more trips satisfied and 32 time steps driven when no round-trips are considered. The increase in the number of time steps driven is much greater than the increase in the number of trips, showing that the model is choosing trips from/to stations further away from the airport, since all the vehicles present in the suburbs' stations are available for use by the one-way service.

5.4.2 Effect of daily demand variations

In addition to the round-trip demand data from May 27, 2014, data for two more days were obtained (June 10 and 11, 2014). This was used to investigate the effect that round-trip demand variations may have on the results. These three days had different vehicle availabilities in most of the stations; however, by running the model for each of them we found that results are similar for all parameters considered.

For the base combination of parameters, the changes in profit for 10% or less demand scenarios are always lower than 9.5% (USD 382.4/day). In the worst case, with respect to the number of parking spots needed at the airport station, the changes correspond to less than 12.5% (3 parking spots). From these results it can be concluded that the variations in profit and the capacity of the airport station are significant across the days. However, considering different days, and thus different vehicle availabilities in each station at each time, the model always finds a solution for the one-way carsharing service that allows the company to make a profit. This is because it adjusts the trips selected to be satisfied according to the availability of vehicles in each station after the round-trip demand is wholly satisfied. However, it may not occur when the utilization rates of the round-trip service are so high that there are no available vehicles left to be used by the one-way carsharing service. Therefore, the company should work out if these one-way trips are profitable enough to make it worthwhile adding more vehicles to the integrated system or if it should stop offering the one-way service. We concluded that for 10% or less demand scenarios, the profit from the one-way carsharing service falls as the number of round-trip entries and exits increases. Summing the number of entries and exits for the round-trip system for each of the three days (May 27, June 10, and June 11, 2014), the following figures are obtained: 2440, 2357, and 2417, respectively. For instance, taking the 1% demand scenario and the base combination of parameters, the profits of the one-way carsharing service on those days are USD 315.6, USD 423.6, and USD 385.1, respectively.

To study the effect that different one-way trip patterns, and therefore different vehicle availabilities at each station, may have on the results, we ran the model for the first day of one-way carsharing service operation, considering: our assumption that the availability at site I at $t = 1$ is 0 (since we are not increasing the existing vehicle fleet and the vehicles in it are at the existing stations or being used by clients); that the model can increase the vehicle fleet by adding vehicles to the airport station at $t = 1$, given that this is done with a cost of the depreciation of these vehicles to the company, which is USD 14.781 per vehicle per day, according to *autos* (2013). Both hypotheses result in significantly different trip patterns (availability of vehicles at each station during this day). However, in terms of the profit obtained, these differences are not that significant as they amount only to a maximum of about 4% for the most realistic scenarios (1, 5, and 10%). Once again, this demonstrates that the model is able to adapt the demand satisfied to the number of available vehicles at each station at each time step, thereby maximizing the profitability of the carsharing company.

5.5 Conclusions

From the user's point of view, one-way carsharing systems are a better option for more trip purposes than round-trip services. While round-trip carsharing is used for short duration activities, such as leisure and shopping (Balac and Ciari, 2014; Barth and Shaheen, 2002), one-way carsharing may be used to other purposes, including commuting (Balac and Ciari, 2014; Ciari et al., 2014; Shaheen et al., 2006). Nevertheless, this type of system is more complex in terms of management, mostly arising from the imbalance of vehicle stocks.

In this chapter, it was assumed that both types of trip should be covered by a carsharing system, depending on the clients' needs. Hence, we studied the adaptation of a system that is operating for round-trips so that it can handle one-way trips for a specific high demand generator in a city. The round-trip service was deemed the priority one, that is, it should be served first, since it is the core business of the company. A mathematical model was developed to decide which one-way trips to accept and reject towards the carsharing station located in the high demand generator.

The application of the model to the case study of Boston, with the high demand generator station located at Logan International Airport, led to the conclusion that the one-way carsharing service is profitable for all the scenarios considered, even when the percentage of trips effectively satisfied by carsharing is very low (0.34%). This is reinforced by the fact that *Zipcar* started to integrate both round-trip and one-way carsharing in Boston during this year (ZipcarOneWay, 2014). However, this study was completed before this change in operations.

Implementing a relocation policy between the round-trip stations and the high demand generator station at the airport and vice-versa had a great impact on increasing profits. For example, for the 5% demand scenario, the profit achieved when relocations are performed is 70% higher than when no relocations are performed, and about 27% fewer parking spots are needed at the airport than when there are no relocations. This airport station capacity corresponds to 8 parking spots, which is a realistic capacity for the airport parking lot. Without relocations, this number grows significantly.

As a general conclusion, it can be said that there is a potential market for integrating two-way and one-way carsharing services - at least for particular high demand generator sites. This is the case of an airport, where the carsharing company may find extra profit while also benefiting travelers by offering them another transportation option that is cheaper than other modes. Even if the carsharing company does not want to resort to a relocation system, providing a one-way service for a selected destination would seem to take advantage of idle vehicle stocks in many stations of a city. It is important to note that the cost to the clients should be lower than the cost of using other more comfortable transportation modes, such as taxi and private vehicles (Alfian et al., 2014), in order to make this service competitive. Nonetheless, they should also be high enough for the company to make profit. Our model also indicates which stations should be open to one-way trips. It was concluded that these stations should be those that have a potential demand (entries plus exists) that is higher than the average potential demand for all the stations, and those with a fleet of 2 or more vehicles.

A significant limitation of this study must be acknowledged, which is the fact that there is no model to relate demand to the price charged; hence, no elasticity of demand to price is incorporated. This is one of the improvements that can be added in the future. Moreover, future work should look at the possibility of increasing the capacity of existing stations in favorable locations to cope with the one-way carsharing service, as well as increasing the vehicle fleet. The interaction between several high demand generators in the city is also an interesting challenge.

Disclaimer: This chapter is the result of an analysis conducted on an existing carsharing service in the city of Boston, called *Zipcar*, however, the chapter does not purport to represent the views of this company nor did this organization contribute to fund any component of this research. Moreover, this study was finished before *Zipcar* started to integrate both types of carsharing in Boston.

Chapter 6

Conclusion

Carsharing can contribute to mitigate the problems caused by private transportation on the environment and can be complementary to and enhance public transportation that is often limited in its ability to serve dynamic mobility demands. Despite this, it also presents some shortcomings, mainly related to vehicle stock imbalances in one-way carsharing systems. In this thesis, we present optimization and simulation approaches to find ways of balancing vehicle stocks' across one-way carsharing systems and providing insights on how one-way carsharing should be integrated in existing round-trip systems, with the objective of maximizing the profit of the carsharing companies. Therefore, these approaches are useful to the companies, but also to the users, since throughout the thesis there was always the concern of developing strategies that better serve users' interests, looking for improving the quality of the service offered. This is also relevant to transportation authorities and local governments that have another alternative transportation mode to be implemented and satisfy the ever changing and more diverse urban mobility needs.

This thesis pursued three global objectives. The first one was related to set out a literature review on carsharing aiming at identifying the existing gaps with a focus on operational problems and the approaches that have been used to solve them. The other two objectives derive from the literature review and consisted of creating models to bridge some of the gaps found. Hence, we developed new methodological approaches to balance vehicle stocks' in one-way carsharing systems, and a method to understand if and how a traditional round-trip system should allow one-way trips in a profitable way. These objectives were fully accomplished through the research developed.

In the review chapter, we were able to access most of the research that has been developed on carsharing in the last few years and until the publication of the corresponding paper (Jorge and Correia, 2013). The objective of this review was to determine the existing gaps in the literature and point out possible paths for researchers to follow in order to bridge those gaps, which constitutes the main contribution of this chapter. This type of research chapter is important for researchers that have in the same document most of the existing literature about this topic compiled and analyzed as well as the indication of possible research directions useful for the field. This review showed that there was a lack of studies to: (1) estimate the demand of these systems, mainly in respect to one-way carsharing, representing also the supply side and its important relationship with the demand side; (2) find ways of balancing one-way carsharing vehicle stocks using approaches and models able to be applied in real size systems; (3) model free-floating carsharing systems, which are the last trend in the implementation of these systems. Moreover and despite not being stated in Chapter 2, we have not found studies addressing the integration of both round-trip and one-way carsharing systems. It is important to note that since the publication of this chapter in 2013, some new studies have appeared on this topic, which address some of the gaps previously found. These new studies were cited throughout the chapters that follow Chapter 2.

In Chapter 3, we propose relocation operations as a way of balancing vehicle stocks in one-way carsharing. The developed approach is based on: a mathematical model that optimizes the vehicle relocation operations, maximizing the profit of the carsharing service and considering that all the trips are known in advance; and a discrete-event time-driven simulation model to test several real-time relocation policies. Previously, other authors developed mathematical and simulation models to address this issue, but always in an incomplete way. For example, Barth et al. (2001) developed an aggregated approach that does not treat each station individually. Kek et al. (2006) and Kek et al. (2009) proposed simulation as a way to evaluate the performance of the system for a solution obtained from an optimization model. And some authors developed optimization models, but not simulation (Nair and Miller-Hooks, 2011) or vice-versa (Barth and Todd, 1999), which does not allow combining both optimization and simulation results that we show to be important. Optimization provides the best possible results to be achieved, while simulation allows testing real time policies, which are easier to apply in reality and can actually take some of the optimization results insights to improve the stocks balance. Both models were applied to a network of hypothetical stations in Lisbon, Portugal, indicating that relocating vehicles contributes to increasing operational profitability. Considering this hypothetical network that covers the whole city without relocations, there are a deficit of 1160.7 €/day. This deficit is due to the fact that by not having relocations, the company has to provide a larger fleet of vehicles to satisfy all demand. When the real-time relocation policies are added, simulation results show profits of 854.9 €/day, even with the added cost of relocating the vehicles, because there is no need for a larger fleet. Using the mathematical model for the same network (assuming that all demand is known at the outset), results are even better, with a profit of 3865.7 €/day. This clearly demonstrates the value of having vehicle reservations to act beforehand, nevertheless requesting 24 hours reservation period would certainly decrease the flexibility of the system.

Still motivated to continue studying the problem of vehicle imbalance in one-way systems, in Chapter 4, we present the work that was done to study trip pricing as a way to reach that balance. The main objective of this study is to research the possibility of increasing the profit of one-way carsharing companies by controlling demand through the price. For this purpose, a mathematical model is presented to define the prices that maximize the profit of a carsharing company, considering that there is a negative price elasticity of demand. Due to the non-linearity of the model, given that demand depends on the price, a meta-heuristic (iterated local search) is also provided to solve it. As far as we know, there is only one other study addressing the trip pricing approach, although contrary to ours, it is based on a simulation model (Zhou, 2012). Therefore, the main contributions of this chapter to the existing literature are the development of an optimization model to implement trip pricing in one-way carsharing systems as well as a solution method to solve it (meta-heuristic), and the proof on the utility of this approach with this purpose. This model may constitute a tool to be used by one-way carsharing operators to manage their vehicle fleets imbalances, improving the quality of service for the users. The algorithm was applied to the same case-study as in Chapter 3 (the municipality of Lisbon, in Portugal), demonstrating that trip pricing is able to significantly increase the profit of the carsharing company by decreasing some of the demand that imbalances it. As previously stated, when no balancing strategy is used, the cost of operating this service corresponds to a deficit of 1160.7 €/day, while applying trip pricing, profits of 2068.1 €/day could be achieved. This profit is lower than the one obtained by using the optimum relocation operations. However, this is still a remarkable result, since we are charging prices per origin-destination pair of zones and not per origin-destination pair of station and per time interval and not per each minute in the operation period. We are also using a meta-heuristic as solution algorithm to determine those prices, which does not provide the optimum price solutions.

In Chapter 5, we introduce a method to understand if a round-trip carsharing system is able to be profitable by allowing one-way trips for specific origin-destination pairs. The idea is to use vehicles and parking spaces that are not being used by the traditional round-trip system. This is the first time, to our knowledge, that the integration of both operating models (round-trip and one-way) is studied through a mathematical approach. An integer programming model was developed to select one-way trips towards a specific high demand generator site, with the objective of maximizing the profit reached with the added one-way service. The main contributions of this chapter are the assessment of the possibility of increasing profit by combining both round-trip and one-way carsharing in a network that was created originally for round-trip carsharing, and the provision of insights on how this integration should be put into action. This model was applied to the case study of Boston, USA, considering that one-way trips are allowed connecting the existing *Zipcar* stations in the city (Zipcar(b), 2014) and the Logan Airport. Results show that this one-way service could be profitable even when the percentage of trips satisfied by one-way carsharing is very low (0.34%). Moreover, the model shows that one-way trips should be offered from/to the stations that present higher demand than the average across the city to/from the Airport, and the ones whose capacity is of at least two vehicles.

Globally the models presented in the thesis are able, at least in theoretical scenarios, to improve the profit of a carsharing company and or improving the level of service provided. In this thesis, most of the research effort has been put into balancing one-way carsharing vehicle stocks. From these studies, we have concluded that: (1) the use of relocation operations may be realistically applied to one-way carsharing systems, benefiting carsharing companies in terms of profit obtained and offering at the same time better quality of service to the users in terms of vehicle and parking spot availability in the desired stations; (2) trip pricing constitutes another possibility for carsharing companies to increase their profits, balancing efficiently the vehicle stocks. It is important to note that when prices are increased, the demand that contributes to imbalance the system is rejected, which is not convenient for the clients of the system that want to perform these trips. Notwithstanding, the overall result presents benefits for carsharing system users' in general.

From the study of the integration of both one-way and round-trip carsharing, it appears that this integration should be beneficial for the company by increasing its profit. The one-way trips can take advantage of idle stocks and serve clients for whom the round-trip carsharing is not suitable.

There was a great effort to build real-world case studies. However, it should be emphasized that the case studies are hypothetical. Some assumptions were made due to lack of data or to restrain the analysis to the thesis objectives. Nevertheless, all the models described in this thesis should be useful in improving results of carsharing operation and should be easily applied in practice as they are, or with minor adjustments.

In Chapters 3 to 5, several improvements and future research developments are mentioned to improve the models and the approaches developed. Regarding the vehicle relocation operations approach, the most important future development should be introducing stochastic trip variability and travel time in both optimization and simulation models to improve their realism. The trip pricing approach, which has the same purpose as the relocation operations, may benefit from improving the solution algorithm (meta-heuristic) in order to try achieving better solutions. Furthermore, other principles to determine the zones should be tested, and the way demand varies towards price should also be more detailed. With respect to the integration of round-trip and one-way carsharing simultaneously, a possible enhancement in terms of the model should be to incorporate price elasticity of demand. While the approach may be enhanced by adding more parking spaces and vehicles to the existing stations at favorable locations for the one-way carsharing service. And a higher number of high demand generator sites should also be considered to offer one-way trips or even all the current round-trip stations.

Despite this, we believe that the methodological approaches introduced and applied in this thesis represent a notable contribution for the existing literature about planning and managing carsharing systems, especially the ones that operate as one-way. The case studies, mostly based on real data, clearly show this contribution for carsharing companies in their service planning and management process, but also for carsharing users.

References

Alfian, G., Rhee, J., Yoon, B., 2014. A simulation tool for prioritizing product-service system (PSS) models in a carsharing service. *Computers & Industrial Engineering*, 70, 59-73.

Arnaldi, B., Cozot, R., Donikian, S., Parent, M., 1996. Simulation Models for French Praxitele Project. *Transportation Research Record: Journal of the Transportation Research Board*, 1521, 118-125.

Atasoy, B., Salani, M., Bierlaire, M., 2014. An Integrated Airline Scheduling, Fleeting, and Pricing Model for a Monopolized Market. *Computer-Aided Civil and Infrastructure Engineering*, 29(2), 76-90.

AutoExpress, 2011. Available at: http://www.autoexpress.co.uk/bmw/1-series/34628/bmw-drivenow-car-sharing-scheme (last accessed July 10, 2011).

Autolib', 2014. Available at: www.autolib.eu (last accessed August 20, 2014).

Autos, 2013. Available at: autos.yahoo.com (last accessed April 20, 2013).

Balac, M., Ciari., F, 2014. Modelling Station-Based Carsharing in Switzerland. Presentation at the 14th Swiss Transport Research Conference, Monte Verità/Ascona, Switzerland.

Barrios, J., 2012. On the Performance of Flexible Carsharing – A Simulation-Based Approach. Working paper, Available at: http://iceusa.org/GS1%20J%20A%20Barrios_On%20the%20Performance%20of%20Flexible%20Carsharing.pdf (last accessed February 10, 2012).

Barth, M., Han, J., Todd, M., 2001. Performance evaluation of a multi-station shared vehicle system. Presentation at IEEE Intelligent Transportation Systems Conference, Oakland, CA, USA.

Barth, M., Shaheen, S., 2002. Shared-Use Vehicle Systems: Framework for Classifying Carsharing, Station Cars, and Combined Approaches. *Transportation Research Record: Journal of the Transportation Research Board*, 1791, 105-112.

Barth, M., Shaheen, S., Fukuda, T., Fukuda, A., 2006. Carsharing and Station Cars in Asia: Overview of Japan and Singapore. *Transportation Research Record: Journal of the Transportation Research Board*, 1986, 106-115.

Barth, M., Todd, M., 1999. Simulation model performance analysis of a multiple shared vehicle system. *Transportation Research Part C*, 7(4), 237-259.

Barth, M., Todd, M., 2001. User Behavior Evaluation of an Intelligent Shared Electric Vehicle System. *Transportation Research Record: Journal of the Transportation Research Board*, 1760, 145-152.

Barth, M., Todd, M., Xue, L., 2004. User-Based Vehicle Relocation Techniques for Multiple-Station Shared-Use Vehicle Systems. Presentation at Transportation Research Board 83rd Annual Meeting, Washington D.C., USA.

Birattari, M., 2005. Tuning metaheuristics – A machine learning perspective. IOS Press, Incorporated, Amsterdam, Netherlands.

Bonsall, P., 1982. Microsimulation: Its application to carsharing. *Transportation Research Part A: General*, 16(5-6), 421-429.

Bonsall, P., Kirby, H., 1979. Microsimulation of Organised Car Sharing – Model Predictions and Policy Implications. Working Paper, Institute of Transport Studies, University of Leeds, England.

BostonGasPrices, 2014. Available at: http://www.bostongasprices.com (last accessed June 18, 2014).

Brook, D., 2004. Carsharing – Start Up Issues and New Operational Models. Presentation at Transportation Research Board 83rd Annual Meeting, Washington D.C., USA.

Bureau of Labor Statistics, 2013. Available at: www.bls.gov/oes/current/oes_ma.htm (last accessed December 13, 2013).

Bureau of Transportation, 2013. Available at: http://www.transtats.bts.gov (last accessed July 7, 2013).

Burkhardt, J., Millard-Ball, A., 2006. Who Is Attracted to Carsharing?. *Transportation Research Record: Journal of the Transportation Research Board*, 1986, 98-105.

Bussieck, M., Vigerske, S., 2014. MINLP solver software. GAMS Development Corporation.

car2go, 2012. Available at: http://www.car2go.com/ (last accessed July 2, 2012).

car2go, 2014. Available at: http://www.car2go.com/ (last accessed August 16, 2014).

Carlier, J.,1982. The one-machine sequencing problem. *European Journal of Operational Research*, 11(1), 42-47.

Catalano, M., Lo Casto, B., Migliore, M., 2008. Car sharing demand estimation and urban transport demand modelling using stated preference techniques. *European Transport*, 40, 33-50.

Celsor, C., Millard-Ball, A., 2007. Where Does Carsharing Work?: Using Geographic Information Systems to Assess Market Potential. *Transportation Research Record: Journal of the Transportation Research Board*, 1992, 61-69.

Cervero, R., 2003. City CarShare: First-Year Travel Demand Impacts. *Transportation Research Record: Journal of the Transportation Research Board*, 1839, 159-166.

Chan, N., Shaheen, S., 2011. Ridesharing in North America: Past, Present, and Future. *Transport Reviews*, 32(1), 93-112.

Chung, B., Yao, T., Friesz, T., Liu, H., 2012. Dynamic congestion pricing with demand uncertainty: A robust optimization approach. *Transportation Research Part B: Methodological*, 46(10), 1504-1518.

Ciari, F., Bock, B., Balmer, M., 2014. Modeling station-based and free-floating carsharing demand: a test case study for Berlin, Germany. Presentation at Transportation Research Board 93rd Annual Meeting, Washington D.C., USA.

Ciari, F., Schuessler, N., Axhausen, K., 2013. Estimation of Carsharing Demand Using an Activity-Based Microsimulation Approach: Model Discussion and Some Results. *International Journal of Sustainable Transportation*, 7(1), 70-84.

citizenn, 2014. Available at: www.citizenn.com (last accessed August 20, 2014).

CityDrive, 2014. Available at: www.citydrive.pt (last accessed August 29, 2014).

Cityhop, 2014. Available at: www.cityhop.co.nz (last accessed August 16, 2014).

Communauto, 2014. Available at: www.communauto.com (last accessed August 16, 2014).

Correia, G., Antunes, A., 2012. Optimization approach to depot location and trip selection in one-way carsharing systems. *Transportation Research Part E: Logistics and Transportation Review*, 48(1), 233-247.

Correia, G., Viegas, J., 2011. Carpooling and carpool clubs: Clarifying concepts and assessing value enhancement possibilities through a stated preference web survey in Lisbon, Portugal. *Transportation Research Part A: Policy and Practice*, 45(2), 81-90.

Costain, C., Ardron, C., Habib, K., 2012. Synopsis of users behaviour of a carsharing program: a case study in Toronto. Presentation at Transportation Research Board 91st Annual Meeting, Washington D.C., USA.

Cucu, T., Ion, L., Ducq, Y., Boussier, J., 2010. Management of a public transportation service: carsharing service, La Rochelle, France. Working paper.

DriveNow, 2014. Available at: de.drive-now.com (last accessed August 16, 2014).

Efthymiou, D., Antoniou, C., Waddell, P., 2012. Which factors affect the willingness to join vehicle sharing systems? Evidence from young Greek drivers. Presentation at Transportation Research Board 91st Annual Meeting, Washington D.C., USA.

Enoch, M., Taylor, J., 2006. A worldwide review of support mechanisms for car clubs. *Transport Policy*, 13(5), 434-443.

Exameinformática, 2014. Available at: exameinformatica.sapo.pt/noticias/mercados/2014-08-28-Mobiag-um-carro-para-as-ocasioes (last accessed August 28, 2014).

Fan, W., Machemehl, R., Lownes, N., 2008. Carsharing: Dynamic Decision-Making Problem for Vehicle Allocation. *Transportation Research Record: Journal of the Transportation Research Board*, 2063, 97-104.

Febbraro, A., Sacco, N., Saeednia, M., 2012. One-way carsharing: solving the relocation problem. Presentation at Transportation Research Board 91st Annual Meeting, Washington D.C., USA.

FICO, 2008. *Getting Started with Xpress - Release 7*. Fair Isaac Corporation - Xpress team, Leamington Spa, UK.

FICO, 2014. *Getting Started with Xpress, Release 7.7*. Fair Isaac Corporation, Leamington Spa, UK.

Firnkorn, J., Müller, M., 2011. What will be the environmental effects of new free-floating carsharing systems? The case of car2go in Ulm. *Ecological Economics*, 70(8), 1519-1528.

Fishman, L., Wabe, S., 1969. Restructuring the Form of Car Ownership: A Proposed Solution to the Problem of the Motor Car in the United Kingdom. *Transportation Research*, 3(4), 429-442.

Flexicar, 2014. Available at: www.flexicar.com.au (last accessed August 16, 2014).

Flightstats, 2013. Available at: www.flightstats.com (last accessed April 4, 2013).

GoogleMaps(a), 2014. Available at: https://maps.google.com/maps/ms?ie=UTF8&hl=en&om=1&msa=0&msid=104227318304000014160.00043d80f9456b3416ced&ll=43.580391,-42.890625&spn=143.80149,154.6875&z=1&source=embed&dg=feature (last accessed August 29, 2014).

GoogleMaps(b), 2014. Available at: www.google.com/maps (last accessed June 15, 2014).

autobloggreen, 2014. Available at: http://green.autoblog.com/2014/05/02/zipcar-honda-announce-oneway-carsharing-with-2015-fit/ (last accessed August 20, 2014).

Hu, P., Reuscher, T., 2001. 2001 National Household Travel Survey: Summary of Travel Trends. U.S. Department of Transportation, USA.

INTERFILE, 2012. Available at: www.excel.interfile.de/Autokostenrechner/autokostenrechner.htm (last accessed June 10, 2012).

Itoataxi, 2013. Available at: www.itoataxi.com/fare_info.htm (last accessed July 5, 2013).

Ji, Y., Geroliminis, N., 2012. On the spatial partitioning of urban transportation networks. *Transportation Research Part B: Methodological*, 46(10), 1639-1656.

Jorge, D., Correia, G., 2013. Carsharing systems demand estimation and defined operations: a literature review. *European Journal of Transport and Infrastructure Research*, 13(3), 201-220.

Jorge, D., Correia, G., Barnhart, C., 2012. Testing the validity of the MIP approach for locating carsharing stations in one-way systems. Proceedings of EWGT2012 - 15th Meeting of the EURO Working Group on Transportation, Paris, France, 138-148.

Jorge, D., Correia, G., Barnhart, C., 2014. Comparing optimal relocation operations with simulated relocation policies in one-way carsharing systems. *IEEE Transactions on Intelligent Transportation Systems*, 15(4), 1667-1675.

Kaspi, M., Raviv, T., Tzur, M., 2014. Parking reservation policies in one-way vehicle sharing systems. *Transportation Research Part B: Methodological*, 62, 35-50.

Katayama, K., Narihisa, H., 1999. Iterated local search approach using genetic transformation to the traveling salesman problem. Proceedings of the 1st

Conference on Genetic and Evolutionary Computation, Orlando, Florida, USA, 321-328.

Kek, A., Cheu, R., Chor, M., 2006. Relocation Simulation Model for Multiple-Station Shared-Use Vehicle Systems. *Transportation Research Record: Journal of the Transportation Research Board*, 1986, 81-88.

Kek, A., Cheu, R., Meng, Q., Fung, C., 2009. A decision support system for vehicle relocation operations in carsharing systems. *Transportation Research Part E: Logistics and Transportation Review*, 45(1), 149-158.

Klincevicius, M., Morency, C., Trépanier, M., 2014. Assessing the impact of carsharing on household car ownership in Montreal. Presentation at Transportation Research Board 93rd Annual Meeting, Washington D.C., USA.

Krumke, S., Quilliot, A., Wagler, A., Wegener, J., 2013. Models and Algorithms for Carsharing Systems and Related Problems. *Electronic Notes in Discrete Mathematics*, 44, 201-206.

Lane, C., 2005. PhillyCarShare: First-Year Social and Mobility Impacts of Car Sharing in Philadelphia, Pennsylvania. *Transportation Research Record: Journal of the Transportation Research Board*, 1927, 158-166.

Larsen, J., 2013. Bike-Sharing Programs Hit the Streets in Over 500 Cities Worldwide. Plan B Updates. Earth Policy Institute, Washington D.C., USA.

Lau, H., 2007. Network flow in A Java Library of Graph Algorithms and Optimization. Chapman & Hall/CRC, Taylor & Francis Group, Boca Raton, FL, USA, 254-272.

Li, L., 2011. Design and Analysis of a Car Sharing System Offering One-way Journeys. Msc Thesis, University of Wisconsin, Milwaukee WI, USA.

Litman, T., 2000. Evaluating Carsharing Benefits. *Transportation Research Record: Journal of the Transportation Research Board*, 1702, 31-35.

Lorimier, A., El-Geneidy, A., 2013. Understanding the Factors Affecting Vehicle Usage and Availability in Carsharing Networks: A Case Study of Communauto Carsharing System From Montréal, Canada. *International Journal of Sustainable Transportation*, 7(1), 35-51.

Lou, Y., Yin, Y., Laval, J., 2011. Optimal dynamic pricing strategies for high-occupancy/toll lanes. *Transportation Research Part C: Emerging Technologies*, 19(1), 64-74.

Lourenço, H., Martin, O., Stützle, T., 2001. A beginner’s introduction to iterated local search. Proceedings of the Fourth Metaheuristics Conference, Porto, Portugal, 1–6.

Lourenço, H., Martin, O., Stützle, T., 2003. Iterated Local Search, eds. by F. Glover, G. Kochenberger. Handbook of Metaheuristics, Kluwer Academic Publishers, 321–352.

Luke, S., 2013. Essentials of Metaheuristics, Lulu, second edition, Available at http://cs.gmu.edu/sean/book/metaheuristics/ (last accessed August 10, 2014).

Martin, E., Shaheen, S., 2011. Greenhouse gas emission impacts of carsharing in North America. *IEEE Transactions on Intelligent Transportation Systems*, 12(4), 1074-1086.

Martin, E., Shaheen, S., Lidicker, J., 2010. Impact of Carsharing on Household Vehicle Holdings – Results from North American Shared-Use Vehicle Survey. *Transportation Research Record: Journal of the Transportation Research Board*, 2143, 150-158.

Martin, O., Otto, S., 1995. Partitioning of unstructured meshes for load balancing. *Concurrency: Practice and Experience*, 7(4), 303-314.

Massport, 2010. 2010 Logan Airport Air Passenger Ground-Access Survey, Boston Logan Airport, Boston MA, USA.

Massport, 2014. Available at: http://www.massport.com/logan-airport/ (last accessed August 15, 2014).

Millard-Ball, A., Murray, G., Schure, J., Fox, C., Burkhardt J., 2005. TCRP report 108: Car-Sharing: Where and How It Succeeds. Transportation Research Board of the National Academies, Washington D.C., USA, 130-155.

Mitchell, W., Borroni-Bird, C., Burns, L., 2010. Reinventing the Automobile: personal urban mobility for the 21st century. MIT Press, Cambridge MA, USA, 130-155.

mobcarsharing, 2014. Available at: mobcarsharing.pt (last accessed August 20, 2014).

Mobiag, 2014. Available at: www.mobiag.com (last accessed August 29, 2014).

Morency, C., Habib, K., Grasset, V., Islam, M., 2012. Understanding members' carsharing (activity) persistency by using econometric model. *Journal of Advanced Transportation*, 46, 26-38.

Morency, C., Trépanier, M., Agard, B., 2011. Typology of carsharing members. Presentation at Transportation Research Board 90th Annual Meeting, Washington D.C., USA.

Nair, R., Miller-Hooks, E., 2011. Fleet management for vehicle sharing operations. *Transportation Science*, 45(4), 105-112.

Nourinejad, M., Roorda, M., 2014. A dynamic carsharing decision support system. *Transportation Research Part E: Logistics and Transportation Review*, 66, 36-50.

Papanikolaou, D., 2011. A New System Dynamics Framework for Modelling Behavior of Vehicle Sharing Systems, *Proceedings of the 2011 Symposium on Simulation for Architecture and Urban Design*, Society for Computer Simulation International, Boston, MA, USA, 126-133.

Pfrommer, J., Warrington, J., Schildbach, G., Morari, M., 2014. Dynamic Vehicle Redistribution and Online Price Incentives in Shared Mobility Systems. *IEEE Transactions on Intelligent Transportation Systems*, 15(4), 1567-1578.

Powell, M., 1964. An efficient method for finding the minimum of a function of several variables without calculating derivatives. *The Computer Journal*, 7(2), 155–162.

Powell, M., 1977. Restart procedures for the conjugate gradient method. *Mathematical Programming*, 12(1), 241–254.

Repoux, M., Boyaci, B., Geroliminis, N, 2014. An event-based simulation for optimising one-way carsharing systems. Presentation at the 14th Swiss Transport Research Conference, Monte Verità/Ascona, Switzerland.

Schmoller, S., Weikl, S., Muller, J., Bogenberger, K., 2014. Empirical data analysis of free-floating carsharing systems. Presentation at Transportation Research Board 93rd Annual Meeting, Washington D.C., USA.

Schrank, D., Lomax, T., Turner, S., 2010. TTI's 2010 Urban Mobility Report. Texas Transportation Institute, Texas, USA.

Schure, J., Napolitan, F., Hutchinson, R., 2012. Cumulative impacts of carsharing and unbundled parking on vehicle ownership & mode choice. Presentation at Transportation Research Board 91st Annual Meeting, Washington D.C., USA.

Schuster, T., Byrne, J., Corbett, J., Schreuder, Y., 2005. Assessing the potential extent of carsharing - A new method and its applications. *Transportation Research Record: Journal of the Transportation Research Board*, 1927, 174-181.

Shaheen, S., Cohen, A., 2007. Growth in Worldwide Carsharing: An International Comparison. *Transportation Research Record: Journal of the Transportation Research Board*, 1992, 81-89.

Shaheen, S., Cohen, A., 2013. Carsharing and Personal Vehicle Services: Worldwide Market Developments and Emerging Trends. *International Journal of Sustainable Transportation*, 7(1), 5-34.

Shaheen, S., Cohen, A., Roberts, J., 2006. Carsharing in North America: Market Growth, Current Developments, and Future Potential. *Transportation Research Record: Journal of the Transportation Research Board*, 1986, 116-124.

Shaheen, S., Rodier, C., 2005. Travel Effects of a Suburban Commuter Carsharing Service: CarLink Case Study. *Transportation Research Record: Journal of the Transportation Research Board*, 1927, 182-188.

Shaheen, S., Sperling, D., Wagner, C., 1999. A Short History of Carsharing in the 90's. *Journal of World Transport Policy and Practice*, 5(3), 16-37.

Shaheen, S., Wright, J., 2001. Carlink II: Research Approach and Early Findings. California PATH Research Record, Institute of Transportation Studies, University of California, Berkeley CA, USA.

Shaheen, S., Wright, J., Dick, D., Novick, L., 2000. Carlink: A Smart Carsharing System Field Test Report. California PATH Research Record, Institute of Transportation Studies, University of California, Berkeley, CA, USA.

Sioui, L., Morency, C., Trépanier, M., Viviani, M., Robert, B., 2013. How Carsharing Affects the Travel Behavior of Households: A Case Study of Montréal, Canada. *International Journal of Sustainable Transportation*, 7(1), 52-69.

Smith, S., Pavone, M., Schwager, M., Frazzoli, E., Rus, D., 2013. Rebalancing the Rebalancers: Optimally Routing Vehicles and Drivers in Mobility-on-Demand Systems. Presentation at The 2013 American Control Conference, Washington, D.C., USA.

Stillwater, T., Mokhtarian, P., Shaheen, S., 2008. Carsharing and the Built Environment: A GIS-Based Study of One U.S. Operator. Institute of Transportation Studies, University of California, CA, USA.

Stützle, T., 2006. Iterated local search for the quadratic assignment problem. *European Journal of Operational Research*, 174(3), 1519–1539.

Stützle, T., Hoos, H., 1999. Analyzing the run-time behaviour of iterated local search for the TSP. Proceedings of the III Metaheuristics International Conference, Rio de Janeiro, Brazil, 1-18.

The Bikesharing Blog, 2014. Available at: http://bike-sharing.blogspot.pt/2014/06/the-bike-sharing-world-first-week-of.html (last accessed August 29, 2014).

The Business Times, 2011. History of car sharing in Singapore. February 2, 2011.

The Straits Times, 2008. End of the Road for Honda Car Sharing Scheme. February 29, 2008.

Uesugi, K., Mukai, N., Watanabe, T., 2007. Optimization of Vehicle Assignment for Car Sharing System. *Knowledge-Based Intelligent Information and Engineering Systems*, 4693, 1105-1111.

USnews, 2013. Available at: http://www.usnews.com/news/articles/2013/06/05/the-exploding-growth-of-bikesharing (last accessed August 29, 2014).

Wang, H., Cheu, R., Lee, D.-H., 2010. Dynamic Relocating Vehicle Resources Using a Microscopic Traffic Simulation Model for Carsharing Services. Presentation at

Computational Science and Optimization (CSO), 2010 Third International Joint Conference, Huangshan, Anhui, China.

Wang, J., Lindsey, R., Yang, H., 2011. Nonlinear pricing on private roads with congestion and toll collection costs. *Transportation Research Part B: Methodological*, 45(1), 9-40.

Weikl, S., Bogenberger, K., 2013. Relocation Strategies and Algorithms for free-floating Carsharing Systems. *IEEE Intelligent Transportation Systems Magazine*, 5(4), 100-111.

Wie, B., Tobin, R., 1998. Dynamic congestion pricing models for general traffic networks. *Transportation Research Part B: Methodological*, 32(5), 313-327.

Wikipedia: Zipcar, 2012. Available at: http://en.wikipedia.org/wiki/Zipcar (last accessed June 1, 2012).

York, B., Fabricatore, D., 2001. Puget Sound Vanpool Marketing Assessment, Office of Urban Mobility, WSDOT.

You, P., 1999. Dynamic Pricing in Airline Seat Management for Flights with Multiple Flight Legs. *Transportation Science,* 33(2), 192-206.

Zheng, J., Scott, M., Rodriguez, M., Sierzchula, D., Guo, J., Adams, T., 2009. Carsharing in a University Community – Assessing Potential Demand and Distinct Market Characteristics. *Transportation Research Record: Journal of the Transportation Research Board*, 2110, 18-26.

Zhou, S., 2012. Dynamic Incentive Scheme for Rental Vehicle Fleet Management. MSc Thesis, Massachusetts Institute of Technology, Cambridge MA, USA.

Zipcar(a), 2014. Available at: http://www.zipcar.com/press/overview (last accessed August 10, 2014).

Zipcar(b), 2014. Available at: www.zipcar.com/boston (last accessed June 12, 2014).

ZipcarOneWay, 2014. Available at: http://www.zipcar.com/oneway (last accessed August 10, 2014).