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One-Way Carsharing Systems: Real-Time Optimization of Staff Movements and Operations

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Supervisor: Doctor Gonçalo Homem de Almeida Rodríguez Correia
Co-supervisor: Doctor José Manuel Caré Baptista Viegas

Thesis approved in public session to obtain the PhD Degree in Transportation Systems

Jury final classification: Pass with Distinction

Jury

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Abstract

Carsharing is a form of collaborative consumption that is being adopted in urban areas as a way to mitigate the negative effects of car dependency. It is a short-time period car rental service that gives access to a car whenever it is required. Cars can be located at stations, in station-based systems, or scattered in an operating area (subdivided by zones for operational purposes), in free-floating systems. The most complex carsharing system configuration is one that allows one-way movements, meaning that clients do not need to return the vehicle to where it was picked up. This freedom of movements gives more flexibility to users, being a critical factor to attract new clients to the system, however it can also lead to having a surplus of vehicles in some stations or zones, and a lack of vehicles in others, greatly unbalancing stocks in urban areas.

One-way free-floating carsharing systems have been the main focus of scientific work in recent years, namely in solving the vehicle imbalance problem through operator-based relocations. In an attempt to contribute to a better process of how to make these relocations, a real-time detailed decision support tool was developed in this thesis work, allowing to define periodic staff orders adapted to system status and aimed to maximize the profit of the company. The structure of the tool is composed by three main elements: a forecasting model, a staff activity assignment model, and a filter. Two different staff activity assignment models were developed in order to compare its effectiveness: a rule-based model and an optimization model. The rule-based model is composed by rules that initiate reactions to the system parameters, while the optimization model uses Mixed Integer Linear Programming to design the staff activity that maximizes the profit. The optimization model considers the option of staff moving together inside the same vehicle when sharing the exact same origin-destination pair (trip joining of staff). A simulator was developed and coded to test the real-time decision support tool. It considered stochasticity of demand. A test application was performed in a virtual environment with the characteristics of the Lisbon municipality.

By running the tool for several scenarios it was concluded that the number of relocations that can physically be performed by each staff member (considering human constraints and current technology) adding to the fact that not all relocations end up in accepted demand, provide a small improvement to the revenues which is unlikely to overcome the costs associated to staff activity (salaries, public transport title, fuel spent in relocation movements). Therefore, the best practice from a profit point of view is to keep enough members of staff to respond to maintenance requests, and fill their idle time by having them performing prioritized relocations (for example: vehicles not being used for an extended period of time). Responding to maintenance requests is of the utmost importance in order to guarantee that the vehicle unavailability does not escalate with time.

Key-words: carsharing, relocations, maintenance, optimization, simulation.

Resumo

Os sistemas de automóveis partilhados, na nomenclatura inglesa designados por "carsharing", são uma forma de consumo colaborativo referenciados como tendo a capacidade de mitigar os problemas relacionados com a dependência do automóvel em meio urbano. Estes sistemas proporcionam um serviço de aluguer de curta duração em que o cliente pode aceder ao veículo sempre que quiser, tendo apenas que fazer uma adesão prévia. Os automóveis podem localizar-se dentro de estações ou estar espalhados por uma área operacional (que é subdividida em zonas para um melhor controlo operacional). A configuração mais complexa destes sistemas permite liberdade de movimentos, significando que os clientes podem deslocar-se de uma determinada origem para um destino não coincidente com a mesma. Esta característica dá maior flexibilidade aos utilizadores e é um factor crítico para atrair novos clientes. No entanto, tem o inconveniente de gerar excesso de veículos em algumas zonas ou estações e falta de veículos noutras, criando desequilíbrios na relação entre a oferta e a procura do sistema.

Os sistemas com liberdade de movimentos e veículos espalhados por uma área operacional têm sido o objecto de estudo de recentes trabalhos científicos, em particular no que se refere à resolução do problema do desequilíbrio entre a oferta e a procura através de relocalizações desencadeadas por funcionários a cargo do operador. Numa tentativa de melhorar o processo de relocalização foi desenvolvido, nesta tese, uma ferramenta de apoio à decisão visando a optimização do lucro, com funcionamento em tempo real e que permite produzir planos periódicos de tarefas adaptados às características do sistema. A sua estrutura é composta por três elementos principais: um modelo de previsão de procura, um modelo para atribuição de tarefas para os funcionários e um filtro. Dois tipos de modelos de atribuição de tarefas foram introduzidos de forma a permitir comparar a sua eficácia: um modelo com base em regras e um modelo de optimização. O modelo com base em regras é composto por regras que desencadeiam reacções à alteração dos parâmetros do sistema. O modelo de optimização utiliza Programação Linear Inteira Mista para estabelecer as actividades dos funcionários que geram maior lucro. Adicionalmente, o modelo de optimização considera que os funcionários que se movimentam entre a mesma origem e o mesmo destino podem partilhar o mesmo veículo. Um simulador foi desenvolvido para proceder ao teste desta ferramenta de apoio à decisão. Considerou-se aleatoriedade entre previsões de procura e procura simulada. O teste foi realizado num ambiente virtual com as características do município de Lisboa. A partir dos resultados obtidos para várias simulações concluiu-se que o número de relocalizações que fisicamente podem ser realizadas por cada empregado, (considerando as condicionantes humanas e da tecnologia actual) adicionado ao facto de nem todas os movimentos de veículos resultarem numa viagem do cliente, permite apenas um ligeiro aumento das receitas, cujo valor é pouco provável que supere os custos associados à actividade dos funcionários (salário, passe de transporte público, combustível gasto nos movimentos de relocalização). Assim sendo, a melhor prática do ponto de vista da obtenção de lucro será a de manter um número adequado de funcionários para as necessidades de manutenção e preencher os períodos sem actividade destes com relocalizações prioritárias (por exemplo, veículos que ficam parados no mesmo sítio sem serem utilizados durante um largo período de tempo). A resposta a pedidos de manutenção é da maior importância por forma a garantir que o número de veículos indisponíveis não aumente com o tempo, afectando o nível de serviço do sistema.

Palavras-chave: automóveis-partilhados, relocalizações, manutenção, optimização, simulação.

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This is it. The research is done and the document is ready. It was not easy. It never is. Today I am able to draw a smile whenever I flashback and realize all the walls that stood between me and my way. Difficulties are there to challenge you, making you wiser and stronger.

The path to finish this dissertation was not a straight line. It was a labyrinth full of dead ends and ways that led me back to previous places. However, this is what made it interesting. Knowing everything beforehand would be like riding a car from home to work once again, you wouldn't feel it or learn anything new about it. One cannot be disappointed noticing that a big part of the work is invisible to the final document. It must be accepted as a consequence of trying to fit years of research inside a limited number of pages structured for others to read.

This research was only possible due to the contribution of individuals and institutions, to whom I present my gratitude. I would like to acknowledge the financial support of:

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[2] Viability analysis of different carsharing system configurations through an innovative large scale agent based simulation model.

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1 Introduction

1.1 Motivation

The evolution of the personal transportation system was marked by the access to affordable technologies that could make people travel faster. During the last century, everything was made to receive the car as the ultimate tool for transportation having behind it the strategy of using such technology as an economic development leverage. Predict and provide policy approach, which consisted in providing infrastructure for the predicted future transport demand, marked the urban landscape. Road transport infrastructure was improved in such a way, that it stimulated people to adopt the private vehicle as their main mode of transportation. The unlimited use of private vehicles in dense urban areas became unbearable as the number of cars got close to the saturation level, which had and still has a negative effect on economy and society.

Sir Rod Eddington wrote in a document whose purpose was to advise the UK government on the long-term and sustainable links between transport and the UK's economic wealth: "As economic growth leads to increasing [transport] demand, an economy can ultimately become the victim of its own success because as congestion rises, so it starts to dampen growth. This is the most direct way in which transport will impact on growth in a developed country" [Eddington, 2006]. Studies confirm that the increasing demand led to daily economic losses due to traffic congestion.

According to Schrank et al. (2012), in 2011 Americans spent a total of 5.5 billion hours stopped in traffic, which makes 38 hours per person per year, on average. The corresponding cost was 121 billion dollars in wasted fuel and lost productivity. Congestion also affects the transport of goods. Freight deliveries arrive with delays to their destination, or are more expensive. Congestion of the transportation network decreases productivity, increasing the cost of transportation services. This is due to higher costs of fleet operations, decreased vehicle utilization, decreased fuel efficiency, increased emissions due to idling, and decreased drivers' productivity. It is estimated that for trucks travelling in the United States the unexpected delays can increment the cost from 50 to 250 percent [FHWA, 2004]. Bus services also suffer delays to their timetable due to road congestion affecting passenger waiting time and travel time and, therefore, decreasing service reliability. For the bus-operating companies, the decrement on reliability levels brings associated costs due to a loss in kilometers travelled and lower fleet utilization.

The predict and provide policy and its already known phenomena of traffic induction shaped today's ground level landscape, which is often composed by cars parked, moving or stopped in a bottleneck, and people trying to move, breath and live between them. Looking at nowadays urban landscape, streets are mostly used for vehicles to move and park. Large avenues created to reduce congestion, work like barriers to the movement of soft modes and increase the safety risk due to over speeding. Pollution and noise, mainly from car traffic, is destroying the quality of air and the quality of life inside urban areas.

During decades everything was done to receive the car as the ultimate tool of economic development, but the scarcity of resources limits growth. Road and parking infrastructure cannot increase indefinitely, since urban space is finite and it has to serve many other purposes and interests of the universe of residents, workers and visitors to maintain its livability. The heavy presence of cars in urban landscapes is creating unbalanced situations. Therefore, predict and provide is no longer considered in the current trends of modern urban design. Nowadays the approach is to create more sustainable urban environments, and for that the vicious car cycle is starting to be inverted by giving greater priority to more sustainable forms of transport (e.g.: public transport and soft modes). The challenge is to find a more proficuous equilibrium between public transport, car and soft modes, by using the existing infrastructure as a raw basis. This perspective is known as the Transport Demand Management (TDM) approach.

Car ownership is one of the barriers to face in order to change the urban environment and transportation system. Owning a car affects the individual's choice of transportation mode concerning the optimization of cost. And the freedom of using the car to perform all daily trips has a negative effect on society, namely in urban spaces (pollution, use of space for parking). Cars are notoriously underutilized. The average car occupation rate is well below two people. In the US the car occupation rate was 1.55 passengers per vehicle in 2011 [Center for Sustainable Systems, 2014], which is less than half of the average total capacity of each vehicle. In urban areas, cars stay parked most of the time and occupy as much space as their driver's workspace, wasting precious space and reducing the livability of streets. The typical American car stays parked approximately 96% of the time, while the remaining time is distributed in 2.6% driving (productive use), 0.8% looking for parking and 0.5% sitting in congestion [Heck and Rogers, 2014].

Today the majority of drivers are simultaneously owners or co-owner of a vehicle. In order to promote a better use of the automobile, authorities need to invest in re-education of drivers and owners. The main options to perform this change are: limiting car use through physical limitations (e.g.: reduction of road capacity, parking spots), by introducing restrictive regulations (e.g.: limited traffic zones, low emission zones), by using pricing strategies (e.g.: parking meters, urban tolls, congestion pricing); by improving infrastructure to comfortably accommodate soft modes, or by promoting alternative transport options (e.g.: carpooling, carsharing, shared taxi, express mini-bus).

Some city authorities are already taking capacity from the dominant road transport mode, the private car. In theory, the removal of capacity from a saturated system could be thought as a way to create more chaos and contribute to adverse economic impacts. But practice evidence allowed concluding that what really happens is a phenomena designated by traffic evaporation. Traffic evaporation is considered to be the opposite of traffic induction and equally relies on the complexity and adaptability of driver reaction to changes in road conditions. A report made in 1998 by the UK Department for Environment Transport and the Regions (now the Department for Transport Local Government and the Regions) and London Transport (now Transport for London) showed how drivers adapt to the reduction of road capacity: "Short-term: Initial cramming of roads was followed by searching for alternative routes and times to travel; Medium-term: More varied and flexible trip planning; changing mode of transport; reviewing the need to travel; trip combining; Long-term: Switching locations of activities or even home or workplace." [Cairns et al., 1998].

The car, as we perceive it, a safe multi-purpose individual transport mode, will continue to be present in urban areas due to its comfort and convenience. Although, as urban population grows, the ability of urban space to accommodate more vehicles will be even more limited. Therefore, streets will need to open space for people and be less look-alike car storage facilities. Some cities in the world already started to limit vehicle access to central urban areas by introducing fees (e.g.: Singapore, London, Stockholm, Milan), in order to mitigate problems related to the excessive presence of vehicles, such as congestion, air and noise pollution. Still, every person that lives in a city should continue to have the opportunity to access a car when needed, and this can be done without the today's ownership levels, with great benefits for the individuals, and without compromising the health and wealth of the urban environment. Vehicle sharing needs to be viewed as a complementary solution for the access restrictions authorities are implementing or intend to implement. Vehicle sharing, besides contributing to the decrease of individual vehicle usage inside urban areas, is able to promote the use of other transport modes. Carsharing, in particular, as a service that promotes vehicle sharing can be a feasible option for reducing car ownership and, consequently, reduce the underuse level of cars stocked on todays' streets [Shaheen and Cohen, 2007].

Carsharing has been intensively studied and has been the focus of transportation research on the last decade, following the appearance of new carsharing organizations and the growth of the existing ones. New types of available services, more adapted to users' needs, were implemented to increase the market share, namely one-way movements and free-float vehicle locations. This introduced complexity to system operations and encouraged the research community to find optimal answers to cope with the new challenges, specifically concerning to planning maintenance and vehicle relocations, and assist carsharing organizations to efficiently reach their goals. Although, a lot has been made, as it can be seen from the published research, still more research is needed in understanding the operation of such urban systems as they grow in fleet size and trip purpose.

1.2 Objective and research questions

The thesis objective is to go further on analyzing the effect of staff daily tasks, including maintenance and relocation, on a one-way free-float carsharing system. This research is integrated in the InnoVshare[3] project financed by the Portuguese Science Foundation. The research questions to be addressed during the research process are:

1) Is it feasible to develop a real-time optimization methodology to delineate staff activity? The operator needs to send staff orders that optimize the overall system costs. Real-time optimization decreases the demand forecast uncertainty level, allowing, in theory, to a faster adaptation to unexpected scenarios. Having an optimization procedure, with enough complexity to consider these daily tasks performed by staff, and

[3] Project identification code: PTDC/ECM-TRA/0528/2012

retrieving solutions on time, theoretically has the potential to increase the competitiveness of a carsharing company. This is only possible if the processing time does not compromise the timely application of the tasks defined by the optimization output.

2) Is the act of joining staff in carsharing vehicles able to decrease maintenance and relocation costs? The idea of using the remaining capacity of vehicles driven by a member of staff to support other staff movements has not, to the best of our knowledge, been studied yet.

3) Can real-time optimized orders for relocations and maintenance have a considerable impact in the overall profit? Maintenance is fundamental to maintain service quality and vehicle active time. Relocations are needed to move the vehicles to where they are needed. Both are part of staff activity, but what is its importance regarding the overall profit for the service provider.

1.3 Methodology

Once the objective and research questions are defined, it is necessary to have an overall view and understanding of the carsharing concept, systems, and research. With this purpose, a literature review is performed, first by analyzing the state of the practice and, then, the state of the art. The state of the practice analyses the context of carsharing, specifically the concept, history, and carsharing systems characteristics of previous and active programs. The state of the art examines the published research which is a reference for the scientific contributions of this dissertation. The state of the art process is based on a task of the InnoVshare project carried out by other members, nonetheless it is complemented with the addition of other significant research outputs.

Subsequently to the literature review, two independent lines of research are established: the gathering of mobility data concerning to the chosen case study which will allow the simulation of mobility in that region, and the development of a real-time decision support tool prepared to work within the simulator.

The gathering of mobility data consists in a survey given to the population of the case study area in order to obtain the necessary sample to proceed with the trip demand estimation for carsharing. The development of the survey is part of this dissertation, while the task that resulted in the demand for carsharing was partially performed by other members of the InnoVshare project and complemented in order to suit the specificity of this research.

The other line of research consists in three main activities: the development of a MIP model to optimize staff activities, the creation of a tool to support operator decisions in real-time, and the integration of this tool within the simulator. A simulator is designed and developed specifically to test the real-time decision support tool. The carsharing realistic demand data obtained feeds the simulator in order to test different scenarios. The tests allow taking conclusions about the performance of the developed tool under different scenarios.

An overall view of the methodology is schematized in Figure 1.

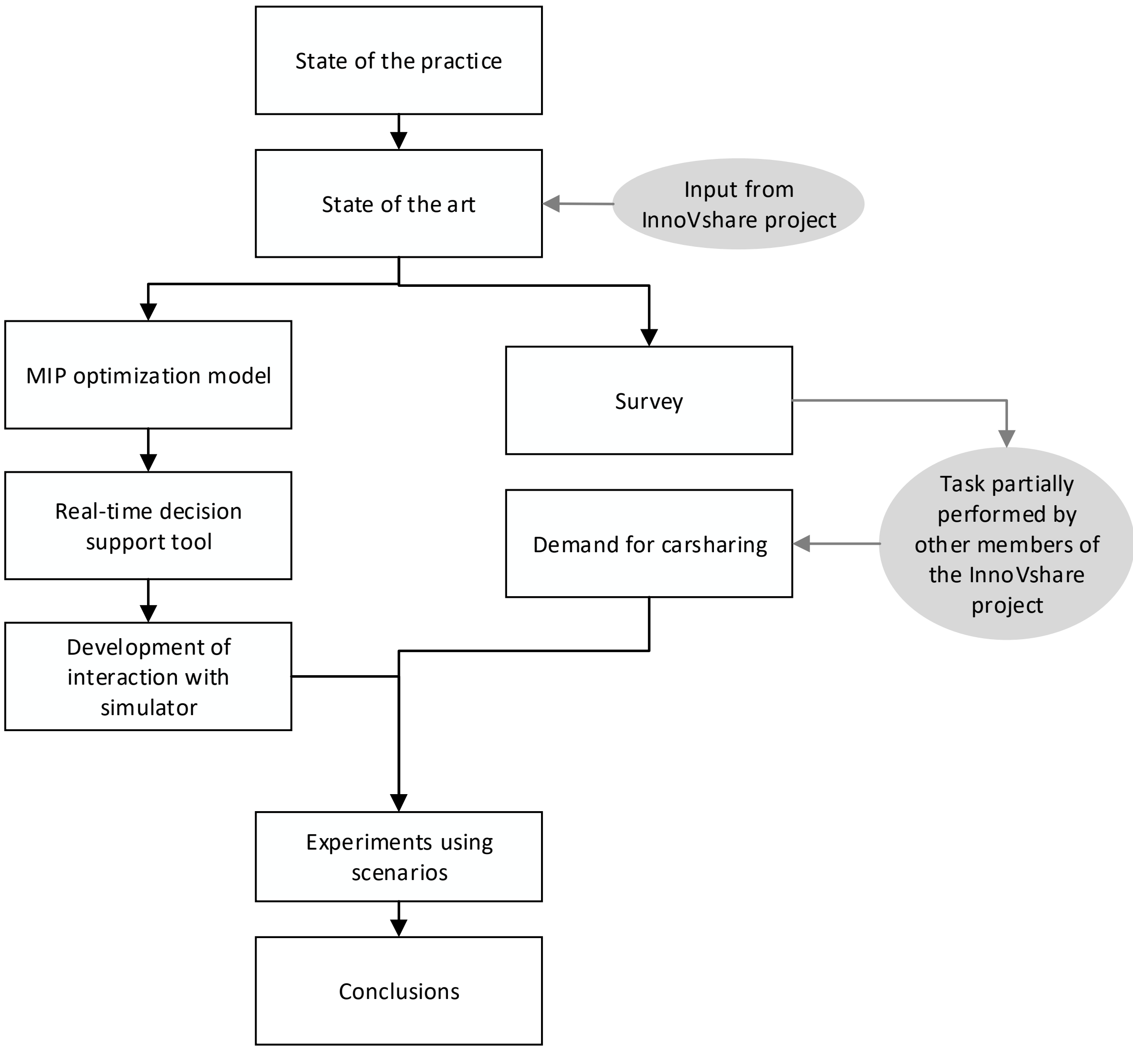


Figure 1: Dissertation methodology

1.4 Structure of the dissertation

The research is structured in six chapters. Each chapter and the correspondent content are described in the following:

This first chapter, "Introduction", includes a brief presentation and contextualization of the research study. It starts with an explanation of what motivated this research, then the objective is defined and the research questions are enumerated and described. This is followed by an overall view of the adopted methodology and ends with the description of the structure of the dissertation.

Chapter 2, "State of the practice", starts by framing carsharing in the collaborative consumption context, namely in terms of vehicle sharing. The different types of vehicle sharing are presented and described, making the differentiation between time sharing and space sharing, and highlighting the different types of time sharing of vehicles, in which carsharing is included. It follows a detailed explanation of carsharing, namely how the concept is defined, how it works, and why carsharing is important in nowadays panorama. Then it is presented the past and the present of carsharing. A brief history section presents the first developments in each continent, as well as the situation in Portugal. Then, an overview of today's services is described individually. This allowed to gather the main characteristics of the most important carsharing services that exist nowadays, namely in terms of business models, operational characteristics, service characteristics and technology level.

Chapter 3, "State of the art", includes an extensive literature review of the scientific research on the topic, namely about the estimation of carsharing demand, and one-way carsharing modelling (the car does not need to be returned to a station). The analyzed scientific research outputs related to the estimation of carsharing demand includes: studies that use surveys to members or data from the existent carsharing organizations to characterize the carsharing market; that analyze the factors behind individual choice of carsharing; that define thresholds or micro geographic characteristics related to the service potential success; studies that approach the influence of operational factors in demand; and studies that estimate demand by using classic and microsimulation approaches. Concerning to one-way carsharing modelling the different approaches to solve the vehicle stock imbalance problem are analyzed, being subdivided in: operator-based relocations, user-based relocations and trips selection. Since the focus of this dissertation is on the use of operator-based relocations, the most influent research publication in the operator-based relocations branch is depicted. The chapter ends with considerations about the bibliographic references analyzed and its importance for this research study.

Chapter 4, “Real-time decision support tool”, describes the tool developed to aid in the process of assigning operator-based relocation movements and maintenance tasks to staff in real-time, by using a rolling horizon approach. The three elements of the real-time decision support tool are presented individually (forecast model, assignment model and filter). For the forecast model, different forecast processes to predict demand are presented, namely activity based microsimulation approach and time series forecasting. For the assignment model, two alternatives are presented: a rule-based model and an optimization model. The rule-based model is a simple algorithm developed to serve as a comparison to the optimization model. The optimization model is a Mixed Integer Linear Programming model designed to produce an optimized assignment plan. In the following it is described how the real-time decision support tool interacts with the system through the usage of a background database, which registers client, vehicle and staff movements and activities. It is also detailed the input data needed to use the developed real-time decision support tool. Indicators to assess the performance of the system are recommended. This chapter ends with the presentation of the simulator built to emulate a real system behavior.

Chapter 5, “Application to the case study”, describes the application of the real-time decision support tool to the Lisbon municipality. It starts by presenting the characteristics of Lisbon municipality, as well as Lisbon Metropolitan Area, which is the major area of influence of Lisbon municipality in terms of commuter trips, and it makes a reference to the previous and current carsharing services in Lisbon. Then a procedure to obtain the carsharing potential demand data is described. Firstly, the development of an online survey to gather information about mobility is described, as well as the strategy to unbias the sample by recurring to Computer Assisted Personal Interviews (CAPI), and how the data was filtered to eliminate invalid entries. Secondly, demand is estimated by using an activity based microsimulation approach. For this purpose, a synthetic population for the Lisbon Metropolitan Area is defined, and a set of activities is established for each individual based on statistical data. Then, for each of the necessary trips that the individual needs to perform in order to undertake its activities, a transport mode is assigned. This attribution is made by using a previously calibrated discrete choice model, where the available modes were defined by location and application of rules related to car ownership and entitlement of driver's license. The resulting carsharing demand is characterized. Afterwards, it is included a description of all the data used in the simulation. Then, the results of the simulations are presented, being subdivided by the three demand scenarios considered. The chapter ends with the analysis of results.

Chapter 6, "Conclusions", presents a broad perspective of the work developed, including the main conclusions, as well as future lines of research.

2 State of the practice

2.1 Introduction

Sharing is a concept that has been around since the beginning of civilization, and is a consequence of living in community. We share knowledge and information. We share resources like housing, public facilities (transportation, health care, education, sports and leisure), vehicles, gardens, food, and also our time. Today, we are in the digital era. We have access to everything at the speed of a click, from news, to photos, files, books, music, etc. Sharing is the concept behind the success of the World Wide Web. The World Wide Web promotes fast connection between people taking sharing into another level. We share because of the benefits behind it. Even if we do not immediately realize them. There is some sort of humanity in sharing that connect us to other people and can make us feel better. Sharing has the potential to save resources and reduce our ecological footprint. We also share because other people give or can potentially attribute value to our "waste", creating new economic systems. These economic systems based on sharing are broadly denominated by collaborative consumption.

Collaborative consumption, peer-to-peer economy, micro-entrepreneurship economy, sharing economy are names that designate the idea of accessing rather than owning. In other words, the use of objects, having the benefits of ownership, without the burdens and costs associated to it. Collaborative consumption is based on systems of organized sharing, bartering, lending, trading, renting, gifting, and swapping. It is an alternative to traditional forms of buying and ownership, which has a lower environmental footprint. The collaborative consumption systems can be organized in three types [Botsman and Rogers 2010]:

> **Product service systems** - consists in having companies offering goods as a service rather than selling them as products, privately owned goods shared or rented peer-to-peer. It is appealing to people that need the benefits of a product, but do not want to own it;

Redistribution markets - involves moving used or pre-owned goods from somewhere they are not needed to somewhere they are. The goods can be given for free, swapped or sold for cash;

Collaborative lifestyles - related to having individuals with similar needs and interests gathering in groups to share and exchange less tangible assets. These exchanges happen mostly on a local or neighborhood level (e.g.: sharing a house, a boat) or on a global scale (e.g.: peer-to-peer lending).

2.2 Collaborative Consumption

In general, collaborative consumption is a way to help communities to reduce and reuse objects ("reduce, reuse, and recycle"), saving money, energy and the environment. Sharing things rather than buying them new, has the power to reduce the load on Earth natural resources.

Collaborative consumption is also associated to the sharing of households or workspaces, and to owners that rent their assets (usually expensive ones) when they are not being used, to reduce costs or create profit. These are denominated by collaborative businesses.

The internet, and particularly social media, has reduced the cost of running a collaborative business. It gave the opportunity for a normal person to run a micro-business, by trading or renting their personal objects. Specialized websites were created to allow owners to advertise their belongings inside a larger network of users. This way people with excess supply can easily find demand, unlocking viable economic activity. The trust issue is toned down by the creation of profiles and by evaluations. Renters promote their asset using photos and other information, the veracity of which is evaluated by users. Users have their own profiles that can be seen by renters. These profiles include information about previous behaviors given by other owners. This exchange of information is important to build confidence between users and owners.

2.3 Vehicle sharing

Vehicle sharing is a form of collaborative consumption that potentially is able to mitigate high car dependency related problems of urban areas. Different types of vehicle sharing examples can be found in cities around the world, hence it is important to categorize them. The first clear classification for vehicle sharing is that vehicles can be shared in time or in space.

Time-sharing designates the sharing of the same vehicle or a fleet of vehicles by different people, each one using it independently at different time windows. Taxi service is the most widespread way of time-sharing of cars, in this case using a driver. An individual can call, wave, find an available taxi on the street and use it, by telling to the driver the origin (in the case of a phone call) and destination. There are other services of time-sharing with driver, which can be called chauffeur-driven services. For example, Uber is an on-demand chauffeur-driven service similar to taxi. You use an app to call a vehicle and in minutes you can have a driver in a car arriving at your side. The service automatically charges the credit card a base fee, a distance fee, when travelling over 11mph, and a time fee, when travelling below this speed. Uber is currently available in 54 countries and still expanding [Uber website, 2015].

The services that promote the sharing of vehicles without a driver can be subdivided in long-term and short-term services.

Long-term services have a minimal renting period of one day. For long-term rentals you need to go to the rental agency, leave your data, a deposit, and sign a rental contract, in order to pick up the vehicle. At the end you typically need to deliver the vehicle at the same agency to receive your deposit. Rent-a-bike and rent-a-car are two types of long-term services. Rent-a-bike systems are mostly local, meaning that you have different local renters at each city and need to deliver the bicycle to the place where you picked it up. Rent-a-car companies are national and multinational (e.g.: Avis, Hertz, Europcar), this adds the opportunity to deliver the rented car in a different agency. Nevertheless, you need to pay a fee, which corresponds to the costs for the company to relocate the vehicle back to the first agency.

Short-term services are the ones that allow renting a vehicle for less than a day. They are intended to complete the gaps of public transport: fill the first/last mile of daily trips, to perform trips which are not well served by the public transportation system, or just to transport shopping bags or other heavy goods. In order to get access to short-term rental vehicles, you previously apply to the service, giving your data and paying a membership fee. Then a card is given to allow you to have access to the fleet of vehicles. That card can be the same as used for public transport, if it fills the necessary technological requirements. You can use any vehicle of the fleet as many times as you want and the cost of the service will be charged and debited from your account. In some services one-way movements are allowed, this means that you can return the vehicle into a different station than the one where you picked it up.

Bike and carsharing are the most common short-term vehicle sharing services. Vélib in Paris and Barclays Cycle Hire in London are two examples among hundreds of bikesharing services in Europe. The short-term sharing of cars is the main scope of this work and, thus, is analyzed thoroughly in the next subchapter.

Space sharing of vehicles consists in sharing the empty seats on a trip, in order to increase the occupancy rate of the vehicle. On a trip, a five seat car with only the driver is about the same, in terms of energy consumption and CO_2 emissions, as if the car had more passengers. Increasing the occupation of the vehicle can contribute to reduce the number of vehicles on the road, and consequently the energy consumed and the environmental impact. People who share the space of their vehicles have the opportunity to share expenses and save money.

Space sharing is technically denominated by carpooling or ridesharing. Carpooling is about matching and sharing trips with potential passengers. Sometimes this is done informally with your neighbors, friends or family. Money exchange is not mandatory, but is becoming more or less instituted. Internet makes it easier to increase carpooling activity by facilitating the matching between drivers and potential passengers. Websites vary from a virtual wall were you can post your offers (such as craigslist, deboleia.com, blablacar), to one that uses social network information (e.g.: Facebook API) to better identify the profile of users and drivers and use it in matching algorithms (zimride.com). With social network information, drivers can be matched with people who work at the same company, go to the same school, or have mutual friends. This reduces the inconvenience of ridesharing with a stranger.

An important note, if the driver wasn't initially traveling in the direction of the potential carpoolers, it is considered taxiing, or chauffeur driven service (Uber like systems). Today ridesharing is accessible on mobile phones, making it possible to share vehicles instantly as an on-demand service, at prices lower than cabs. Lyft.me and Side.cr are two examples of this type of platforms. Using a mobile phone a driver sends information about his vehicle position and availability. Users can request a trip to the driver and check in every instant the current position of the vehicle requested. A minimum price is recommended, but driver and user can agree on another value. On demand space sharing system is becoming, in some circumstances, a time sharing with a driver, because owners see this as an opportunity to use their spare time to make extra money. The referred platforms keep a fee of about 20% from all the trips performed by the users [Cutler, 2012].

Figure 2 summarizes the previously presented information by using a schematic overview of the existent vehicle sharing types that exist nowadays.

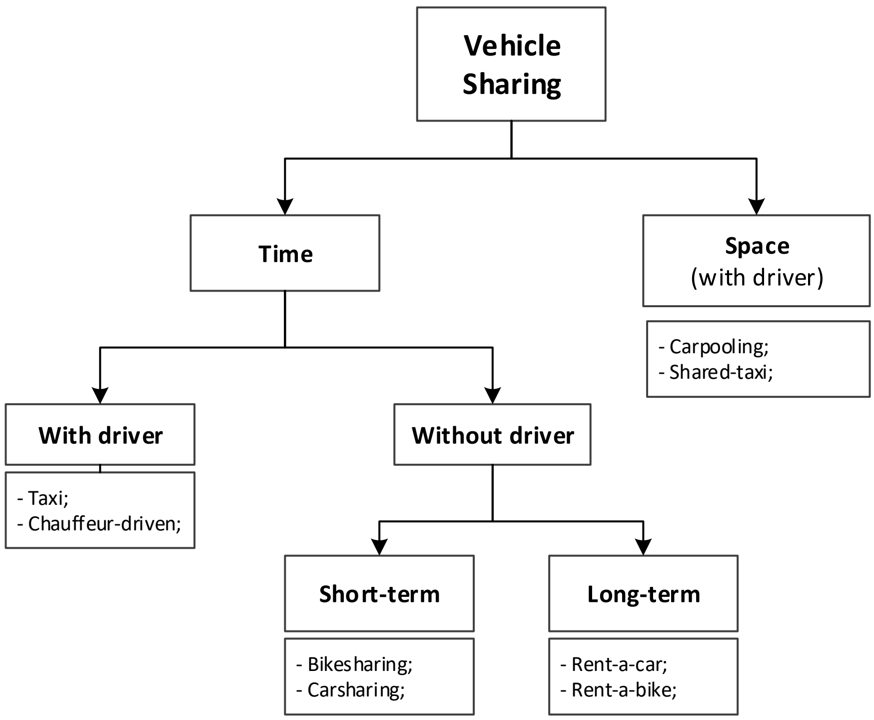


Figure 2: Types of vehicle sharing

2.4 Carsharing

Carsharing appears in different forms and can be described as being an open-access shared vehicle program, intended to provide cars for occasional trips. Carsharing normally includes the following features: an organized group of participants; one or more shared vehicles; a decentralized network of parking locations; rentals for short-time periods (less than a day); and self-accessing vehicles [Millard-Ball et al., 2005]. The main idea of this concept is that people who only occasionally need to drive a car, pay a membership fee to have access to cars positioned inside stations or parked at streets in a certain urban area. Members typically may use mass transit for work commutes, yet have access to a car when needed without buying, owning and maintaining a vehicle.

2.4.1 Definition

The definition of carsharing varies from author to author. Nonetheless, the basic idea of having a fleet of shared vehicles that are rented for short periods of time is commonly accepted.

Central and local government entities had the necessity to define carsharing for legal purposes. This is important to define which organizations can be considered carsharing, and therefore receive support, such as, funding, tax breaks, free parking or other sort of incentives.

Millard-Ball et al. (2005) recommends, in the TCRP Report 108, the use of the definition adopted by the Washington State because it provides the "most concise and effective way" to address the fundamental points of carsharing. The Washington State defines carsharing as "a membership program intended to offer an alternative to car ownership under which persons or entities that become members are permitted to use vehicles from a fleet on an hourly basis". This is a generalized definition that is wide-ranging. Other public entities have a more detailed definition of carsharing.

The Planning and Transportation Committee of the City of Toronto (Canada) defines carsharing as: "the practice where a number of people share the use of one or more cars that are owned by a profit or non-profit carsharing organization. To use a vehicle a person must meet the membership requirements of the carsharing organization, including the payment of a membership fee that may or may not be refundable. Cars are reserved in advance and fees for use are normally based on time and miles driven. Carsharing organizations are typically residentially based with cars parked for convenient access within the area of the membership served by the organization" [City of Toronto, 2000].

The Swedish National Road Administration goes a little bit further by specifying the difference between a local carsharing cooperative and a company. According to this institution: “Carsharing means that a number of persons share the use of one or more cars. Use of a car is booked beforehand, the user paying a fee based on the distance driven and the length of time the car was made use of. Although this is similar in some ways to traditional car rental, it differs in the possibility it provides of booking a car for short periods of time and in the rental agreement being made for an extended period of time, rather than each time a car is used. In addition, each household has its own set of keys, and cars are placed in the vicinity of where members live. In the case of company carsharing, the keys and the cars are being readily available at the place of work. Key is here equal to smartcard or similarities” [Schillander, 2003].

To sum up, it can be said that carsharing refers to the short period car rental service intended to replace private vehicle ownership, giving access to a vehicle whenever is required, while providing an incentive to minimize driving. The main characteristics that define a carsharing service are: different users can use the same vehicle at different times; vehicles can be rented for periods of time lower than one day; a member has to pay a fixed cost and a variable one, being the fixed part of the cost an annual fee for insurance and registration, and the variable part linked to the use of the vehicle (time, mileage); insurance and fuel are already included in the time and distance related price.

2.4.2 How it works

As discussed above, carsharing is a service that promotes the shared use of vehicles on a membership basis.

To become a member is necessary to apply to the service, and some documents need to be presented, namely ID, driver’s license, credit card or bank account data. The user is usually charged for an application fee. Besides the application fee, an annual and monthly fee can also be charged. It is important to notice that some systems have age restrictions. To access a vehicle of the carsharing system, the user can do a reservation and, after that, go to the vehicle and open it. To open the vehicle the user can use a key or swipe a card through a card reader installed near the vehicle windshield. Once inside the vehicle he may need to type his PIN code into an input device, and enter additional information (e.g.: trip data, clean status). To start the vehicle the user uses the car key, that if not already in his possession, it is stored inside the vehicle. In some vehicles there is no key and the user only needs to press a button. The user can drive anywhere, but he needs to take into account that the renting period only finishes after he returns the vehicle into the required place: the same station for roundtrip station-based services; the same or another station for one-way station-based services; or somewhere inside the operating area for operating area based services. After the car is returned to the required place the user can finish the renting period, by locking the car using the key or swiping his card. The cost of the trip is debited from the user's credit card or bank account. The bill is normally based on trip time and distance.

2.4.3 Why carsharing

Carsharing is becoming part of urban areas as people understand that collaborative consumption has advantages for the individual and for the society. For the individual, choosing carsharing service in detriment to other modes can be related only to convenience, although the aggregated result of users migrating to this mode of transport contributes to the reduction of the burden on transport and the environment.

Carsharing reduces car dependency and social exclusion. Until recently, you needed to own a car in order to use one. With the arrival of carsharing services, transportation users have the opportunity to use a car whenever they want, on a pay as you go basis, without worrying about buying one. Users can be free of fixed and some variable ownership costs (parking, taxes, insurance, and maintenance). Studies in US and Canada showed that 15% to 32% of carsharing members sold their personal vehicles and 25% to 71% avoided the purchase of a car because of carsharing. [Shaheen et al., 2009].

It is true that rent-a-car services were already available, but its pricing structure and complex renting process makes it not suitable for short trip durations. Carsharing introduced simplicity, quickness and flexibility in the renting process, making it more convenient to users.

Another convenience of carsharing is assuring vehicle availability, between commuting trips, even if you did not bring a car with you. This gives you the freedom of choosing the most adequate transport mode for your daily trips, even if you need a car in the middle of the day.

Carsharing has the potential to relief the number of stationary vehicles in urban areas, since one shared car can replace 9 to 13 owned vehicles (including shedded autos and postponed purchases) [Martin et al., 2010]. There is no reason of putting more thousands or millions of cars on roads if they stay idle more than 90% of the time [Santos et al., 2001]. Liberating hectares of space that nowadays are assigned to parking and re-assign it to other uses can potentiate street livability.

As mega cities continue to grow and change, the efficient usage of public space needs to be more valued. Carsharing is able to act on the demand side, reducing car usage levels and promoting awareness of the existence of other transport alternatives. In the Netherlands a study shows the influence of carsharing systems in 2000. People were driving less after participating in carsharing programs – the difference was as high as 11,000 kilometers. Individuals who did not own a car before participating drove a bit more after joining (370 km more in average) [Derkse, 2000]. A Swiss study concluded that without carsharing service available, the kilometers travelled with public transport would decrease by 12%, and, in contrast, the kilometers travelled by car would increase 28% [Haefeli et al., 2006]. In fact, carsharing users choose transport modes more wisely [Loose, 2009] and make their trips more efficient for the individual (micro level) and society (macro level). The micro level impacts are the reduction of costs and travel-time. In a macro level, each car that is not using the roads represents an additional gain in terms of reducing congestion and pollution.

Carsharing can help carmakers. The automobile industry is trying to implement electric vehicles technology, but its success is being deterred by battery range and cost. On the other hand, small steps are taken towards autonomous driving vehicles in order to reduce human error. Innovation has its price and the market is not prepared to pay the difference in cost for new technology that has equal or less perceived performance than current technology. Carsharing companies are keen to promote technologies labelled as green and cities can be a test bed for early market deployment. Car companies can even become mobility service providers by offering intelligent mobility services, such as carsharing. And this way create other type of vehicles, more adapted to the urban needs. BMW (with DriveNow) and Daimler-Benz (with Car2Go) are examples of car companies which have adhered to the carsharing business.

2.4.4 History of carsharing

Europe was the host of the very first carsharing programs. The first reference to carsharing is Selbstfahrergenossenschaft, known also as Sefage, a house cooperative carsharing program in Zurich, Switzerland, in 1948 [Shaheen et al., 1999]. Other services emerged in the 1970's and 1980's: Procotip (1971) in Montpelier, France; Witkar (1973) in Amsterdam, The Netherlands; Green Cars in UK, Vivalla Bil (1983) in Orebro, Sweden [Millard-Ball et al., 2005]. This first wave of carsharing experiments did not last.

From the enumerated services, Witkar in Amsterdam is a curious example of a service ahead of its time and, for that reason, it is worth to write some more lines about it.

In 1973 Witkar was a service with postmodern characteristics, since it made a complete rupture with the conventional systems and technologies of that time in order to create a new one that had the potential to change society for the better. The service was composed of three-wheeled electric vehicles specially designed for urban areas and controlled by a computer system. The Witkar concept was prepared by Luud Schimmelpennink, the same person that some years before was behind Amsterdam's White Bicycle Plan. The service never had support of the government and never went beyond its demonstration phase. It started as a co-operative with around 3,000 members, which gathered enough money to build the computer system, 35 cars and 5 stations.

The system worked in a very complex way for the technology available at that time. The computer registered the trips made by members aiding to process payment bills by direct debit service. To access the vehicles, members would have to go to a station, introduce their personal magnetic key in the station system and dial the number of the destination. The computer then checked the status of the client's account, and also if there was a space available at the destination. In conformity, the system would show a green light and release a vehicle. At the end of the trip the user returned the vehicle to the destination station (that could be different than the origin) and the car would start to recharge. A fully charge of the vehicle would take 5 to 7 minutes [Bendixson and Richards, 1976].

There was a plan to expand the Witkar system, having an ultimate goal of 150 stations and 1000 vehicles [Bendixson and Richards, 1976], but due to lack of interest from the public authorities the system closed in 1988 [Van Winkel, 2002]. This was the first one-way station-based carsharing service.

In 1987 the companies ATG-AutoTeilet and ShareCom started their services with 17 days of difference. ATG initially had 8 people for one vehicle in the town of Stans, and ShareCom started with 17 members for one car in Zurich. In 1997, the two companies merged creating Mobility Genossenschaft Switzerland also known as Mobility Carsharing Switzerland, which is the oldest service still active. There was no technology involved at the beginning. The two root cooperatives simply had a log book to register reservations, and the ignition key was kept in a safe box. Founders were not expecting to create a business, but only wanted to use cars without owning them individually.

Nowadays, the Mobility Carsharing Switzerland cooperative has 96,000 customers, 2,700 vehicles and 1,380 stations in Switzerland. Zurich has an average of a vehicle in every 250 meters. The service still has its traditional characteristics, not allowing one-way trips, that is, the vehicles need to be returned to the origin station. [Mobility website, 2013] [Lechner, 2013].

Other successful traditional carsharing services were founded in the 80's and 90's. At the end of the last century, Europe had 200 carsharing organizations active in 450 cities, throughout Switzerland, Germany, Austria, The Netherlands, Denmark, Sweden, Norway, Great Britain, and Italy [Shaheen et al., 1999].

It is important to highlight the leap taken in terms of operation by Car2go, a company owned by the German carmaker Daimler. In March 2009, Car2go started its services in the German city of Ulm, introducing a new form of operation [Daimler, 2008]. Besides the one-way movements, introduced for the first time by Witkar, it also allowed vehicles to be delivered and parked at any place inside an operating area. Meaning that the service did not have any movement restrictions inside a pre-defined area by the operator, a characteristic denominated by free-floating (limited to an operating area).

In North America the carsharing experiences started in the early 80's, with two demonstration programs: Mobility Enterprise in the state of Indiana, and Short-Term Auto Rental (STAR) in San Francisco, California. These programs began at the year of 1983 and ended in 1985 and 1986, respectively. After this, only in 1994 carsharing re-emerged with Auto-Com later denominated by CommunAuto (USA), followed by Dancing Rabbit Vehicle Cooperative (USA), Cooperative Auto Network (Canada) and Victoria Carshare Coop (Canada). [Shaheen et al., 2006]. The 2000's decade started with the launch of Zipcar, one of the biggest carsharing companies still in service today. The company, co-founded by Robin Chase and Antje Danielson, started its service in the year 2000 at Cambridge (Massachusetts), and is currently spread throughout the US, Canada and Europe, being the world's carsharing leader [Eha, 2013]. Ten years later, in June 2010, RelayRides, the first peer-to-peer carsharing service started at the same city - Cambridge (Massachusetts) [Hamilton, 2012]. It is important to add that, a month before, in May 2010, Austin (Texas) was the second city to receive the Daimler innovative service Car2go [Salton, 2010].

In Asia carsharing has seen some activity in Japan and Singapore. In Japan, carsharing systems first emerged in late 1990's. The first services were promoted by car industry. Honda launched Intelligent Community Vehicle System (ICVS) and Toyota the Crayon System in Toyota City. In 1999, Japan's Ministry of Construction sponsored three systems: the ITS mobility system in Osaka; the tourist electric vehicle system, in Kobe; and the Ebina Eco Park & Ride. The first carsharing program in Singapore was launched in 1997 by NTUC Income, an insurance company, some years after the former communications minister, Mah Bow Tan, recognized that carsharing could be a possible alternative solution. In 2002, CitySpeed and Honda DIRect ACCess (DIRACC) started operating. Whizzcar followed them in 2003. [Barth et al., 2006]

The first Portuguese carsharing experience was carried out by two companies: Mobcarsharing operating in Lisbon and Citizenn operating in Porto. The first was Mobcarsharing, a company launched by Carris (Urban Bus company) in the city of Lisbon in 2008. In 2010 the system had 220 clients (100 individuals and 120 companies) using the service. In February 2010, Transdev decided to start a carsharing system in Porto, named citizenn.com. In September 2012 these two companies made an agreement allowing members of each company to access both carsharing services without the need for a new registration or access card (roaming). At that time, Mobcarsharing had 8 stations and 9 vehicles, while Citizenn had 8 stations and 10 vehicles [Mobcarsharing website, 2012][Citizenn website, 2012]. Both companies suspended their services in 2015, Citizenn in February and Mobcarsharing at the end of June. In 2014 a third company, named Citydrive started to operate in Lisbon. It was the first Portuguese company allowing one-way trips. It started with a small operating area (1.44 km2 in Avenidas Novas, Campo Pequeno, Saldanha and Picoas) and 20 vehicles. The perspective of the founders in 2015 was to expand this service to the entire city of Lisbon [Citydrive website, 2015].

2.5 An overview of today's services

Carsharing is a service concept that gives a label of environmental consciousness to urban areas. City mayors are accepting and supporting vehicle sharing to promote a more efficient transportation system. The number of companies around the world is continuously increasing, some of them having distinctive characteristics. Relevant active carsharing services were examined, to serve as the base to produce a detailed and categorized analysis of the business models, operational, service characteristics and technology level. The services analyzed were: Mobility Carsharing, City Carshare, Zipcar, GoGet, Car2go, Hertz 24/7, Autolib, DriveNow, RelayRides, Buzzcar, and Getaround.

Mobility Carsharing and City Carshare are non-profit services, being both cooperatives. The remaining services analyzed are profit driven. From those, Zipcar, GoGet, Car2go, Hertz 24/7, Autolib, and DriveNow have their own fleet of vehicles, while RelayRides, Buzzcar, and Getaround rely on the utilization of individually owned vehicles.

- **Mobility Carsharing Switzerland**

Mobility is the oldest carsharing service still in activity and resulted from the merge between ATG Auto Teilet Genossenschaft and ShareCom cooperatives, both founded in 1987. Mobility has 1,380 stations and 2,700 vehicles throughout Switzerland serving more than 102,000 customers [Mobility website, 2013]. It is a cooperative service and nearly half of the customers are members of the cooperative.

To be a member of the cooperative, users buy a share certificate of 1,000 CHF (refunded without interest when leaving) and pay a one-off admission fee of 250 CHF. Members of the cooperative do not pay annual fees and benefit from a mileage discount. The fleet has a variety of vehicle types: “electric”, “budget”, “micro”, “economy”, “combi”, “comfort”, “cabrio”, “emotion”, “minivan”, and “transport”.

In terms of operation, the service does not allow one-way movements. A reservation must be made with a minimum of one hour in advance. After the reservation, the user can collect the reserved vehicle from the desired station. The user enters the vehicle using the member card and the ignition key is inside the glove box. An on-board computer assists the user in verifying and managing his reservation [Mobility website, 2013].

- **City Carshare**

City Carshare is a non-profit carsharing organization available in the San Francisco Bay Area (San Francisco, Oakland, Berkeley and Palo Alto). It started in 2001, founded by a group of transportation activists. At the beginning, the service had a fleet of 12 Volkswagen Beetles. Today the service has a varied fleet with 25 different models, including 4 fully electric vehicle models, 5 hybrid vehicle models, and 2 models with a wheelchair elevation system [Citycarshare website, 2013].

It is a station-based service. Each station has at least one vehicle, and in some cases 7 or more [Citycarshare Handbook, 2010]. In June 2013, City Carshare had a total of 239 stations in the San Francisco Bay Area. Users can pick up a vehicle from one of the stations, but need to return it to the same station. Vehicles are rented in an hourly basis [Palmer, 2013].

The system accepts reservations by phone or online. You can perform reservations a moment before picking up the vehicle or with 3 months in advance. In terms of technology, it uses a key fob and a key fob reader to open and close the vehicles, and has an on-board computer to register the car usage by the client. To open the vehicle the user needs to have a reservation. The ignition key is attached inside the vehicle [Citycarshare Handbook, 2010].

- **Zipcar**

Zipcar is probably the most known carsharing company in the world. Its success was in part due to the social media marketing strategy, making it closer to its potential clients. The service was founded in the year 2000 by Robin Chase and Antje Danielson in Cambridge, Massachusetts. Zipcar spread to other locations in United States, Canada and Europe and nowadays is present in 30 major metropolitan areas and in over 400 college and university campuses, having a fleet of more than 10,000 vehicles and serving more than 900,000 members [Zipcar website, 2015]. In March 2013, Zipcar was bought by Avis Budget Group, one of the world’s biggest companies in the rent-a-car business [Gorenflo, 2013]. Zipcar is a station-based carsharing service with a multi-purpose fleet of vehicles. One-way movements are not allowed. Vehicles need to be returned to the same reserved parking spot at the end of the reservation.

- **Goget**

Goget is a station-based carsharing service available in Adelaide, Brisbane, Melbourne and Sydney (Australia). The company was launched in 2003 and nowadays has 829 cars in Sydney, 96 in Melbourne, 5 in Brisbane and 7 in Adelaide. Cars are located in stations (specially identified parking spots) and each station has only one car. The average age of GoGet vehicles is 1.3 years. Users need to return the vehicle to the station where the vehicle was picked up. The website provides a map to help find the vehicles. Members pay a joining fee, and they can also pay a monthly fee depending on the plan chosen. The monthly fee paid decreases the renting price, which is charged per hour and per kilometer. There is no hourly charge between midnight and 6 in the morning. Members need to book the vehicle in advance and the duration of renting period is required. Booking needs to be extended if user is running late (more than 5 minutes) [Goget website, 2013].

- **Car2go**

Car2go is a company owned by Daimler, launched with a pilot scheme in Ulm, Germany, in 2008. The system only includes Smart ForTwo vehicles (a two seat car produced by Daimler). Car2go is a one-way carsharing service that is based on an operating area. Drivers can go anywhere inside it and also travel with no limits to the outside of the operating area, with the condition that, to finish the rental period, the vehicle needs to be inside the operating area. Vehicles can be parked anywhere in the operating area. Users pay by the minute (only). Car2go members receive a membership card with a unique PIN number in the mail to unlock the vehicle. Cars can be booked in advance or used spontaneously (on demand).

Staff teams relocate cars that have not been recently driven to designated hot spots in the area. Teams also fix problems with cars that users flagged as dirty or damaged.

The second city to receive Car2go was Austin, Texas. Nowadays Car2go service is available in 21 cities, throughout Germany, USA, Canada, the United Kingdom, Austria and the Netherlands. The number of vehicles in each city varies from 125 (Denver, USA) to 957 (Berlin, Germany) [Car2go website, 2013].

- **Hertz 24/7**

Hertz 24/7, also known has Hertz On Demand, is a service offered by the worldwide rent-a-car company Hertz, to take advantage of the increasing demand for short-term rental service in urban areas [Hertz 24/7, 2013].

The service started in December 2008 and is currently available in Australia, Canada, Germany, Spain, France, UK and USA. In June 2013, there were 1,800 Hertz 24/7 locations with a total of 35,000 vehicles [Blanco, 2013]. The company has plans to spread the service worldwide and expects that the 24/7 service will have a fleet 10 times the size of the current carsharing industry. Hertz will use the vehicles currently available on their fleet and equip them with technology to allow a 24/7 access. The company will not be buying more vehicles [Shaya, 2013].

The service is round-trip and station-based, although in Manhattan one-way trips are allowed between some locations and the airports of La Guardia, JFK and Newark. The service is simpler to use than rent-a-car provided by the same company. The user applies to the service to receive a membership card that works as a key fob. There is no membership, monthly or annual fees. Cars can be booked by the hour or by day. To open the vehicle, the user uses his card, and then drives the car wherever he wants during the reservation period. If needed the reservation period can be extended.

- **Autolib**

Autolib is a station-based carsharing service with a fleet of electric vehicles working in Paris (France) and its surroundings. It started in 2011, following the Vélib program (bicycle sharing program in the city of Paris), launched in 2007. Lib is a short word for "liberté", which means freedom.

The system works with one-way movements and a dense network of stations. All vehicles are fully electric. There is no booking service. The access to vehicles is performed on demand only. To access a vehicle, the user waves his card into an available vehicle parked in a station. The user can use a mobile phone app to locate the nearest available vehicle [Autolib website, 2015]. At November 2014 there were 877 stations, totalizing more than 4710 parking places with charging plugs. The system has 2608 vehicles (named Bluecars) being all fully electric [Le Figaro, 2014].

The subscription of the service is simple and can be done instantaneously at any time in kiosks near some of the stations. The membership cost varies from free to 120 Euro per year. The usage rate is only charged per time, and users pay for each half an hour.

The system provider only allows users to drive within the administrative area of the Ile-de-France. Ile-de-France is the region where Paris is located, and it has 12 thousand square kilometers. Any time a vehicle leave this area, the call center contacts the user inside the vehicle informing that he needs to turn around and go back to the authorized zone [Autolib website, 2015].

- **DriveNow**

DriveNow is a carsharing venture by BMW group (car manufacturer) and Six AG (rent-a-car service provider) founded in 2011. The company offers carsharing services in Munich, Berlin, Dusseldorf, Cologne (Germany) and San Francisco (USA) [DriveNow website, 2013]. At the end of 2012, Drive Now had a total of 60,000 members [EDTA, 2012].

DriveNow vehicles are spread inside an operating area, denominated by business area. Users can check the location of available vehicles on a smartphone app or directly on the website. Fifteen minute reservations are available for free. The service allows one-way movements, but the vehicle needs to be delivered inside the business area. Besides that, there is no other limitation. Only trip duration is charged, the price per minute starts at 24 Euro cents (if you buy a 500 minute package, valid for 30 days). Service teams refuel vehicles when the fuel level is less than 25%, but if the user refuels the vehicle (using the company fuel card), he will receive 20 minutes driving credit.

A middle trip stop (without ending the renting period) is free between midnight and 6 a.m. from Monday to Friday. The company charges 10 Euro cents per minute outside this nocturnal free period [DriveNow website, 2013].

- **Relay Rides**

RelayRides is a peer-to-peer carsharing service launched in Cambridge, Massachusetts (USA) in 2010. Nowadays the service is available across the country, with the exception of the New York state.

The service works with an online platform that gathers owners and renters. Car owners list their car for free and set the renting price per hour, day, week and month. The company takes a fee of 25% from each renting revenue. Each reservation can be reviewed by the owner, leaving to him the last decision. The owner meets the renter for car key delivery. The company used to have the option of installing keyless access technology in vehicles, but due to the costs involved it was removed.

To reduce the risk for owner RelayRides reviews driving history of potential renters and provides a one million dollars insurance that covers any vehicle damage or theft. Potential users need to provide information about driver license and credit card to join the service.

Users can choose from a great variety of vehicles the one that is more adapted to trip needs. At the end of the experience user and owner leave a review to help community and improve service quality [RelayRides website, 2013].

- **Buzzcar**

Buzzcar was launched in 2011 and is a peer-to-peer carsharing service co-founded by Robin Chase (former CEO of Zipcar). The system is working in France and is active nationwide. In June 2013 the system had 55120 users sharing 7130 cars [Buzzcar website, 2013].

Owners put their cars for rent applying to the system's online platform, and then the vehicles become visible to users that intend to rent one. Owners set the renting price for their cars (by day or by hour and distance), and the company takes a fee of 30% on each transaction. The fee covers insurance, financial system and administrative costs. Owners are always in full control because, beside rental prices, they also can decide on availability and are free to accept or reject requests. The system does not require any technology to be previously installed in vehicles. User and owner meet during key exchange and make a walk around the vehicle.

The advantages of a simple peer-to-peer system such as Buzzcar are: quick scalability, low investment, and small administrative and operational structure. The team that manages the system has less than 10 people. This is possible because the owners are responsible to keep their vehicles clean and working. A rating system of the users' experience is an incentive for owners to promote their own vehicles.

The main obstacle to overpass in such a system is insurance companies' contract models, where the owner of the vehicle is always responsible for what happens to his car. In France, Buzzcar achieved an agreement that protect the owner's insurance when the vehicle is being used under the peer-to-peer service [Spaggiari, 2013]. Buzzcar joined with Drivy in order to improve its service, having now, under the name Drivy, 26,000 vehicles and 500,000 users [Drivy website, 2015].

- **Getaround**

Getaround is a peer-to-peer carsharing service. The service was launched in 2011 and is available in San Francisco, San Diego, Austin, Portland and Chicago. The company's objective is to solve the problem of car overpopulation.

Owners list their vehicles on the platform, set the price by hour or day, and decide who can rent it and when it is available. The vehicle needs to be built after 1995 and under 150,000 miles to be eligible for the system. To promote confidence in owners a full insurance is provided during rentals and the company assures an advanced identity identification of the user. The Owner can decide if he wants to meet the user in person and deliver the keys in hand or opt to install a free carkit developed by Getaround that allows the user to access the vehicle without the owner's presence.

The Getaround Carkit is a small piece of hardware that allows the car to be unlocked and locked using a smartphone and locates the vehicle by using GPS technology. It also detects vehicle tampering and has an optional engine immobilization.

Users apply to the service by registering on the website and providing credit card and driver's license data. Anyone over 19 years old and with a good driving record can join, even drivers with international driver's license. Users can choose the more adequate car to the purpose of their trip from the variety of cars made available by owners, and wait for owners' acceptance [Getaround website, 2013]. The rental transactions are done online or through mobile phones. A rating method allows owners and users to classify their experience. There are no membership fees (monthly or annual). The fee of Getaround over the rate set by owner is 40% [Kim, 2011].

2.5.1 Business models

The different services previously described have common characteristics that can be categorized for a better understanding of the variations and nuances existent in today's carsharing concept (see Figure 3). The analysis was subdivided in business models, operational characteristics, service characteristics and technology.

A carsharing service can be structured to simply serve a community in a self-sustainable way (non-profit driven) or with the objective of maximizing profit (profit driven).

On the non-profit driven side, there are co-operatives. Co-operatives are founded by members of a local community that share the main goal of changing car usage habits. Co-operatives can aim to generate capital surplus to keep or improve its quality, in order to better serve its members.

Carsharing business models can also be profit driven. This is the case of Business to Consumer (B2C) and Peer to Peer (P2P) services.

In B2C services, the company owns a fleet of cars and provides the sharing amongst members. Three types of B2C services can be identified:

- Carsharing Brands founded to be totally dedicated to the carsharing business;
- Rental Brands that have long-term renting as their main business and carsharing as an option to increase the target market and vehicle usage;
- Auto-Manufacturers that enter carsharing business to promote their brand and follow the changing of the market from owning to usage.

P2P is a Consumer to Consumer (C2C) service, characterized by promoting direct transactions between consumers. The fleet of cars is owned by individuals of the community (peer owned). A promoter matches available cars from owners with drivers that want to rent a vehicle, charging a 20% to 40% fee for the service. The idea is to allow car owners to convert their personal vehicles into shared cars when they are not using them. By doing so, owners get some revenue from their idle vehicle. A peer-to-peer carsharing system is the basis for starting a carsharing service without the need of a large investment.

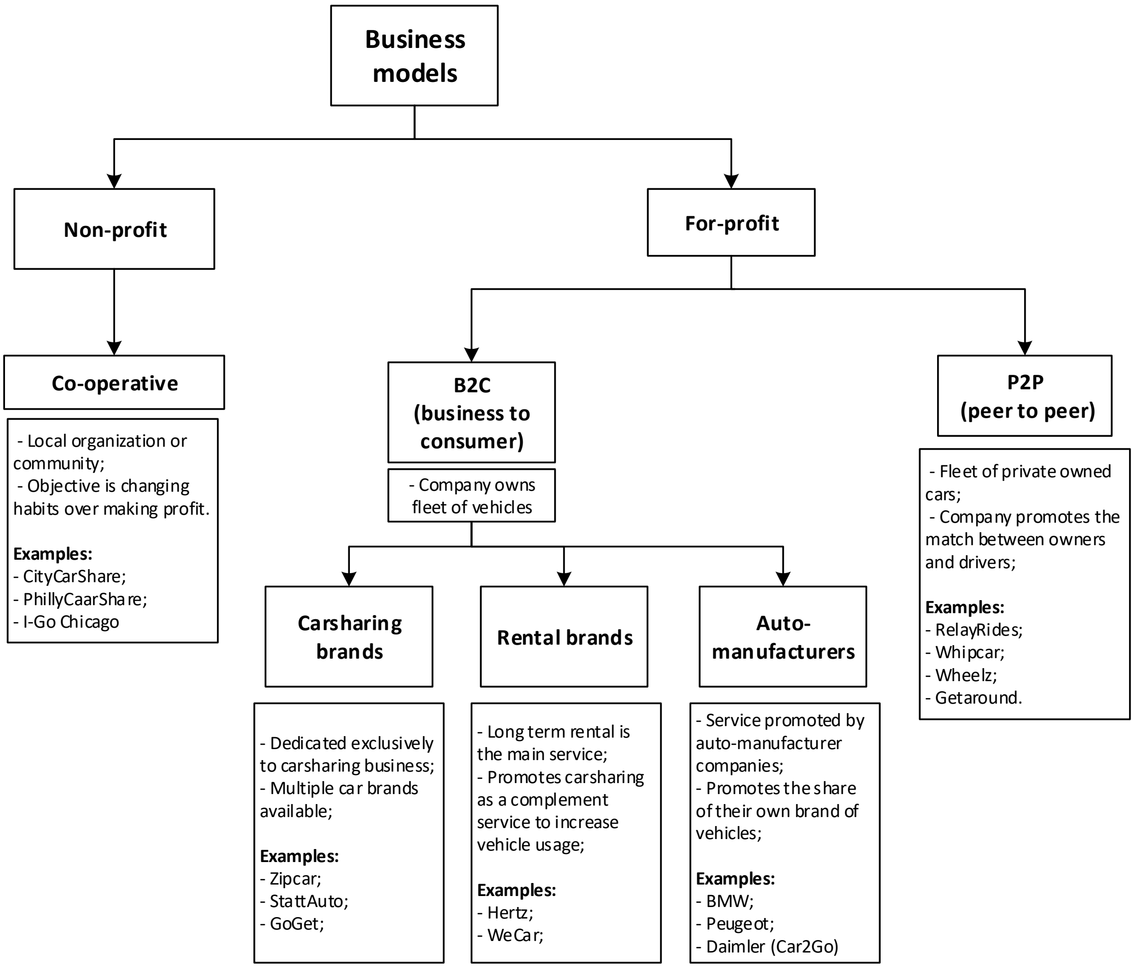


Figure 3: Carsharing business models

2.5.2 Operational characteristics

This section describes the characteristics that influence the operational procedures, known as operational characteristics. The operational characteristics define the main outline of the carsharing service and are important to perform simulations. Five groups were identified from the analysis of the carsharing systems implemented by the date: fleet source, fleet type, location of vehicles, allowed movements, and rebalancing strategies.

2.5.2.1 Fleet source

In terms of fleet source, two different types can be distinguished: organization owned and peer owned vehicles.

In what concerns to organization owned, the carsharing entity is the direct provider of the fleet of vehicles that is made available to users. This is a characteristic of co-operative and business to consumer services. Peer owned fleet is a fleet composed by private vehicles, meaning that each vehicle of the fleet is owned by a single individual.

Connecting peer owned vehicles with potential users is a characteristic of P2P carsharing systems. P2P systems provide scale and spread at great speeds, having vehicles with a wide range of characteristics (different cars, different prices and different locations), which is difficult to reach by other carsharing business models. The main issue of a peer owned fleet is being dependent on individuals with different wills and desires, affecting the control to deliver a standardized service that is consistent over time. The two vertexes of the problem are uncontrolled availability and quality. To minimize availability issues, a balance between owners and users per time and per geographic area is needed. The use of social networks, public profiles, ratings and comments can promote quality distinction. In P2P systems, individuals can promote their own vehicles and innovate in order to increase their revenue. This makes P2P service functioning as a platform that matches clients with the individuals' micro-businesses. Company acts as a broker and saves money on cleaning, maintenance and innovation departments, since each individual acts as an entrepreneur.

2.5.2.2 Fleet type

In terms of fleet type carsharing services can have a homogeneous or a heterogeneous fleet of vehicles. With a homogeneous fleet, all vehicles operate in the same way and have the same characteristics, making integration of on board equipment consistent and the vehicle selection process simpler (only based on vehicle parameters, such as fuel). A heterogeneous fleet provides a variety of choice in terms of vehicle types, making it possible to match a vehicle to the trip purpose (e.g.: a station wagon to transport large items). Having a heterogeneous fleet makes the management problem a little more difficult, since dealing with multiple vehicle parameters increases the complexity of algorithms.

2.5.2.3 Location of vehicles

Concerning location of vehicles, the system can be station-based (discrete) or free-float (continuous). In station-based services, vehicles are located at pre-defined places. Those can be stations, parking lots or reserved street parking areas. Station-based are the most common, namely if technology is not used. Free-float services are characterized by having its vehicles parked at any place, with legal public access. The allowed area to park a vehicle and end renting period can be limited and pre-defined, being designated by operating area. Vehicles have on-board GPS equipment to ease management and allow users to locate them by using a smartphone. The occupation of public parking spaces of free-float carsharing services can lead to costs that need to be payed to the parking management services. The charged costs can be controlled using the GPS equipment, if the carsharing company is under a time based contract. Normally the parking manager charge a daily fee per vehicle.

2.5.2.4 Allowed movements

Allowed movements can be subdivided in round-trip, and one-way movements.

Roundtrip movements have been the most used among carsharing companies since the beginning. This type of system is easy to manage and control, since it does not have vehicle imbalance problems, but it is not adapted to the complete range of user needs. One-way movements, as previously referred (see 2.4.4), were first used by the Witkar system in 1974, and are nowadays considered the next level of carsharing.

One-way carsharing services allows moving the vehicle to another destination different than the origin, which means that participants do not have to return the car to any particular place. This type of movements is more adapted to users' needs, because of its flexibility in space, but needs rebalancing strategies. It also allows a higher utilization of vehicles as they do not need to be idle during the rental period as it happens when clients are forced to a roundtrip movement. During the rental period, movements are normally restrained. Restrictions are applied to the final destination of the rental trip or even to the range of trip movements. For station-based systems, where vehicles are located inside stations, the service provider can allow free car movement, with the only condition that at the end of the rental period the vehicle is returned to the same station or another station different than the origin, however, sometimes an operating area is added to stations limiting trips to the inbound area. In terms of movement freedom, similar situations can be observed in operating area systems: users can drive anywhere they want, but the rental period can only be finished if the vehicle is inside the operating area (e.g.: Car2go); or users need to stay inside the operating area and be advised to return once the system detects the vehicle is outside the allowed boundary (e.g.: DriveNow).

2.5.2.5 Rebalancing strategies

Rebalancing strategies are applied to one-way carsharing systems. For systems that allow one-way movements, stations or zones with high demand as origin will have a shortage of vehicles, while stations or zones with high demand as destination will have an excess of vehicles. This leads to an unbalanced distribution of supply. If vehicles are not redistributed the system won't be able to fully satisfy the demand, which will most probably result in a loss of customers. Therefore, in one-way systems rebalancing is necessary. Two types of rebalancing strategies can be used: user-based and operator-based relocations. In user-based relocation methods, customers relocate vehicles being attracted by a price incentive or by a credit bonus. Operator-based relocations use staff members of the carsharing company to relocate vehicles. It is important to note that the relocation strategies here discussed are related to operational activity of systems that exist in reality (state of the practice). Trip selection, a proposed upstream relocation strategy found in research publications, which consists in authorizing only the trips that promote system balance, is addressed in the state of the art (see 3.3.2).

The described operational characteristics are interrelated (see Figure 4). Cooperative and B2C business models are characterized by the available fleet of vehicles being organization owned. The fleet can be homogeneous or heterogeneous. In terms of location of vehicles, services can be station-based or free-float. In the case of station-based services, there are organizations that allow one-way movements and others that follow the traditional and basic way of carsharing, only allowing round-trip movements. If one-way movements are allowed, it is necessary to use relocation strategies in order to balance the system. For that purpose user-based or operator-based strategies can be implemented.

P2P business models have a fleet composed by individually owned vehicles – peer owned – and consequently is heterogeneous. The location of each vehicle is dependent on the will of the peer that own the vehicle. The vehicle can be inside a garage, a parking lot or at an on-street parking place (the precise location of the vehicle is communicated to potential users). This uncertainty is a result of the freedom given to owners to decide where is the best place to park their vehicles in order to meet their interests. Accordingly, the location of vehicles is considered to be some sort of station-based, being the "station" somewhere in the vicinity of the owners' house. Regarding to the allowed movements, there is also some unclearness. Normally the users need to return the vehicle to the area nearby the owner's house. Although, if arranged with the car owner the user can drop the vehicle at another location. For example, the vehicle can be delivered to the owner at the local airport or at a local train station, being the owner responsible to relocate the vehicle. Either way, since most of the trips start and end at the area of the owner's house, it is considered that the majority of the allowed movements are round-trip.

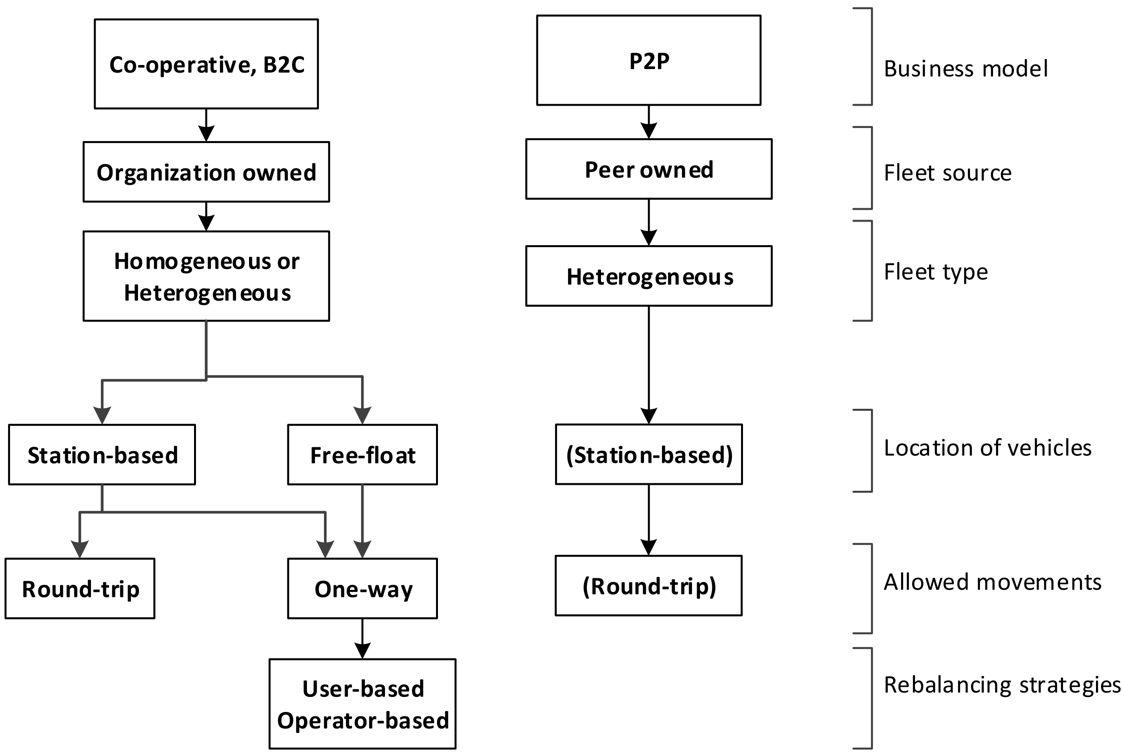


Figure 4: Relation between business models and operational characteristics

2.5.3 Service characteristics

The service characteristics here described are related on how the user perceives the system and relates it to carsharing provider convenience. A registration is the first step to join a carsharing system. To register, the user needs to fill an application form with his personal and credit card data and wait for an approval. To be eligible to register the user must be at least 18 years old (for some organizations the minimum age can be above this number), have a valid driving license, and in some cases need to have at least two years of driving experience and a driving history that meets minimum safety requirements. It is required to pay a one-time registration fee plus an annual or monthly fee, besides the usage rates. Some carsharing organizations offer different types of plans, charging a monthly or annual fee according to the chosen plan. In cooperatives, users may have to buy a share certificate to enter the system, or optionally, to benefit from a different pricing plan.

After a user becomes a member, he has access to the vehicles of the system. The usage of vehicles is charged per time and space, and the price includes fuel, insurance and parking. The access to vehicles can be done instantaneously without previously notifying the operator, designated by on demand or walk in access, or by reserving a vehicle in advance. Vehicles can be found inside stations – station-based - or in public access parking spaces – free-float (as previously referred).

On demand, or walk in, access to vehicles consist in the instant access to vehicles, that is without previously notifying the operator, while reservations require that the user communicates its intention to use a vehicle to the system operator, that can additionally request that the user specifies the duration of the renting period.

Reservations can be used to hold a vehicle in case of a pre-planned trip. Reservations give security to customers by making the vehicle available for them at a specific time and location. They are also useful for managing the system by allowing a prior knowledge of demand, partially or totally. A reservation only process is the most used by carsharing companies, due to its convenience. When performing a reservation, it can be necessary to specify trip destination or trip ending time, or both, depending on the demand control level of the organization.

Modern carsharing companies, namely one-way and free-float, additionally allow on demand access to vehicles. On demand access to vehicles is convenient for users, but adds complexity into the system management. If the system is not station-based, the operator needs to provide the location of vehicles, in order to aid the users in finding a car near them. Information about fuel level should be added to help user to find an appropriate vehicle for his trip.

For one-way systems, reservations can have an important role, making it possible to know beforehand part of the demand allowing to perform corrective actions to maintain an adequate distribution of vehicles throughout the day.

On demand access can be transformed into a short-term reservation. Users can look for a vehicle using the internet and choose a vehicle that is more adequate to their trip. The chosen vehicle will be locked until the user accesses it. The use of a smartphone is central for this type of on demand service to work, giving on the way access to the system, and allowing the user to easily locate the vehicle, which is important for systems that are not station-based. The short-term reservation allows the management algorithms to run and optimize users' choice. In the case of a homogeneous fleet of vehicles, the vehicle or vehicles with the most appropriate fuel level for the trip will be highlighted. The management system will take in consideration the rotation of vehicles in order to secure equilibrium in terms of vehicle usage. If electric vehicles with a short range and high recharge periods are used, parameters like time and distance of trip are important to check which vehicles have enough energy. There is also the possibility to introduce a time buffer, by advising clients to wait for a certain time, in order to guarantee that vehicles had time to recharge properly. If this is done timely, the client can use his time to perform other tasks instead of simply being there waiting.

For peer-to-peer carsharing systems, the registration does not require any type of payment by the user or owner. P2P companies work in a low cost basis, they do not have any extra expenses besides: keeping the website running, assuring a valid insurance for the period when vehicles are used as carsharing vehicles, keeping the website running and controlling transactions. To cover those expenses a commission is charged for each transaction between the owner and the user.

The user needs to provide his personal and credit card data, and his eligibility is subjected to approval. The owner list his vehicle for free and sets the price charged to the users. The usage price charged includes insurance, assured by the P2P carsharing organization whose cost is included in the commission charged. When listing a vehicle, the owner gets an advice about the price range for his vehicle based on the car market value, location and competitive pricing in order to allow the maximization of earnings. The owner is able to review every request and decides who rents and when his vehicle is rented.

The access to vehicles is done in a different way. The owner and user arrange a meet up for key delivery. The owner checks the user driving license to assure that the user is the same person that requested the vehicle, by confirming with the data provided by the carsharing company. This assures that the owner is delivering the keys to a user that passed the safety requirements set by the carsharing company. Another meet up between owner and user needs to be schedule to return the vehicle. Some companies provide the option of installing technology that allows instant access to vehicle, dismissing the presence of the owner.

2.5.4 Technology level

2.5.4.1 Access control

As it was verified through the analysis of carsharing companies in service, the vehicle access control is done by one of three ways: using a lockbox, a common key, or key less access technology.

The lockbox is the simplest solution and was used in the first carsharing systems. The keys for the vehicles are stored inside a lockbox and every user has a key to open it. The lockbox is accompanied by a logbook where users register the time and distance driven.

A variation of this simple access system is to give users a common key that can open any single vehicle. Normally the common key can only unlock the vehicle's doors. To start the engine, the user needs to find the original key inside the vehicle.

The use of key-less access technologies confers more secure systems. The installation of a card reader connected to the door lock mechanism allows the replacement of the common key by a smart card. The user needs to wave the smart card (RFID) next to the reader to open the vehicle. Cell-phones can also be used to open the vehicles by short range communication with the vehicle. This technology is useful to control access to previously reserved vehicles, by giving access only to the user that performed the reservation. Once inside the vehicle the user may additionally need to introduce a pin code into a numerical pad to unlock the ignition system.

2.5.4.2 Communication and information processing

The communication and information processing can be fulfilled without a great level of technology. The most basic implementations of carsharing, like the ones used in the primal carsharing systems, are supported by a log-book, physical or electronic, to manually record the data related to the use of the vehicle (distance and time). In some cases, telephone or internet reservations are available.

However manual operations are only viable to manage small fleets, due to its time consuming nature. The process of registering the booking, collecting the data, doing the book keeping and managing the fleet manually becomes virtually impossible as the number of vehicles and usage increase.

The advanced carsharing systems use ITS technology. The adoption of vehicle electronic equipment and communication devices eases carsharing management processes and allows having larger fleets and different types of user services (e.g.: one-way trips), while also improving efficiency, friendliness and operational manageability. Real-time communication between system management and vehicles, and system management and users, is supported by an architecture that normally includes an operations center, a car on-board system and, in some cases, local communications architecture.

The operations center is considered the core of the system. A system management server controls the management of booking (automatically through internet or semi-automatically by assisting call center operators), and gathers all the information required to process payments and monitor the service.

The on board system has normally the following components: a computer, a smart card reader, GPS, telecommunications system, on board sensors and devices to prevent theft and abuse. The computer is connected to the telecommunications system allowing data interchange with the operations center. The GPS allows locating the vehicle in real-time. Sensors installed inside the vehicle provide useful information of its current status (e.g.: fuel level, engine diagnosis and odometer). Sensors are connected to the computer allowing the data to be stored and sent back to the operations center. The smart card reader allows the user to access the vehicle after checking permission from the operations center. Some control devices can be added to prevent the engine from starting in case of theft.

The local communications architecture is used to send and receive data from vehicles through a local network, normally by using dedicated short range communication (DSRC) technology, which exempts the need of accessing to a GSM network. [Barth el al., 2003].

2.5.4.3 The case of P2P

P2P carsharing companies can work with a minimum level of technology, only using an operations center that updates the listing website, process the requests, provide support and control transactions, for the cases where car keys are personally delivered to users. As previously referred, an option can be available to owners in order to install a car kit that allows users to locate the car and open the vehicle without using a key. For these situations simple on-board technology is installed in the vehicle, which uses telecommunication and GPS technology.

3 State of the art

3.1 Introduction

A state of the practice was provided in the previous chapter, which described the different carsharing services available today. From the carsharing operational characteristics described, two main categories can be distinguished: location of vehicles and allowed movements.

Concerning the location of vehicles, the system can be station-based (discrete) or free-floating (continuous). In station-based services, vehicles are located at pre-defined places. Those can be stations, parking lots or reserved street parking areas. Free-floating services, are characterized by having its vehicles parked at any place, with legal public access, inside a pre-defined zone. Vehicles in free-floating systems have on-board GPS equipment to ease management and allow users to locate them by using a smartphone [Shaheen et al., 2015].

Allowed movements can be subdivided in round-trip and one-way. In roundtrip services users need to return the vehicle to the same place where it has been picked up. In one-way carsharing services, movements to another destination different than the origin are allowed, which means that there is no imposition to return the car to any particular place [Barth and Shaheen, 2002].

The simplest operational set up is round-trip and station-based. This is the choice of systems with a small number of vehicles and stations, since it is easy to manage and does not require many staff hours, nonetheless it is not adapted to users' needs.

By increasing one step on the level of operational complexity, we have one-way and station-based systems. One-way movements give more flexibility to users, being a critical factor to attract new clients to the system [Efthymiou et al., 2013]. Additionally, it lets a higher utilization of vehicles as they do not need to be idle during the rental period as it happens when clients are forced to a roundtrip. The downside is that it can lead to having a surplus of vehicles in stations with high demand as destination, and a lack of vehicles in stations with high demand as origin, unbalancing the demand and supply quotient [Barth et al., 2004].

The most complex operational set up is one-way and free-floating. This allows individuals to use a vehicle of the system as if it was their own vehicle. However, it does not mean complete freedom, since vehicles need to be delivered inside an operating area [Shaheen et al., 2015].

Due to the fact that the purpose of this research is to develop a real-time decision support tool that is able to aid the daily carsharing operators that adopted one-way and free-float operational characteristics, the literature review is centered on two main topics: carsharing demand estimation and one-way carsharing modelling.

The review of publications concerning to the demand estimation processes for carsharing was necessary to understand how the carsharing potential demand could be determined for the study area. On the other hand, the analysis of the accumulated knowledge concerning to one-way carsharing modelling, aided to find a gap to explore and, therefore, contribute to improve practice.

The state of the art review follows the same logic of the extensive literature review carried by Jorge and Correia (2013), as a task of the InnoVshare project, which was adapted to this research and complemented with other important bibliographic references.

3.2 Carsharing demand estimation

Studies have been published that use surveys to carsharing members or data from existent carsharing organizations to characterize the carsharing market and its potential. These are based on descriptive analysis and revealed patterns related to carsharing usage.

Cervero and Tsai (2004) used data from a U.S. carsharing organization that included members and non-members, and defined member profiles and trip purposes. The authors stated that the service is mainly used by professional members that do not own cars, and live either alone or in non-traditional households, to perform trips related to individual affairs such as: personal business, shopping and medical appointments (this is a round-trip carsharing system).

Lane (2005) characterizes members of a US carsharing organization by demographic profile, and their motivation to join. The results are compared to other two US carsharing service providers. From the comparison with the other services, it was revealed that education, and not income, appear to be the strongest predictor of membership, followed by "commuting using transit" and "living in a non-traditional household" attributes. The author adds that U.S. carsharing adopters have different characteristics than the European ones, namely are more concerned with personal utility than social or environmental benefits, and less by affordability.

Millard-Ball et al. (2005) denote, based on the data provided by US carsharing services, that the demographic market includes individuals in their 30's or 40's, highly educated, with middle to upper income, and highly concerned about environmental and social issues, while the geographic market is characterized by highly populated areas that are pedestrian friendly, with mix of uses and high parking pressure.

Shaheen and Rodier (2005) by analyzing the data of two U.S. carsharing program field tests, named CarLink I and CarLink II, identified that the typical member of the carsharing service was more likely to be highly educated, with upper income, professionally employed, with sensitivity to congestion, revealing environmental concern, and willing to try new experiences.

Burkhardt and Millard-Ball (2006) uses a web-based survey of carsharing members and focus groups to identify who most likely will join a carsharing organization. The authors recognized that individuals attracted to carsharing generally live in dense urban areas with multiple transportation options. An intensive description is provided for the carsharing adopter profile: highly educated, with middle to upper income but cost sensitive, from smaller households, in their 30's or 40's, not an high mileage driver, with the need to use a car as a preferred mode several times per month, highly concerned about environmental and social issues, considering himself or herself an innovator, not liking to support car ownership expenses, sensitive to transport costs, and not interested in the status given by using certain car brands.

The potential demand was also addressed by studying the different factors besides price, laid under each individual choice. Models were calibrated based on stated preference data to predict choices related to service joining.

Zhou et al. (2011) used stated preference survey data to calibrate two ordered probit models to investigate the factors influencing the probability of joining decision for two different pricing plans, with the intention of helping carsharing providers to identify potential clients and important program features. The results provided by the model revealed that the higher vehicle ownership and the higher income per household adult ratio decrease the likelihood to join the program, while education level exhibits a convex relationship.

Zheng et al. (2009) performed a study at a U.S. university community. Data was gathered by a survey. Stated preference questions were included to evaluate if the respondent would join or not the carsharing program given the pricing plan presented. The question was made using a monthly and annual plan. The authors analyzed the demand of the two carsharing plans independently by recurring to two logistic regression models. This study identified distinctive features that particularly affect a university community demand for carsharing.

The expansion of the carsharing market increased the amount of data that could possibly be collected, allowing to quantify the already qualitatively described trends in intervals.

Celsor and Millard-Ball (2007) present thresholds for carsharing level of service to be used by the operators as guidelines to understand the likelihood of success of a carsharing service implementation. The research is based on the data analysis of 13 U.S. regions which had significant carsharing operations at the time of data collection (fall 2004). The authors concluded that neighborhood and transportation characteristics are more important for carsharing success than the demographics of individual members.

The large amount of data available, not only carsharing service related, but also for the micro geographic characteristics of the service placement, allowed the development of studies with increased level of complexity.

Stillwater et al. (2009) assess the influence of built environment and demographic factors in carsharing. The study uses 16 months data from 2006 to 2007 of an urban US carsharing operator combined with built environment information measured in Google Maps satellite imagery for each defined cluster. Based on this data, an exhaustive method was performed to pick the best least-square regression model based on the previously chosen candidate explanatory variables. The explanatory variables for the carsharing demand at each cluster were found to be: street width, a nominal rail LOS measure, percentage of drive solo commuters, percentage of households with one vehicle, and average age of pods that constitute each cluster. The authors concluded that carsharing pod age, households with one vehicle and the existence of light rail service have a positive impact on demand, while pedestrian friendly areas (related to street width), the number of commuters that drive alone and the existence of only regional rail services or no rail service at all, have a negative impact on demand.

The interest of the carsharing operators also shifted from understanding the success of implementation to the success of operation, which changed the research objectives into build a comprehensive study of other key variables related to users' behavior.

Lorimier and Geneidy (2011) study the factors that affects vehicle usage and vehicle availability in a station-based and round-trip carsharing system. The authors use data provided by the carsharing operator to calibrate a multilevel regression model for vehicle usage and a logistic regression model for vehicle availability. It was concluded that the size of carsharing stations have a large positive impact on both models, since large stations offer more vehicle options and, therefore, have a larger catchment basis. Concerning to location of stations, it was concluded that stations located near metro stations decrease availability and increase vehicle usage. The authors also verified that there is a seasonal effect on both availability and usage, being the summer months characterized by usage increases and having the opposite impact on availability. They verified that vehicle age was a key factor to decrease vehicle usage and increase availability, since members tend to prefer newer vehicles. The authors include advices for future actions of the carsharing operator to improve usage levels and availability.

Constain et al. (2012) analyzed the data of a Toronto (Canada) carsharing company. The descriptive analysis revealed that the majority of members access the service from distances of less than one kilometer (the proximity of the service decreases trip duration), more than 60% of members travel distances less than 40 kilometers per year, less than 10% of members make more than three trips per month, the majority of trips are made between 9 and 11 a.m., only 40% of members remain active one year after joining the service, trip rates are higher on weekends, membership level increases more with the spatial spreading of the service than with the escalation of the vehicle fleet size, and membership duration is high in dense neighborhoods. This research includes models that describe the decision processes of the carsharing members as a function of carsharing service, members, aggregate population and land use attributes, namely an accelerate future hazard model for membership duration, a negative binomial regression model for monthly frequency of usage, a multinomial logit model for vehicle type choice, and a multivariate regression model for monthly vehicle kilometer travel and total vehicle hour travel demand.

Morency et al. (2012) used empirical data from one of the largest carsharing companies in the U.S. to understand the behavior of carsharing users. The authors developed a two-stage approach to perform a microsimulation. First, the probability of a member being active in any month is calculated by using a binary probit model, and, given the fact that the member is effectively active during the considered month, the probability of that member using the service multiple times is estimated using a random utility based model. The approach developed by the authors revealed that the activity of carsharing members is positively related to the revealed behavior for up to the previous 4 months, which influence weakens over time, and also that members behavior is related to some personal attributes, such as gender and age (favorable to males between 35 and 44).

Seeking to estimate demand using classic approaches, Catalano et al. (2008) calibrates a demand model to forecast the modal split of the urban transport demand in an aggregated way, allowing for the possibility of considering innovative transport systems such as carsharing and carpooling. The authors performed a survey containing revealed and stated preferences questionnaires. The revealed preferences part of the questionnaire was aimed at obtaining the respondents' household characteristics (composition, age and sex of members, number of available vehicles, income, number of members travelling daily to work or study), and the trip characteristics performed by the respondent (mode used, time spent, origin and distance covered for a journey to work or study). The stated preferences part consisted in choice games requiring the decision for one of our alternatives: private car, public transport, carsharing, and carpooling. It considers that the carsharing service allows one-way movements. The authors used a multinomial logit model to simulate transport mode choice behavior for commuting trips, and analyze the potential demand for a future scenario. The future scenario is based on assumptions taken by the authors that favor a low environmental impact transport system (new parking rules and pricing strategies, improvement of public transport service). It is shown, that for the future scenario the carsharing market share grows from almost 0% to 10%.

Ciari et al. (2013) went further and estimated travel demand for carsharing by using activity-based microsimulation approach, which simulates modal choice at a micro level based on the activities of each individual. The authors argue that classic modelling tools are not suitable for carsharing demand modelling, since carsharing is a new transport option and classic models use general behavioral rules that are estimated on data representing the current transportation system, which in turn, normally considers only private car and public transport. Carsharing is a car mode with characteristics of both private and public transport. Therefore, the modal choice modelling need to accommodate a high level of detail due to similarities between choices, and travel should be modelled at a micro level. The approach, presented by the authors, uses a synthetic population of agents that act in a virtual world with similarities with reality. The synthetic population is linked with census data, while the virtual world reflects the infrastructure, land use, available transport services, and potential activities. Each agent has sociodemographic attributes (e.g.: age, gender, occupation, home location and car availability) and a daily activity plan with information where and when activities are taken and also which mode of transport is used. The activity chain is attributed according to individuals' socio-demographic characteristics. The plans are executed along with the traffic flow simulation. Agents are able to vary departure time, transport modes, routes and location of some activities. The transport modes included in the simulation were: car, public transport, bicycle, walk and carsharing. Authors concluded that the model gave plausible results in terms of overall carsharing usage, when compared with real values, and that needs to be improved, namely by introducing the physical simulation of carsharing cars and a reservation system with a limited number of cars available at each station.

All the references analyzed consider carsharing systems that only allow round-trip movements, with the exception of Catalano et al. (2008) who modelled a discrete modal choice considering one-way movements for the carsharing mode. Furthermore, the conclusions taken by the authors, with the exception of Ciari et al. (2013) are context specific and cannot be generalized, although they can serve as a reference for other studies, and methodologies can be replicated for other locations. The work of Ciari et al. (2013), opens new perspectives for using simulation to estimate demand, although some limitations need to be analyzed and improved, namely the fact of not considering one-way movements, neither the physical limitations related to the supply side.

3.3 One-way carsharing modelling

One-way movements are more adapted to users' needs, but introduce a new level of complexity to the operator. Allowing a vehicle to be returned at a destination different than the trip origin generates an unbalanced distribution of vehicles relatively to demand, meaning that, at some moments during operation, low demand zones or stations may have a surplus of vehicles, while high demand zones or stations may have a lack of vehicles. The imbalance problem has been addressed in different ways.

According to Jorge and Correia (2013), there are three main approaches to assist the daily system management operations: operator-based relocations, user-based relocations, and trip selection. In operator-based relocations, staff is used to periodically drive vehicles from a station with an excess of vehicles to a station with a shortage of vehicles. In user-based relocations, balancing movements are performed by clients reacting to incentive mechanisms, usually based on price. Trip selection consists in controlling the demand by allowing only the trips that are favorable to the balance of vehicle stocks.

3.3.1 Operator-based relocations

Looking at the research outputs available by the scientific community, it can be verified that operator-based is the most studied relocation approach. The reason is that the use of operator-based relocations give a competitive edge to organizations, since it assures privacy, simplicity and convenience to users [Kek et al., 2006]. The incipient studies regarding the balancing of a one-way carsharing system recurred to operator-based mechanisms and assumed the use of towing or platooning to perform relocations, by considering that a truck could be used to tow several vehicles between stations in simultaneous, or that the vehicles could group in platoons and move under their own power, respectively [Dror et al., 1998; Barth and Todd, 1999].

Dror et al. (1998), apparently the first authors to analyze the one-way carsharing rebalancing problem, considered a fleet of electric vehicles made available for users, at no cost, for short distance in city trips. The vehicles were redistributed among stations by a fleet of tow trucks stationed in various depots on the road network, having each tow truck the towing capacity of more than one vehicle. The study provides a tool to generate the best pickup and delivery routes for the fleet of tow trucks. The authors use a simplified graph with information about vehicle shortage or surplus and define a MIP model based on a Euclidean path to redistribute the vehicles on the network. Additionally, a heuristic approach is developed to solve problems of greater dimensions. This research assumes that the surplus and deficit of vehicles per station are known, and based on that, a similar problem to the vehicle routing problem is solved. The authors do not propose a way to estimate the number of vehicles needed or in excess at stations.

Barth and Todd (1999) considered that the number of vehicle relocations is variable and proposed three algorithms to determine when and how a relocation occurs: static relocation, historical predictive relocation and exact predictive relocation. Static relocation is based on immediate needs of a station. Historical predictive relocation uses knowledge of expected demand of vehicle in the future (it looks approximately 20 minutes into the future), based on historical data, to process stock movements. Exact predictive relocation assumes exact knowledge of future demand, even though this is impossible to achieve in the real world. The authors developed a queuing-based simulation model to evaluate the carsharing system performance. The model is subdivided in three stages: trip generator, traffic simulator and analysis tools. The trip generator stochastically generate vehicle trips using an O/D matrix as a primary input data and some control parameters. The output is a time-sequenced list of trips that is the input for the traffic simulator. The traffic simulator is a hybrid discrete-event and time-stepped simulation model, which models the operation of the system by simulating the events and updating system status. The events related to relocations are performed according to the relocation algorithm in consideration. During the traffic simulator execution, a number of critical parameters are recorded (e.g.: average wait time, total average wait time, number of customers waiting, number of relocations, average battery state of charge) and subsequently evaluated using analysis tools. The carsharing system tested was considered to be composed by a fleet of electric vehicles, with the battery state-of-charge for each vehicle updated for each time step, according to vehicle's activity (useful to induce the availability of vehicle). The relocations were supported by large trucks that can carry or tow several shared vehicles, or by vehicle platooning. The authors concluded that the carsharing system is most sensitive to the vehicle-to-trip ratio (function of total average wait time and number of relocations), the relocation algorithm used, and the charging scheme employed when electric vehicles are used.

The assumption of using towing trucks to relocate vehicles in one-way carsharing systems was, somehow, dropped by authors. Instead, operator-based relocations were considered to be done by personnel hired by the carsharing organizations. The use of staff was not limited to driving the vehicles into favorable locations considering the potential demand. Tasks such as refueling, cleaning, and vehicle inspection were also assigned to staff members, making the use of staff workers a necessity to maintain level of service. Simple relocation mechanisms using simulation, and based on forecasted demand were the focus of Kek et al. (2006) and Wang et al. (2010).

Kek et al. (2006) developed a simulation model based on operator relocation techniques and able to provide insights on performance. The model is a time-stepping simulation with operational set-up and real-time events (e.g.: vehicle usage, refueling, cleaning and inspection of vehicles) as input parameters. The simulation model uses an adapted version of the static relocation approach proposed by Barth and Todd (1999). Vehicles are relocated by staff based on a virtual station status. A virtual number of vehicles that considers the real number of vehicles at a station, the total number of vehicles scheduled to be returned to that station and the number of vehicles reserved or awaiting for basic jobs is compared with a minimum threshold. When the virtual number of vehicles violate the threshold a relocation request is sent to the operator. Three key performance indicators were proposed to measure effectiveness: zero-vehicle time, full-port time (users cannot return vehicles, because station is in full capacity) and number of relocations. The model was tested and validated using real data obtained from a carsharing operator. The authors considered that the model exhibited a "high fidelity" in replicating trends observed in real data.

Wang et al. (2010) dedicated their research to the forecast process and the use of microsimulation to simulate network movements and collect travel time for each link. To forecast demand different processes are used and the most accurate is chosen. The chosen process is the one that, for the previous historical time period, got closer to the verified values. The method described to rebalance the system is named inventory replenishing by the authors and has similarities to the one presented by Kek et al. (2006). The inventory replenishing is based on inventory decision of vehicle stocks. A station with excess of vehicles is considered an overstocked station, and constitute a candidate supplier. On the other hand, a station with deficit of vehicles is considered an under-stocked station, and is a potential receiver. Once the relocation decision is made, taken based on defined considerations and guidelines, the under-stocked station will be replenished from the nearest overstocked station.

Other authors, recurred to Linear Programming models to achieve the best outcome in terms of vehicle relocations, which were then tested using simulation [Nair and Miller-Hooks, 2011; Smith et al., 2013; Nourinejad and Roorda, 2014; Kek et al.,2009].

Nair and Miller-Hooks (2011) presented a stochastic MIP model, involving chance constraints, to generate optimal redistribution plans that accommodate the needs of a proportion of all near-term scenarios for a one-way vehicle sharing system (the system operator plans for a fixed short-term planning horizon). This research overcomes the prior works that assume static or known demand by using a probabilistic characterization of demand. It considers that the system operator has perfect information on available vehicles and free parking spaces at each station, that the operator performs redistribution actions throughout the day, and redistribution tasks are assumed to be completed before the beginning of the planning period. The optimization seeks to achieve a least-cost redistribution plan while assuring a level of service based on a p-proportion that control excess and deficit of vehicles at each station. If the p-proportion is satisfied for all possible demand scenarios, then no corrective actions are necessary. If available vehicles are insufficient then vehicles are relocated from adjacent stations. If available spaces are inadequate then vehicles can be repositioned to other stations, in order to free parking capacity. The authors used simulation to test the proposed relocation strategies and concluded that it improves reliability levels of the system. It is also referred that future developments should include immediate fleet relocation and incorporate staff availability to perform redistribution in order to relax some assumptions. Moreover the application to heterogeneous fleets should be regarded.

A different perspective was presented by Smith et al. (2013). The authors considered that in rebalancing operations for one-way carsharing systems, two objectives are aligned, rebalancing of vehicles and rebalancing of drivers, and, therefore, an optimal solution is obtained by solving two different linear programs in a fluid model of the system. Routing algorithms are applied that minimize the number of rebalancing vehicles, minimize the number of drivers needed, and ensure that the number of waiting customers remain bounded. The rebalancing of vehicles (without customers) is performed using hired human drivers, and the rebalance of drivers can rebalance themselves by using an empty vehicle or by acting as a taxi driver during a customer trip. The authors concluded that in Euclidean network topologies the number of drivers needed was between one quarter and one third of the number of vehicles and this fraction could decrease when drivers share trips with customers.

More recently, a dynamic tool to support relocation decisions and able to work in real-time, was presented by Nourinejad and Roorda (2014). The authors propose two models for supporting relocation decisions: a benchmark model (static) assuming that all daily user requests are known in advance, and a dynamic model that reacts to online user requests. The purpose is to study the effects of relocations and reservation time required in the operation of carsharing services. The benchmark model serves to obtain an optimistic solution for comparison to the dynamic model, since it assumes perfect knowledge of demand (not realistic).The dynamic model is composed by an optimization model working with a discrete event simulator. The optimization model is subdivided in: vehicle relocation optimization and parking inventory optimization. The first allows the optimization of vehicle relocation movements, while the second finds the corresponding relocation times. Both models use a trip generator to generate customer information. For the benchmark model all trips are generated at once, while for the dynamic model trips are generated continuously during simulation. In the dynamic model, the generation of the arrival of a customer (event) triggers the optimization process that determines if the user is accepted, the vehicle relocation origin and destination, and start time of relocation movement to serve the user. Authors tested the models using data form an active carsharing organization and concluded that the fleet size can be reduced by increasing the reservation time (time between the request and vehicle pick up), and that higher fleet sizes require less relocation hours. It was also stated that the characteristics of the dynamic model allows it to adapt to changes in the system, being it demand or supply related. These models do not take into account staff movements.

Using the simulation model developed in 2006 [Kek et al., 2006], Kek et al. (2009) innovate by optimizing all staff related movements and tasks in the same linear programming model. The authors present a three-phase optimization-trend-simulation decision support system to determine a near-optimal manpower and operating parameters for the vehicle relocation problem, to serve as a decision support for carsharing operators. A station-based carsharing system with one-way movements with limited parking stall capacity is the focus of the authors' research. The first phase is an optimization model that receives data from the carsharing system stations, and with the objective of allocating staff resource and activities in order to minimize the generalized cost associated with the vehicle relocation activities. The second is a trend filter that sieves the optimized outputs from phase one through a series of heuristics. After filtering the optimization outputs, a simulator is used to evaluate the effectiveness of the recommending actions. The simulator used was based on the work described in Kek et al. (2006). The problem is described by the authors as "given a set of geographically scattered stations, with each station having a capacity (number of parking stalls) and customer pick-up and return patterns, plus the maintenance schedule for the vehicle fleet, the objective of the optimization problem is to allocate staff resource and staff activities so as to minimize the generalized cost associated with the vehicle relocation activities" (Kek et al., 2009). Staff resource, that is time, is used to fulfil assigned activities. Each staff member is assigned, at any time, to one of the activities: waiting (wait at a station for a new activity), maintenance (inspect or clean vehicles at a station, refueling, drive a vehicle to a workshop), movement (travel between stations without driving a vehicle), or relocation (drive a vehicle from one station to another). Staff members use vehicles not only to perform relocations, but also to move themselves between stations to complete maintenance tasks. The model was tested on a set of commercially operational data from a carsharing company. The results suggested a reduction of 50% in staff cost, a reduction between 4.6% and 13.0% in zero-vehicle-time ranging, and a reduction in number of relocations between 37.1% and 41.1%.

3.3.2 Trip selection

Other authors consider a demand control mechanism to balance the vehicles in the system. It consists in selecting the trips favorable to the system's equilibrium. Trip selection is, therefore, an operator-based strategy that avoids or minimizes the need for relocations.

Fan et al. (2008) assumed an operational trip selection working in parallel with relocations. The authors developed a multi-stage stochastic linear integer model with recourse to address the vehicle allocation problem in a carsharing context for a finite planning horizon. It is considered that customers make reservations at the end of each day. The approach of this research is to decide, based on the initial location of vehicles, which vehicle reservations to accept or refuse and how many vehicles to relocate or hold in order to achieve a more favorable future vehicle allocation. The model considers that the carsharing manager declines the demand requests that are unprofitable or that cannot be accommodated by the service capacity. Limited assumptions were made, namely travel times between all carsharing locations are uniformly equal to one day. The authors recognized the limitations in computation time and tested the problem for a small network using a short-time horizon.

Correia and Antunes (2012) proposed an upstream approach, in a strategic level, to solve imbalance problems created by one-way carsharing. The authors focus exclusively on selecting the station locations that, per se, minimize system imbalance levels. Nevertheless, it is assumed that relocation movements occur at the end of the day to restore vehicles' original positions. The output is the location of stations that leads to a more balanced system. The research considered three trip selection schemes: controlled service, full service, and conditional service. The first scheme, controlled service, considers that the carsharing organization has total control over the selection of trips from the list of client requests, meaning that a trip is only accepted if it is advantageous on the profit point of view. The second scheme, full service, considers that all client requests are accepted (no trip selection), although only trips between existing stations are satisfied (if there is no station inside a walking distance from trip origin or trip destination the trip is not considered). The third scheme, conditional service, is a combination of the previous ones, that is, not all client requests are satisfied and only the requests that do not have a vehicle at the pick-up station are rejected. MIP optimization models are defined for each scheme and a test is performed using realistic data from an urban area (potential trip matrix, candidate depot locations, driving and walking travel times, and costs of running the system). The authors concluded that, for the testing site, satisfying all the demand for carsharing trips would lead to severe financial losses, although these could be reduced by choosing the appropriate number, location, and size of the stations, and positive profits would only be possible if trips were optimally selected from the total demand.

Correia et al. (2014) used a more advanced approach to the MIP models presented by Correia and Antunes (2012). Instead of assuming that people would use only the station closest to their origin and destination, the authors considered that in real situations people are more flexible and willing to use a second or even a third station. Real-time information can also be given to the user in order to improve level of service. The effect of flexibility and information is measured by considering three scenarios. The first scenario considers that users are inflexible and only use the nearest stations to both origin and destination. The second scenario considers that users are flexible and willing to use a second or third station, but since information is not available the user risks entering a station without an available vehicle. The third scenario considers that users are flexible and that real-time information is available about: vehicles at the three closest stations and free parking spaces at the three stations closest to the destination. Stations have a limited capacity in what concerns to parking spaces and no vehicle relocation movements is used to balance the system. Realistic data of an urban area was used to test the model. The authors concluded that the level of service and economic results of a carsharing service can improve by providing real-time information about current supply.

Jorge et al. (2014) uses the MIP model presented by Correia and Antunes (2012), adapted to use one minute time steps. The alteration was performed to account for the fact that the service charges the user based on by the minute fees. The adapted MIP model optimize relocation movements based on profit maximization and sets station locations. The model considers, as decision variables, the number of vehicles relocated, the capacity of each station in number of parking spaces, and the number of available vehicles at each station. The optimal solution obtained using this model is then compared with real-time operator-based relocations, built in agent based simulation model policies (this reference could be also included in the previous subchapter 3.3.1). A set of policies were defined varying in the time step increments (5 to 20 minutes, and 1 minute) and in different variant conditions. Three variant conditions were established: each supplier station is required to keep at least one vehicle; the distribution of vehicles at the beginning of the day is set by the MIP model; and the distribution of vehicles is set by MIP model at the beginning of the day plus priority is given to stations with greater demand for vehicles. All policies classify a station as a supplier or demander, based on the in and out trips of that station for the same period of the previous day. The relocation of vehicles is obtained by solving a classic transportation problem with the objective of finding the minimum cost distribution of vehicles from m origin nodes to n destination nodes, with the costs equal to the total travel time. The MIP model and simulation were applied to real data. The authors concluded that the methods developed to relocate vehicles can produce substantial profit growth.

3.3.3 User-based relocations

Another approach is inducing users to perform trips that are more favorable to the carsharing operator. User-based relocations are dependent on the will of individuals, but can reduce operator's costs by reducing the parcel related to relocations.

Barth et al. (2004) introduces two user-based relocation mechanisms to reduce the number of relocations performed by system staff. The mechanisms proposed are designated by trip joining and trip splitting. Trip joining consists in the share of the same vehicle space by different customers, if they are traveling from the same origin station that has a deficit of vehicles to the same destination station. Trip splitting, conversely, incentivizes users that carry passengers, traveling from a station with excess of vehicles to a station with deficit of vehicles, to split and use different vehicles. Price incentives are used to potentiate trip-joining and trip-splitting. The authors have implemented the concepts on a university campus and in "high-fidelity" computer simulation system (the simulator used was the one described by Barth and Todd, 1999). The results revealed that a 42% reduction in relocations is possible by implementing these user-based techniques.

Uesugi et al. (2007) proposed a method for optimizing vehicle assignment according to the distribution of vehicles and balance needs. The authors propose a similar process included in Barth et al. (2004), extensively describing the simulation and assignment process. The main difference is instead of having price incentives the authors consider vehicle assignment to users. That is, users have no other choice than using the vehicle attributed by the operator, although it is stated that the consideration of incentives should be taken in future developments. Three ways of assignment are used: normal assignment, divided assignment, and combined assignment. In normal assignment the user rides in one vehicle. In divided assignment, considered for trips performed by user and passengers, the individuals will travel using different vehicles (trip splitting). In combined assignment user groups travel in the same vehicle (trip joining). The results showed that the method is effective for one-way carsharing system, although the authors haven't test it using real data.

Febbraro et al. (2012) proposed a user-based methodology to perform an optimal user-based relocation policy in real-time. It is based on a rolling horizon framework and is applicable to one-way and free-float carsharing systems. The authors use a discrete event system to represent the complex dynamics of the carsharing system. The events considered were: vehicle booking, booking modification, booking cancellation, vehicle pickup, and vehicle drop-off. The model considers that the users need to book vehicles in advance, and during this process they need to specify departure time, trip origin, trip destination, and delivery time. The methodology considers that relocations are performed by users, thus a choice is given either to return a car at the user's desired location or to agree to drop it in a place proposed by the operator. The destination proposed by the operator is a location close to the user's destination zone with a shortage of vehicles, and is determined by using an integer linear programming model. A faire discount is used as an incentive for users to change their destination, and the value of the discount is calculated using a binomial logit model. A rolling horizon approach is adopted for the procedure, having new optimal solutions being computed slightly before any drop-off event. The model was tested in a real scenario to evaluate its efficacy. The test location was an urban traffic restricted zone with only public vehicles, carsharing vehicles and where only local residents were allowed to use the car. The authors concluded that the number of vehicles needed to run the system efficiently could be significantly reduced by using this methodology.

3.4 Staff activity optimization

The interest of companies in the use of operator-based relocations is to have a competitive edge by assuring privacy, simplicity and convenience to users [Kek et al., 2006]. Carsharing operations involve much more than relocations, for instance cleaning, inspection and maintenance of vehicles, besides refueling and recharging, can be present on the daily carsharing duties. These tasks are performed by contracted staff members, and the optimization of staff scheduling is fundamental to assist the carsharing organizations in attaining their goals. From all the operator-based relocation mechanisms presented in research publications, the one published by Kek et al. (2009) is more adapted to the specified needs of the operator, since it provides optimal guidance not only for relocation, but also for other types of staff activities. In fact, the referred research work is the seminal structure that can lead to the development of a real-time optimization methodology to delineate staff activity, including relocations and the most frequent maintenance activities. Therefore a detailed analysis of the optimizer module is detailed subsequently.

The problem is defined by a two-dimensional time-space network, as shown in Figure 5, the time is represented by the x-axis, while space is represented by the y-axis. The problem has $S \times T$ nodes, where S is the number of stations and T the number of considered time-steps. Considering N the set of stations, being $N = \{1, \dots, i, \dots, S\}$. For each station i, T nodes are created representing the referred station at instants $t = 1,2, \dots, T$.

The result is a time-space network V including all the $S \times T$ nodes, being $V = \{1_1, \dots, i_t, \dots, S_T\}$. The set of arcs connecting the V nodes is denoted by A.

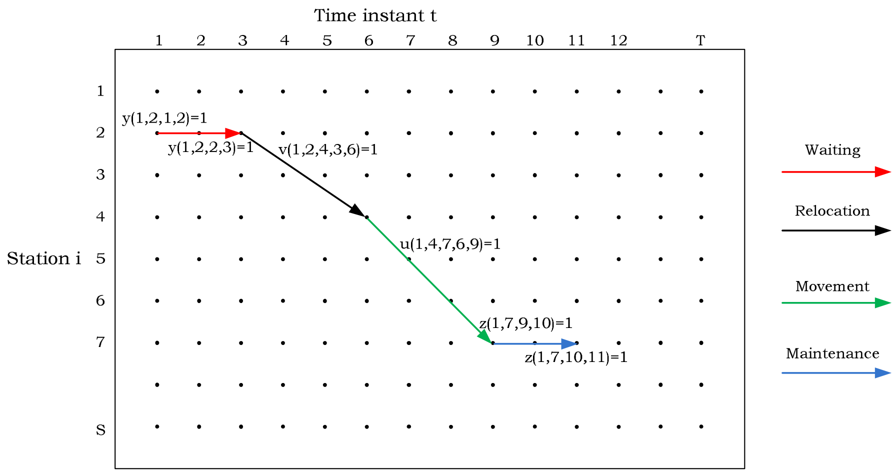


Figure 5: Optimization space and binary variables – in Correia (2009)

The authors consider four subsets of arcs, each one related to the four different possible staff activities (waiting, maintenance, movement and relocation). The consideration of these subsets allow the reduction of the number of decision variables. Waiting is an activity that is performed at a station i from time step t to $t + 1$, therefore the set of arcs for waiting activity is $A_1 = \{\dots, a_1(i_t, i_{t+1}), \dots\}$. Maintenance activities are performed at station i, between time steps t and $t + t_m$, therefore the set of maintenance arcs is $A_2 = \{\dots, a_2(i_t, i_{t+t_m}), \dots\}$. It is considered that during maintenance a vehicle can move out of station i and turn back to the same station in the period of time t_m. The next staff activity considered is moving without a vehicle. A member of staff can travel from station i to station j from t to $t + t_{ij}$, $j \in N$ and $i \neq j$. A set of $S - 1$ arcs is created for each node $i_t \in V$. This set of arcs is denoted as $A_3 = \left\{\dots, a_3\left(i_t, j_{t+t_{ij}}\right), \dots\right\}$. The activity relocation consists in a member of staff driving a vehicle from a station i to a station j, from t to $t + t_{ij}$. Similarly to the activity moving, a set of $S - 1$ arcs is created for each node $i_t \in V$, being denoted as $A_4 = \left\{\dots, a_4\left(i_t, j_{t+t_{ij}}\right), \dots\right\}$. The authors assume that the time that staff uses to move towards the vehicle location and the driving time are included in t_{ij}. A number of staff members W, is included to perform the considered activities. The activities for each member k are discriminated. The set of staff members is denoted as $L = \{1, \dots, k, \dots, W\}$.

The MIP model proposed by Kek et al. (2009) uses seven types of decision variables:

- x^k- binary variable related to staff usage, taking value 1 if staff k is ever used, and 0 otherwise, $\forall k \in L$;
- $y^k(i_t, i_{t+1})$ – binary variable associated with A_1 representing waiting activity, taking the value 1 if staff member k waits at station i from time steps t to $t+1$, and 0 otherwise;
- $z^k(i_t, i_{t+t_m})$ – binary variable associated with A_2 representing maintenance activity, taking the value 1 if staff member k maintains a vehicle at station i from time steps t to $t+t_m$, and 0 otherwise;
- $u^k\left(i_t, j_{t+t_{ij}}\right)$ – binary variable associated with A_3 representing staff moving without a vehicle, taking the value 1 if staff member moves from station i to station j from time steps t to $t+t_{ij}$, and 0 otherwise;
- $v^k(i_t, j_{t+t_{ij}})$ – binary variable associated with A_4 representing vehicle relocations, taking the value 1 if staff member k relocates a vehicle from station i to station j from time steps t to $t+t_{ij}$, and 0 otherwise;
- $d^r(i_t)$ – integer variable representing the rejected demand for vehicles at station i from time steps $t-1$ to t due to unavailability of empty parking stalls at the station;
- $s^r(i_t)$ – integer variable representing rejected customer return of vehicles at station i from time steps $t-1$ to t.

Two additional dependent variables:

- $r(i_t)$ – number of available vehicles at station i at time step t;
- $\bar{r}(i_t)$ – number of unavailable vehicles at time step t.

And the following known constants:

- $c(i,j)$ – fixed cost of a movement or relocation trip from stations i to j;
- c_x – fixed cost of utilizing one staff;

- c_d – fixed cost of rejecting the demand of one customer-vehicle trip;
- c_s – fixed cost of rejecting the return of one vehicle by a customer;
- $r(i_0)$ – number of available vehicles at station i at time step $t = 0$;
- $\bar{r}(i_0)$ – number of unavailable vehicles at station i at time step $t = 0$;
- $d(i_t)$ – demand for vehicles at station i from time steps $t - 1$ to t;
- $s(i_t)$ – number of vehicles returned by customers at station i from time steps $t - 1$ to t;
- $m(i_t)$ – number of returned vehicles in need of maintenance at station i from time steps $t - 1$ to t;
- $p(i)$ – number of parking stalls at station i.

The formulation of the MIP model for the problem is:

$$\min(Z) = c(i,j) \sum_{\left(i_t, j_{t+t_{ij}}\right) \in A} \sum_{k \in L} \left(u^k\left(i_t, j_{t+t_{ij}}\right) + v^k\left(i_t, j_{t+t_{ij}}\right)\right) + c_x \sum_{k \in L} x^k + c_d \sum_{i_t \in V} d^r\,(i_t) + c_s \sum_{i_t \in V} s^r\,(i_t) \tag{3.1}$$

Subject to:

$$\sum_{i \in N} y^k(i_t, i_{t+1}) + \sum_{i \in N} z^k\left(i_t, i_{t+t_m}\right) + \sum_{\substack{i,j \in N \\ i \neq j}} u^k\left(i_t, j_{t+t_{ij}}\right) + \sum_{\substack{i,j \in N \\ i \neq j}} v^k\left(i_t, j_{t+t_{ij}}\right) = x^k \land t = 1, \forall k \in L \tag{3.2}$$

$$y^k(i_{t-1},i_t)+z^k(i_{t-t_m},i_t)_{(i_{t-t_m},i_t)\in A_2}+\sum_{(j_{t-t_{ji}},i_t)\in A_3}u^k(j_{t-t_{ji}},i_t)$$
$$+\sum_{(j_{t-t_{ji}},i_t)\in A_4}v^k(j_{t-t_{ji}},i_t)-y^k((i_t,i_{t+1})$$
$$-z^k(i_t,i_{t+t_m})_{(i_t,i_{t+t_m})\in A_2}-\sum_{\left(i_t,j_{t+t_{ij}}\right)\in A_3}u^k\left(i_t,j_{t+t_{ij}}\right)$$
$$-\sum_{\left(i_t,j_{t+t_{ij}}\right)\in A_4}v^k\left(i_t,j_{t+t_{ij}}\right)=0,\forall i_t\in V|t>1,k\in L \tag{3.3}$$

$$r(i_t)=r(i_{t-1})+\sum_{\left(j_{t-t_{ji}},i_t\right)\in A_4}\sum_{k\in L}v^k\left(j_{t-t_{ji}},i_t\right)-\sum_{\left(i_t,j_{t+t_{ij}}\right)\in A_4}\sum_{k\in L}v^k\left(i_t,j_{t+t_{ij}}\right)$$
$$+\sum_{\substack{(i_{t-t_m})\in A_2\\k\in L}}z^k(i_{t-t_m},i_t)+s(i_t)-s^r(i_t)-d(i_t)+d^r(i_t)-m(i_t),\forall i_t$$
$$\in V \tag{3.4}$$

$$\bar{r}(i_t)=\bar{r}(i_{t-1})-\sum_{\substack{(i_t,i_{t+t_m})\in A_2\\k\in L}}z^k(i_t,i_{t+t_m})+m(i_t).\forall i_t\in V \tag{3.5}$$

$$r(i_t)+\bar{r}(i_t)\le p(i),\forall i_t\in V \tag{3.6}$$

$$d^r(i_t)\le d(i_t),\forall i_t\in V \tag{3.7}$$

$$s^r(i_t)\le s(i_t),\forall i_t\in V \tag{3.8}$$

$$x^k=(0,1),\forall k\in L \tag{3.9}$$

$$y^k(i_t,i_{t+1}),z^k\left(i_t,i_{t+t_m}\right),u^k\left(i_t,j_{t+t_{ij}}\right),v^k\left(i_t,j_{t+t_{ij}}\right)=(0,1),\ \forall i,j\in S\wedge i\ne j,k\in L \tag{3.10}$$

$$d^r(i_t),s^r(i_t),\bar{r}(i_t)\in\mathbb{N}\cup\{0\},\forall i_t\in V \tag{3.11}$$

The objective function (3.1) minimizes the generalized cost function Z which includes: the cost of staff movements without a vehicle, the cost of relocating vehicles, the cost of using a certain number of staff members, cost of rejecting demand, and the cost of rejecting the return of vehicles by the customers due to lack of empty parking stalls. Constraints (3.2) has a dual purpose, it assigns a non-zero value to variable x^k when staff is used from time step $t = 1$ and it restricts staff to perform only one activity $t = 1$. Constraints (3.3) assures the conservation of staff activities at each station i and time instant t. It restricts staff to start another activity only after finishing the previous one. Constraints (3.4) updates the number of available vehicles. The number of available vehicles is attuned by vehicles coming in and out of the station resulting of relocation activities, vehicles returning from maintenance, vehicles picked up and returned by clients, and vehicles returned by clients in need for maintenance. Constraints (3.5) updates the number of unavailable vehicles considering the vehicles coming out of maintenance and the vehicles returned by customers in need of maintenance. Constraints (3.6) assures that the number of vehicles, available and unavailable, inside a station do not exceed the total number of parking stalls. Constraints (3.7) and (3.8) ensures that the number of rejected demand, does not exceed the number of client demand, and that the number of rejected returns does not exceed the requested returns, respectively. Constraints (3.9) and (3.10) sets binary variables and constraints (3.11) impose non-negativity conditions. An analysis of the work of Kek et al. (2009) performed by Correia (2009), allowed to understand that the model requires large sets of binary variables, creating difficulties in producing results in an acceptable time limit for real size problems.

3.5 Conclusions

Demand estimation is important to understand the impact of the carsharing mode as part of an urban transportation system, namely to assess the number of potential users, in order to be possible to optimize operations, being it for real situations or for simulation purposes. The use of aggregate models loose the details that implicitly induce modal change into carsharing. These details are intrinsically related to the individual, as it can be seen in the studies that identified the main characteristics of carsharing users recurring to data gathered from existing carsharing systems. Contrary to what is used in classical demand estimation approaches, for the demand estimation of a system with such specificities as the carsharing mode, the analysis of modal choice behavior at the level of the individual is necessary to produce quality estimations.

Concerning solving the imbalance problem of carsharing systems, several research approaches were analyzed, which were subdivided in: operator-based relocations, user-based relocations and trip selection. Operator-based relocations mechanisms use staff to periodically drive vehicles from a location with excess of vehicles to a location with shortage of vehicles. In user-based relocations, operators induce clients to perform more favorable trips, normally using price incentives. Trip selection consists in controlling the demand by allowing only the trips that are favorable to the balance of vehicle stocks. From the three types analyzed operator-based relocations are more suitable to simultaneously fulfil operator and users' needs without compromising the perceived service quality. These operations do not restrict users' movements and intentions to use the service, which could reduce the potential demand and compromise the financial sustainability of the organization, and are totally controlled by the operator. The only drawback is that it represents an increased cost for the operator, due to the need of hiring staff members. However, staff members are also needed for other activities, such as cleaning, inspecting vehicles, refueling, therefore relocating vehicles is just part of the multi-purpose duty of staff members. Returning to the analyzed research, namely the operator-based related, only Kek et al. (2009) presented an approach that simultaneously optimizes carsharing staff scheduling for maintenance and relocations. Nevertheless, to create an optimization model adapted to the operator needs, several essential improvements need to be made:

1) adapt to real-time system changes - updating the system variables in real-time is useful to better plan staff activities and increase the adaptability to demand.
2) use carsharing vehicles to also power staff movements - it makes sense that, in a large-scale system allowing one-way movements, staff could move inside system vehicles. The movements can be optimized considering all the tasks that need to be performed.
3) allow trip joining of staff - having staff members sharing the same vehicle to perform common movements, potentially increases the minimization of costs.

The hypothesis is that building an optimization model that includes these features will possibly have a considerable impact in the cost of system operations.

4 Real-time decision support tool

4.1 Introduction

The system studied is a one-way and free-float carsharing system based on an operating area, having no limitations concerning to parking. Which means, that a vehicle can park at any public parking space inside the operating area. The operating area is subdivided by zones to allow spatial differentiation and aggregation of variables, easing the complexity level of a mathematical model design, while facilitating the definition of operational borders. Each zone of the operating area has a walkable size. This guarantees that a client can walk to a vehicle if both entities (client and vehicle) are at the same zone of the operating area.

The vehicles serve movements of clients but can also serve movements of staff between zones. All vehicles share the same characteristics and have the same capacity. It is considered that vehicles need certain types of maintenance and refueling. Refueling or recharging is mainly supported by clients by recurring to price incentives, and maintenance is performed by employees of the carsharing company.

Clients use the service to serve their personal transportation needs. Vehicles are rented in an on-demand basis, and mobile communication devices (e.g.: smartphones and tablets) are used by clients as a means to locate vehicles. When a vehicle is being used by a client, there is no information about its destination, since the system does not require this information from the client. Although, in-vehicle communication and GPS systems allow to track and trace vehicle positions in real-time.

Staff perform maintenance tasks and relocations. The maintenance procedures are based on the staff activities of service providers currently in operation [Citydrive website, 2015 and Car2Go website, 2013]. The activities are related to client incorrect check out procedure, such as: intervention to correct vehicle parking, intervention to turn off lights, intervention to close doors (including rear door), intervention to close windows, intervention to enable parking brakes, simple cleaning intervention, and intervention to solve discharged battery. The service provider receives information related to client incorrect check out procedure, and the operator send orders to staff to perform the corrective measures, here designated by maintenance procedures. The relocation of vehicles is based on the current location of vehicles and the forecasts. Staff orders are established using one of the assignment models considered: rule-based model or optimization model. Each member of staff is considered to have a smartphone or a tablet in permanent communication with the service controller to receive instructions about the next tasks. The staff start their working day at a zone identified by the operator. The starting zone of a staff member can be previously agreed with the operator being a location that benefit both parts. The employees, here denominated as staff, relocate vehicles and perform minor maintenance tasks locally. It is considered that the equipment transported by staff does not affect its mobility.

This chapter describes the decision support tool developed to aid in the process of assigning tasks to staff in real-time. The support tool is composed by three elements: a forecasting model, an assignment model and a filter (see Figure 6).

The **forecasting model** allows to predict the demand for the immediate future, in order to allow a better position of staff and vehicles. The forecasting process uses historical data from the carsharing system to produce an estimate of the expected demand for each zone.

The **assignment model** designs a reaction plan for the staff activity based on forecasts and the current status of the system, in order to optimize the profit-costs balance. Two assignment models were developed. The first is a rule-based model based on simple routines triggered by variables of the system status. The second undertakes an optimization process, through a MIP model, which delineates optimized staff tasks. Both are prepared to work in real-time.

Finally, the orders pass through a **filter** to discard the ones that cannot be fulfilled. Some staff orders included in the output plan may not be applicable, due to differences between predicted and real demand. For example, a relocation movement may not be fulfilled due to the fact that there is no car at the zone of origin. The filtered orders are then transmitted to staff allowing to undertake movements that help the system to adapt to the demand forecast predictions. This changes the system status leading to new data that need to be processed once more.

The entire procedure is cyclic and based on the use of a rolling horizon approach to promote a real-time interaction between the optimization process and the system status. The use of a rolling horizon approach allows to look further than the planning period, for which optimized actions are retrieved and transmitted to the system. The real-time interaction results from updating the system status data, at the beginning of each cycle.

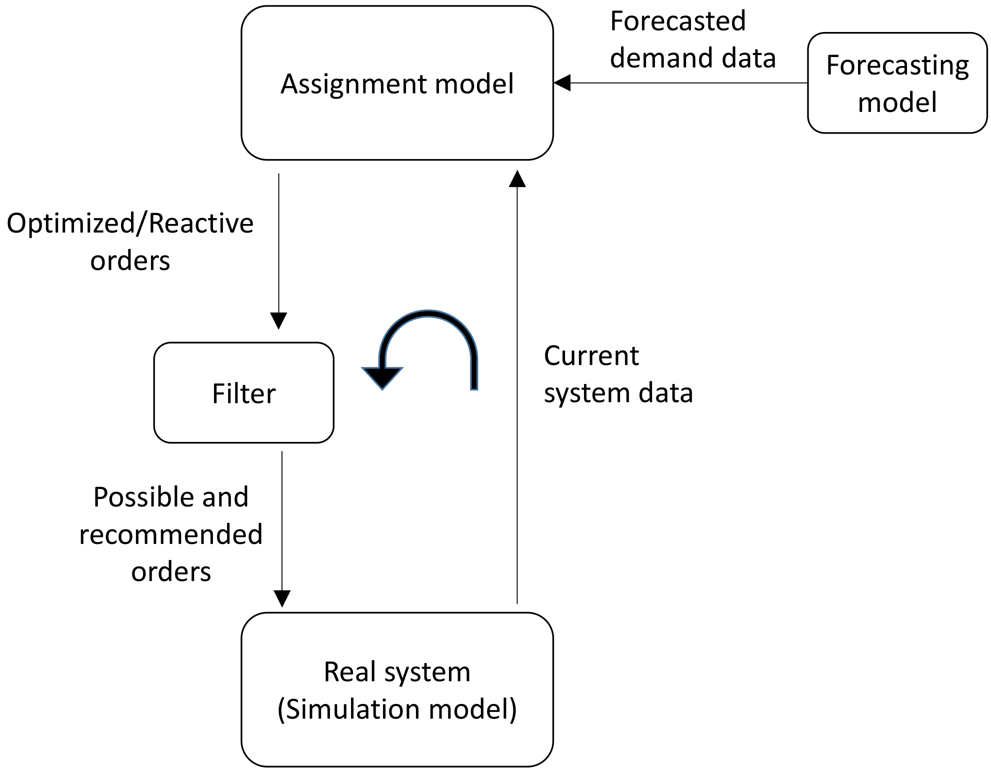


Figure 6: Real-time decision support tool scheme

We propose a rolling horizon approach for the staff activity assignment in which, at each iteration, short-term staff assignment is decided. However, in a look-ahead perspective, a longer horizon is considered when looking for the forecasted demand.

The use of a rolling horizon approach introduces dynamic interaction between the system and the assignment process. The adopted framework was the rolling horizon planning with fixed intervals [Wang and Kopfer, 2013], since there is a need to frequently retrieve information from the system.

A rolling horizon planning with fixed interval approach considers that the entire operation period is subdivided in planning periods, $p = 1,2, \dots, \infty$. Each planning period has a fixed length τ. A horizon H (also denominated by planning horizon) is a group of n planning periods, being n a constant. Each horizon length L_h is, therefore, equal to $n \times \tau$.

At planning time instant t_0, a first plan, Ω_1 is scheduled for the first horizon $H_1 = \{1, \dots, n\}$. The actions for the first planning period ($p = 1$) of the considered horizon are unaltered. The actions defined for planning periods $p = 2, \dots, n$ are updated by the forthcoming horizon plans, using updated data dynamically retrieved from the system during the execution of the first planning period. For the following horizons H_i with $i > 1$, a new plan Ω_i is established at the end of the planning period $p = i - 1$, at time $t_{i-1} = (i - 1) \times \tau$. The new plan Ω_i establishes the activity for planning periods $p = i$ to $p = i + n - 1$. Once more, the partial plan defined for period $p = i$ will be fixed, while the remaining periods can change when the next plans are determined (see Figure 7).

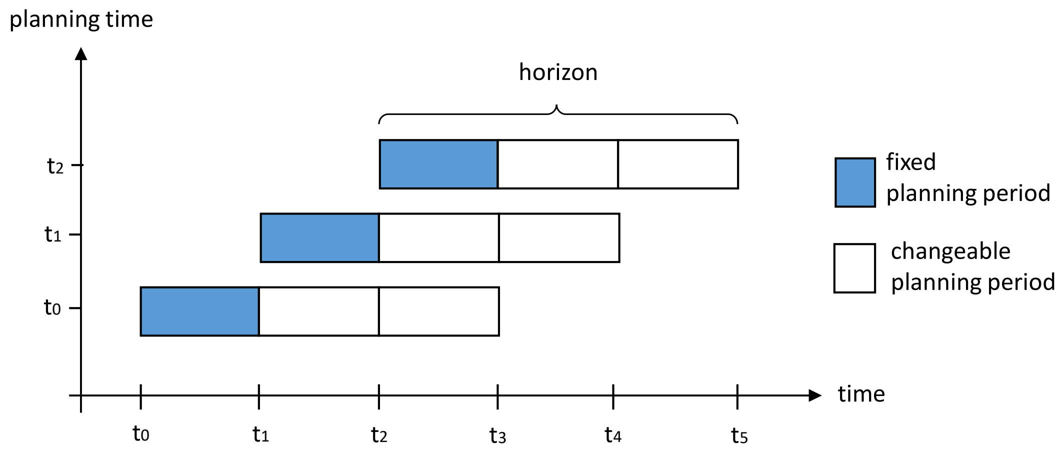


Figure 7: Framework of rolling horizon planning with fixed interval - adapted from [Wang and Kopfer, 2013]

This approach allows to send recommended orders for the first planning period (fixed planning period), taking into account an assignment process that uses demand data that looks beyond the fixed planning period by $n - 1$ planning periods. It also allows adjustments for the previous schedules by accommodating new input data from the system at the beginning of each horizon.

To allow the use of a rolling horizon approach the MIP model was set to receive the information relatively to staff ongoing activities, that is, the staff boundary data can be introduced as input data. This way, it is possible to produce optimized orders for the new horizon taking into account the positions and ongoing activities of staff.

4.2 Forecast model

If we are facing a new transportation service and there is lack of data concerning to system demand, we can use an activity based microsimulation approach (e.g.: Ciari et al., 2013) to obtain demand information. On the other hand, if there is numerical past information available about the system demand, it is reasonable to assume that some characteristics of past patterns will be repeated, and quantitative forecasting methods based on time series or artificial neural networks can be applied. When mentioning demand, we refer to the characteristics of client trips, such as origin, destination, start time and end time.

4.2.1 Activity based microsimulation approach

Carsharing is a recent transport option which has attributes of both car and public transport. Thus, the estimation of carsharing demand using the four steps classic modelling approach is not adequate, since using an aggregated analysis based on estimated data representing the current transportation system to produce a modal market share for a non-existent modal choice can lead to unrealistic results [Ciari et al., 2013]. In order to have more realistic values, travel choice should be modelled at the individual level, by gathering the necessary detail to describe the available modes, emulating, this way, the decisions taken by users of the system. To simulate decisions at the individual level, one should have the characteristics of the individuals that interact with the target area, and also their individual mobility patterns. And, adding this information to the supply side parameters, the decisions of each individual can be emulated and the demand estimated.

The process of estimating carsharing demand, if the system is not operating yet, can be subdivided in four steps: Characterize target population; characterize the activity log for each individual; calibrate a discrete choice model; and estimate demand. A detailed overview of each individual's characteristics as well as its activities is important to have a valid understanding of the underlying travel behavior, since travel is a "physical mechanism to access an activity site for the purpose of participating in some activity" [Hensher and Button, 2000].

4.2.1.1 Characterize target population

Firstly, we must have a broad knowledge of each individual's characteristics of the target population. Demographic, socio-economic and information about transportation tools or assets need to be gathered, for example: home location, age, gender, marital status, education level, employment status, income, driving license, vehicle ownership, and public transport pass ownership. If this information is not available by the statistics bureau, due to data privacy protection, an iterative proportional fitting process [Birkin and Clarke, 1988] can be applied to disaggregate the Census data, originating a synthetic generated population. Specific characteristics not included in Census data can be obtained by surveying a representative sample of the population. A web-based survey can be designed to gather the necessary demographic and socio-economic data, combined with revealed and stated preferences towards transport options (needed for steps described in 4.2.1.2 and 4.2.1.3). The sample retrieved from the web-based survey needs to be unbiased to become representative of the population. This can be done by Computer Assisted Personal Interviews (CAPI).

Each individual should be assigned to a household. This can be undertaken by applying a stochastic method to geo-statistical household data [Lenormand, M., Deffuant, G., 2013]. Household information is important to characterize mobility, namely if we specifically want to understand how assets or trips can be shared.

4.2.1.2 Characterize activity log for each individual

By applying an activity-based travel demand model, we can generate travel related activity schedules for individual travelers. The travel demand derives from those activity schedules since most activities occur at different locations and people need to travel from one location to the other. The travel related activity can be obtained for a representative sample by the means of a revealed preference survey. The survey has to associate mobility data to purpose, by identifying type of activity. It should hold information about activities each traveler perform, sequence, duration, and the mode used to travel between activities. The activities can be classified as mandatory and non-mandatory. Being mandatory travel related activities associated to work or study, and the non-mandatory related to extra activities.

The generation of synthetic activity-travel patterns can follow one of the two broad classes of approaches: sequential (incremental) or simultaneous. Sequential approaches adopt rules to generate, one by one, the next activity of the each individual's activity log, while simultaneous approaches apply behavioral paradigms concerned with the entire daily activity-travel pattern [Kitamura et al., 1997].

For this research it was adopted a sequential approach based on Eiró (2015). The author adds non-mandatory activities to each person's agenda being the mandatory trips already characterized. Two types of individuals are defined: with mandatory trips and without mandatory trips.

The mandatory trips characteristics for the synthetic population can be generated by using mobility survey data and a synthetic mobility generator presented by Viegas and Martínez (2010), which expands the mobility survey data to the total universe of trips using a fuzzy sets theory approach.

To establish non-mandatory activity-travel data, a set of probabilities are calculated based on a representative survey sample. Four categories of non-mandatory activities are defined: personal, well-being, social and meal related. The individuals with mandatory trips are sub-categorized by distance to work or study and age stratum, since it is considered that people with mandatory trips change their behavior according to age and distance travelled for mandatory purposes. The individuals with no mandatory trips are categorized only by age.

Applying these categories to the survey sample allows defining probability distributions to characterize: number of activities for people with mandatory trips, number of activities for people without mandatory trips, type of activity and time of day for people with mandatory trips per age stratum, type of activity and time of day for people without mandatory trips, average and standard deviation of travel distance of each type of activity at a time of day, probability distribution of the start hour of the day and duration for each activity type. Land-use distribution data is used to link a location to each activity. To model the selection of a location a distance decay function is adopted, making further away locations less likely to be chosen. The agenda for each individual is limited by a maximum travel time budget that varies according to the number of non-mandatory activities.

The activities generator model is subdivided in two stages: The first stage defines the number of non-mandatory activities for each person, the starting time, the duration, the maximum travel distance, and also check if those activities can fit in an admissible agenda. The second stage generates the destination of all activities and validates travel times according to the maximum travel budget limitation. The output of this model is the activity agenda for each individual and respective travel needs (trip start time, trip end time, origin and destination).

4.2.1.3 Modeling mode choices

To understand how individuals react to a new transport mode, like carsharing, that is not yet known, we can adopt a stated preference survey. Stated preference data refer to choices taken or stated based on hypothetical scenarios. To obtain quality data, the hypothetical scenarios need to be as realistic as possible. Using stated preference data we can estimate utility. Utility maximization is the basis of the discrete choice model, being utility a measure of the satisfaction provided by attributes related to specific choices. The utility function can assume different mathematical forms [Hensher et al., 2005] [Ben Akiva and Lerman, 1985]. The most simple is the linear mathematical form

$$U = V + \varepsilon$$

$$V = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_n x_n$$

where,

U − total utility;

ε − random part of utility;

V − systematic part of utility;

$x_1 \dots x_n$ − values of factors 1 to n;

$\alpha_1 \dots \alpha_n$ − utility weights for factors 1 to n.

The first step is to define the variables of interest (factors) and the values (levels) to include in the stated preference study. Then we need to define the experimental design. The purpose of the experimental design is to delineate the combinations of the variables and values to include in the experiment, in such a way that they are completely uncorrelated between alternatives. The total number of combinations obtained is called full factorial design. Due to the fact that the respondent can only evaluate a certain number of experiments, a full factorial design can only be used if there are very few factors and levels. In situations in which the total number of combinations is high in relation to the answering capacity of the respondent, a fractional factorial design can be implemented. In this case, the number of alternatives presented to the respondent is reduced. If the number of alternatives is still high, we can use subsets or blocks of the fractional factorial design, assuring that a common factor is included in all separate exercises, to enable linking the utilities [Kroes and Sheldon, 1988].

Adding the information of the stated preference experiments to the socio-demographic information about users we can calibrate a discrete choice model. The discrete choice model yields the probability of using each mode. For this study we consider all the modes present in the target area plus the additional mode that we are studying – carsharing.

The decision we want to simulate is the choice of a transport mode for the trip that the individual has to perform according to its activity log. Since we have multiple transport options we need a multinomial choice model. Different multinomial discrete choice models can be applied: Among the many potential models that can be derived, the most popular are the Multinomial Logit and the Multinomial Probit. Logit family models are based on a Gumbel probability distribution function that is used to model the maximum of a series of random variables, while the Probit models are based on the Normal distribution and Central Limit Theorem.

The Multinomial Logit has been the most popular due to its tractability, although it imposes restrictions on the covariance structure, since it assumes that the ratio of the probabilities of any two alternatives is independent of the choice set – property known as Independence from Irrelevant Alternatives [Ben-Akiva and Bierlaire, 1999]. Other models were added to the Logit family that relax restrictions while maintaining tractability, among them is the Nested Logit model. The Nested Logit model proposed by Ben-Akiva (1974) is an extension of the Multinomial Logit model designed to capture possible correlations among alternatives. Nested Logit models allow grouping alternatives that are similar in an unobserved way, in other words, alternatives that have correlated error terms.

Catalano et al. (2008) defined a mode choice model for a transportation system that included the non-existent modes of carsharing and carpooling. The authors tested various Nested Logit models and compared the different nested structures with the Multinomial Logit model, and verified that the hypothesis of correlation was always rejected by data.

4.2.1.4 Estimate demand

The process to estimate the demand for carsharing is subdivided in two steps. First the population is filtered according to the conditions:

i. Individuals must have a driving license - this is a logical constraint, once a licensed driver is necessary to drive the vehicle. This study only contemplates this condition, although other restrictions could be added, such as age limitations, and historical driver's data (normally used by insurance companies)

ii. Trips must have both ends inside the operating area - the considered carsharing system is one-way with operation limited to an urban area, therefore, to use the system, the client trip needs to start and end inside this delimited area.

The second step is to calculate the probabilities of using each transport mode for each trip of each individual of the filtered population, recurring to the calibrated discrete choice model and transport system status data (e.g.: travel time, fares, and availability), and randomly generate a choice.

4.2.2 Time series forecasting

Time series data is a sequence of observations collected with equally spaced periods of time. Time series forecasting methods use past data to predict future demand, being adequate to situations where we need to continuously forecast the demand to update system status. The objective of such methods is to discover a pattern in the historical data and then extrapolate the pattern into the future. The major components in past demand are: base (level), trend, seasonal and cyclical. The base component is the average level of demand which may or not may not change over time. The trend component is related to the upward and downward variation in demand that can occur along time. If there is no trend in the time series, it is classified by stationary. If a trend is present, the time series is classified as non-stationary. The seasonal component is related to patterns that repeat in fixed periods (e.g.: a certain hour of the day, a certain day of the week, or a certain month of the year). The cyclical component doesn't have a fixed period and is identifiable in long series of data, with many years of length [Blocher et al., 2004; Gardner, 2005].

Time series forecasting methods were not used in this work, since there was no historical data available for the case study. However, several types of forecasting methods can be used to predict demand having time series data as an input: smoothing methods, Box-Jenkins method, Bayesian methods or artificial neural networks.

4.3 Staff activity assignment model

The mid-term staff activity assignment is generated by one of the assignment models proposed. The difference between the two assignment models are explained further, although it can be highlighted that the rule-based model uses the forecast of the demand to define minimum and maximum stock levels that trigger action of staff; while the optimization model, recurs to linear programming to minimize a cost function based on penalties and potential losses related to not satisfying demand (client and maintenance) and cost of staff activity.

4.3.1 Rule-based model

The rule-based model is a simple algorithm that does not use optimization but simple rules that are established to respond to changes of the system status (staff location, vehicle location, and forecasted demand). It is based on the minimum and maximum stock levels. Minimum and maximum levels of vehicle stocks are defined for each zone. These values are established to regulate staff actions and are considered to be valid for the time extent of the operation.

- If the value of vehicles at the zone is below the minimum, the zone is classified as in-need of vehicles;
- If the value of vehicles at the zone is above the maximum number, then the zone is classified as a giver.

At each planning period movements are defined for staff based on the in-need - giver criteria

First, the status data of the system is determined, being the data discriminated by zones. For each zone it is determined the number of available staff members, the number of cars needing maintenance, and the number of available vehicles. Comparing the available vehicle values with the minimum and maximum stock levels, zones are classified as in-need or givers.

The activities of staff are ordered by priority level. The main priority is to perform maintenance, and secondly to relocate vehicles. Activities are attributed to staff according to its availability, and to each available staff member and its position relatively to vehicles. Four sets of orders are attributed according to the following priority order:

1) Available staff and vehicle needing maintenance at the same zone

   The order sent to the available staff is to maintain the vehicle that is located at the same zone of the considered staff element;

2) Available staff and vehicle needing maintenance at different zones

   Order sent to the nearest available staff. The order is decomposed into two tasks. First move to the zone where the vehicle needing maintenance is located using public transport, and, once there, perform the necessary maintenance task;

3) Available staff at a giver zone

   The order is to move a carsharing vehicle to the closest in-need zone. After the order is sent the provisory value of available vehicles is updated, by adding one vehicle to the target receiver zone, and removing one vehicle from the donator zone.

4) Available staff at a zone which is not a giver zone

   The remaining available staff members receive orders to move to the closest giver area, and then to move the vehicle into the in-need zone that is closer to the giver area. The temporary difference between available vehicles and demand is once again updated.

The process of establishing orders is repeated for every time period, that is, each cycle of the simulation (at the beginning of each planning period). The structure of the code is:

For each zone

- Count the number of available staff members;
- Count the number of cars needing maintenance;
- Count the number of available vehicles;
- Classify the station as a giver or in-need of vehicles using the defined stock level limits;

End for

For each car needing maintenance

- Identify the zone where the car is located;

If there are available staff members at that zone **then**

- Register maintenance order in the orders list;

Else

- Identify closest available staff member;
- Register movement using public transport in the orders list;
- Register maintenance order in the orders list;

End if

End for

If there is available staff remaining **then**

For each station

- Identify if exists an in-need station;

If an in-need station exists **then**

For each staff member

If the member is at a giver zone **then**

- Register movement using car in the orders list from zone where staff member is at, to the closest in-need zone;
- Update available vehicles;

Else

- Register movement using public transport in the orders list, from zone where staff is at, to the closest giver zone;
- Register movement using car in the orders list, from previous zone to the closest in-need zone;
- Update available vehicles;

End if

End for

End if

End for

End if

The minimum and maximum vehicle stock levels are based on the demand forecast data. Having the set of forecasted arrivals and departures, per planning period, for the entire period of operation, we determine the difference between arrivals and departures. From this difference we determine the number of vehicles in need to satisfy all forecasted demand, for each planning period (the minimum number of vehicles to add in order to have all positives for the difference between arrivals and departures). Using the set of in-need vehicles, the average and standard deviations are determined. The minimum limit for the stock of vehicles is the rounded average of the in-need vehicles from the set of values of the planning periods contained in the operation period. The maximum limit considered is the sum of the average with the standard deviation. In Table 1 is shown an example of the process to determine the minimum and maximum limit levels of stock.

Considering that the number of in-need vehicles follows a normal distribution, we can state that, by guaranteeing the minimum number of vehicles equal to the average, half of the probable needs are covered. And, on the other hand, by setting the maximum number as the average plus one standard deviation, the action of letting excess vehicles leave, only discard 16% of the possible situations (68-95-99.7% rule for normal distributions).

Table 1: Example of the process to determine minimum and maximum limit values for stock of vehicles

Planning period	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Forecasts:										
#arrivals	8	8	0	1	2	0	1	3	0	0
#departures	0	1	0	3	0	3	4	0	4	0
#arrivals-#departures	8	7	0	-2	2	-3	-3	3	-4	0
#in-need	0	0	0	2	0	3	3	0	4	0

 # in-need

Average (μ)	Std. Dev.(σ)	Min= μ	Max= $\mu + \sigma$
1.2	1.62	$1.2 \approx 1$	$2.82 \approx 3$

4.3.2 Optimization model

A mixed integer linear programming model designed to work in real-time and aid in the management of one-way carsharing systems was formulated. The process of creating a complete MIP formulation was a step by step process, where each constraint was carefully implemented and tested. The final result is a model adapted to allow a real-time interaction between optimization and system data.

The MIP formulation has three main improvements, when compared with the work of Kek et al. (2009). First, the designed model is prepared to be used in a rolling horizon planning approach by allowing the initialization of staff with previous tasks. Second, it considers that staff movements are performed using carsharing service vehicles or public transport according to the advantage in terms of cost minimization. And third, it allows trip joining of staff, meaning that staff members can travel inside the same vehicle, benefiting from the use of the available vehicle seats to reduce costs.

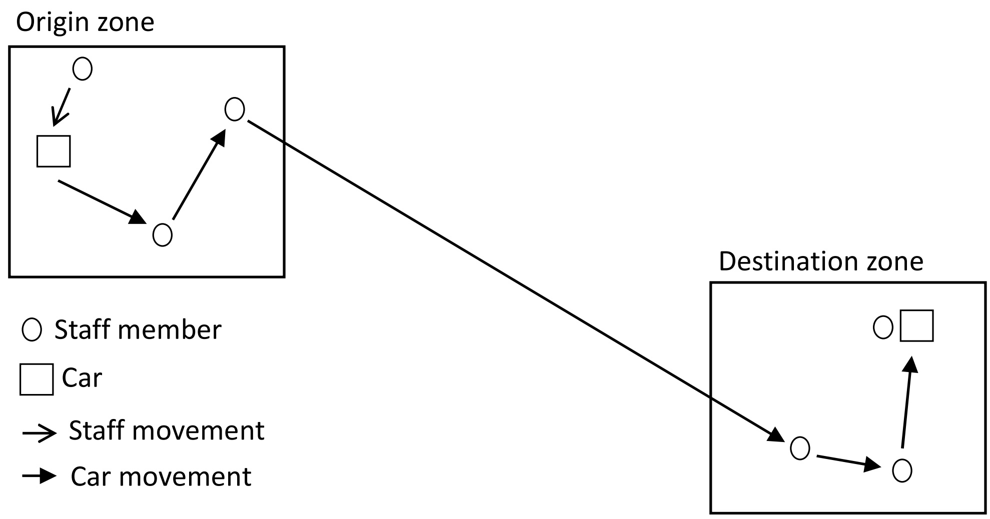


Figure 8: Trip joining movement

Trip joining consists in joining in the same vehicle staff members who have movements with the same origin and destination zones when this contributes to minimizing the cost for the operator. The maximum number of members that can share the same vehicle depends on its capacity. When members share the same vehicle, the first member gets to the vehicle (driver), drives it towards the staff members waiting at the same zone, and when getting to the destination zone distributes the passenger staff to their final destination (see Figure 8). Sharing the same vehicle has the potential to minimize the cost related to movement and also is useful to manage the number of vehicles at each zone. For example, the action of sending one vehicle from a zone with excess of staff to a zone with excess of vehicles, increases the number of drivers at the destination zone allowing the relocation of the excess vehicles.

As referred, the optimization process is repeated during an operation day, for each moving horizon, to allow an acceptable data update rate from the system and produce a real-time interaction. Each optimization is performed considering a number of time steps that enfold the period of optimization. To accommodate the tasks that were initiated previously to the current optimization, the lower limit of the optimization period is extended to the beginning of the earliest incomplete staff activity that started before the optimization (B), considering that the first time step of the current optimization cycle is equal to one. Therefore, the set of time steps considered is $I = \{B, \dots, t, \dots, T\} \subset \mathbb{Z}$. The model discretizes space in zones. The set of zones is $N = \{1, \dots, i, , \dots, S\} \subset \mathbb{N}$, being S the number of considered zones (if the space is discretized in stations, each zone can be considered as a station). A time-space network $V = \{1_B, \dots, i_t, \dots, S_T\}$ denots all the $S \times I$ nodes, $V = N \times I = \{1_B, \dots, i_t, \dots, S_T\}$. The set of arcs between the nodes defined in V, is designated by A. The travel time between zones using carsharing vehicles is defined by variable t_{ij}, and the travel time using public transport is defined by variable t_{ij}^s .

A set of staff $L = \{1, \dots, k, \dots, W\}$ is available to carry out the maintenance and relocation activities. Members of staff are discretized and each member is assigned to perform only one activity at each time. Idling $y^k(i_t, i_{t+1})$, moving inside a carsharing system vehicle $u^k\left(i_t, j_{t+t_{ij}}\right)$, moving by using public transport $s^k\left(i_t, j_{t+t_{ij}^s}\right)$, and performing maintenance $z^k\left(i_t, i_{t+t_z}\right)$, are the possible activities of the staff members.

Staff use vehicles to simultaneous move along the network according to maintenance needs and to perform relocation activities. The maintenance procedures performed by the staff members (k) have a fixed time duration (t_z). Maintenance procedures include cleaning and other small tasks that can be performed locally. Relocation activities are a response to the client demand requests.

The number of vehicle requests for the considered horizon period, $d(i_0)$, and the number of vehicle arrivals by clients, $r(i_0)$, are defined before the optimization process for each zone i, using a forecasting method. Moreover, the number of vehicles per status type per zone are input data previous to each optimization cycle. The status considered are: number of available vehicles $a(i_0)$, and the number of vehicles needing maintenance $b(i_0)$.

The problem is defined to move vehicles from zones with excess (potential suppliers) to zones that need vehicles (potential receivers) in each optimization period (horizon). This allows to simplify the optimization process when compared with the formulation of kek et al. (2009), which is only possible due to the fact that we consider a cyclic process allowing a continuous update of system status. To produce this simplification, the number of vehicles at the beginning of the horizon per zone, $a(i_0)$, is transformed into number of overstocked vehicles, $a'(i_0)$. The number of overstocked vehicles at each station equals to the number of vehicles located at station (i) at the beginning of the planning period, $a(i_0)$, plus the balance between the forecasted values of vehicle arrivals, $r(i_0)$, and vehicles taken by clients, $d(i_0)$.

$$a'(i_0) = \begin{cases} 0, \text{ if } a(i_0) + r(i_0) - d(i_0) \leq 0 \\ a(i_0) + r(i_0) - d(i_0), \ \text{otherwise} \end{cases}$$

The number of vehicles needed at station, $d'(i_0)$, derives from the demand for vehicles by the clients, $d(i_0)$, and the number of vehicle arrivals by clients, $r(i_0)$, whose values are forecasted.

$$d'(i_0) = \begin{cases} 0, \text{ if } d(i_0) - a(i_0) - r(i_0) \leq 0 \\ d(i_0) - a(i_0) - r(i_0), \ \text{otherwise} \end{cases}$$

The values of $a'(i_t)$ and $d'(i_t)$ are updated for each instant of the time horizon. Clients and staff can only use available vehicles $a'(i_t)$ to move, and staff can use available vehicles and public transport.

The model considers that the fulfilled component of the transformed demand, $d'(i_t)$, at each zone and instant is described by $k(i_t)$. The vehicles requested by clients "disappear" from the $a'(i_t)$ vector during the optimization process, this data is updated for the next optimization process, after new data is retrieved from the system.

Vehicle movements are described in aggregated variables. The set of variables $v_a(i_t, j_{t+t_{ij}})$ quantify the number of available vehicles moving from zone i at time step t to zone j at time step $t + t_{ij}$. To quantify the number of seats available on those movements, the number of vehicles moving is multiplied by the constant g, the vehicle capacity in number of seats. It is considered that all vehicles have the same capacity.

The problem formulation has six sets of decision variables:

- $v_a(i_t, j_{t+t_{ij}})$: variable quantifying the number of available vehicles (not needing maintenance) moving from zone i at time step t to zone j at time step $t + t_{ij}$.
- $u^k(i_t, j_{t+t_{ij}})$: binary variable associated with a staff movement inside a vehicle, taking value 1 if staff k moves from zone i at time step t to zone j at time step $t + t_{ij}$, and 0 otherwise.
- $s^k(i_t, j_{t+t_{ij}^s})$: binary variable associated with a staff movement using public transport, taking value 1 if staff k moves from zone i at time step t to zone j at time step $t + t_{ij}^s$, and 0 otherwise.
- $y^k(i_t, i_{t+1})$: binary variable associated with a staff member waiting for the next task, taking value 1 if staff k is waiting at zone i from time step t to time step $t + 1$, and 0 otherwise.
- $z^k(i_t, i_{t+t_z})$: binary variable associated with maintenance activity, taking value 1 if staff k is maintaining a vehicle at zone i from time step t to time step $t + t_z$, and 0 otherwise.
- $d'(i_t)$: number of vehicles in need to balance zone i at time step t.

With three additional sets of dependent variables:

- $a'(i_t)$: number of vehicles available to perform movements at zone i at time step t.
- $b(i_t)$: number of vehicles needing maintenance at zone i at time step t (can only be used by staff)
- $k(i_t)$: number of fulfilled client demand at zone i at time step t.

The known constants are:

- g: vehicle capacity in number of available seats;
- t_{ij}: travel time between zones using a car;
- t_{ij}^s: travel time between zones using public transport;
- t_z: time to complete maintenance procedure;

- $d'(i_0)$: number of vehicles in need to balance zone i at time step $t = 0$;
- $a'(i_0)$: number of vehicles available to perform movements at zone i at time step $t = 0$;
- $b(i_0)$: number of vehicles needing maintenance at zone i at time step $t = 0$;
- $c_v(i,j)$: cost of a vehicle movement by staff between zones i and j;
- $c_s(i,j)$: cost for staff movement using public transport between zones i and j;
- $c_d(i)$: penalty for not fulfilling or delaying one client demand request, which is proportional to zone i client average time of service usage. Being related to the potential profit outcome allows the optimization process to be smart and give more importance to more profitable zones when relocating vehicles;
- c_b: penalty for maintenance not fulfilled or delayed to the next time step;

The linear programming formulation for the problem is:

$$\min(\Pi) = \sum_{\left(i_t, j_{t+t_{ij}}\right) \in A} c_v(i,j) \cdot v_a\left(i_t, j_{t+t_{ij}}\right) + \sum_{k \in L} \sum_{\left(i_t, j_{t+t_{ij}}\right) \in A} c_s(i,j) \cdot s^k\left(i_t, j_{t+t_{ij}^s}\right) + c_d(i) \cdot \sum_{i_t \in V} d'(i_t) + c_b \sum_{i_t \in V} b(i_t) \tag{4.1}$$

Subject to:

$$\sum_{t=B}^{t=0} \sum_{i \in N} y^k(i_t, i_{t+1}) + \sum_{t=B}^{t=0} \sum_{i \in N} z^k(i_t, i_{t+t_z}) + \sum_{t=B}^{t=0} \sum_{\substack{i,j \in N \\ i \neq j}} u^k(i_t, j_{t+t_{ij}}) + \sum_{t=B}^{t=0} \sum_{\substack{i,j \in N \\ i \neq j}} s^k(i_t, j_{t+t_{ij}}) = 1, \forall k \in L \tag{4.2}$$

$$y^k(i_{t-1}, i_t) + z^k(i_{t-t_z}, i_t)_{(i_{t-t_z}, i_t) \in A} + \sum_{(j_{t-t_{ji}}, i_t) \in A} u^k(j_{t-t_{ji}}, i_t)$$
$$+ \sum_{(j_{t-t^s_{ji}}, i_t) \in A} s^k(j_{t-t^s_{ji}}, i_t) - y^k(i_t, i_{t+1}) - z^k\left(i_t, i_{t+t_z}\right)_{(i_t, i_{t+t_z}) \in A}$$
$$- \sum_{\left(i_t, j_{t+t_{ij}}\right) \in A} u^k\left(i_t j_{t+t_{ij}}\right) - \sum_{\left(i_t, j_{t+t^s_{ij}}\right) \in A} s^k\left(i_t, j_{t+t^s_{ij}}\right) = 0,$$
$$\forall i_t \in V | t > 0, k \in L \tag{4.3}$$

$$\sum_{k \in L} u^k\left(i_t, j_{t+t_{ij}}\right) \geq v_a\left(i_t, j_{t+t_{ij}}\right), \forall (i_t, j_{t+t_{ij}}) \in A \tag{4.4}$$

$$\sum_{k \in L} u^k\left(i_t, j_{t+t_{ij}}\right) \leq g \times v_a\left(i_t, j_{t+t_{ij}}\right), \forall \left(i_t, j_{t+t_{ij}}\right) \in A \tag{4.5}$$

$$a'(i_t) \geq v_a\left(i_t, j_{t+t_{ij}}\right), \forall (i_t, j_{t+t_{ij}}) \in A | t > 0 \tag{4.6}$$

$$a'(i_t) = a'(i_{t-1}) + \sum_{\left(j_{t-t_{ji}}, i_t\right) \in A} v_a(j_{t-t_{ji}}, i_t) - \sum_{\left(i_t, j_{t+t_{ij}}\right) \in A} v_a\left(i_t, j_{t+t_{ij}}\right)$$
$$+ \sum_{\substack{(i_{t-t_z}, i_t) \in A \\ k \in L}} z^k\left(i_{t-t_z}, i_t\right) - k(i_t), \forall t \in T | t > 0 \tag{4.7}$$

$$b(i_t) = b(i_{t-1}) - \sum_{\substack{\left(i_t, j_{t+t_{ij}}\right) \in A \\ k \in L}} z^k\left(i_t, i_{t+t_z}\right), \forall t \in T | t > 0 \tag{4.8}$$

$$d'(i_t) = d'(i_{t-1}) - k(i_t), \forall t \in T | t > 0 \tag{4.9}$$

$$u^k\left(i_t, j_{t+t_{ij}}\right), y^k(i_t, i_{t+1}), z^k\left(i_t, i_{t+t_z}\right), s^k\left(i_t, j_{t+t^s_{ij}}\right) = (0,1), \forall k \in L \tag{4.10}$$

$$v_a(i_t, j_{t+t_{ij}}) \in \mathbb{N} \cup \{0\}, \forall (i_t, j_{t+t_{ij}}) \in A \tag{4.11}$$

$$a'(i_t), b(i_t), k(i_t), d'(i_t) \in \mathbb{N} \cup \{0\}, \forall i_t \in V \tag{4.12}$$

Note that the formulation does not contain any continuous variables, being specifically an Integer Linear programming model. Although, by following the research publications trend, we continue to designate it by MIP model.

The objective function (4.1) minimizes the generalized cost function Π which includes: the cost of vehicle movements used for staff operations, the cost of staff moving by using public transport, the potential profit losses of not fulfilling demand, and a penalty for maintenance requests not fulfilled. Constraints (4.2) aids the initialization of variables from the previous cycle, by limiting the staff operations initiated until the instant $t = 0$ to only one task per staff member. Constraints (4.3) assures the conservation of staff activities at each station i and time instant $t > 0$. It restricts staff to start a new activity only after finishing the previous one. Constraints (4.4) and (4.5) relate in vehicle staff movement with the system vehicles, by imposing a minimum and maximum number of staff traveling in each vehicle. The minimum of one member is needed to drive the vehicle and the maximum number is related to the vehicle's capacity in number of seats. This allows having trip joining in staff movements. These two sets of constraints also assure that the vehicle movements initiated until $t = 0$ fulfil the same criteria, being the domain extended to all $(i_t, j_{t+t_{ij}}) \in A$. Constraints (4.6) imposes that a vehicle can only depart from a station where vehicles exist. Constraints (4.7) and (4.8) update the values of the variables between time steps. Constraint (4.9) is a conservation equation related to demand. Constraint (4.10) sets the binary variables, and constraints (4.11) and (4.12) set the non-negative integer variables.

The MIP model has six sets of decision variables, whose number of elements depends on the problem characteristics (see Table 2). The number of variables for the primal problem related to y is $W \times S \times (T - 1)$, since the relation between start time and ending time is $t_{end} = t_{start} + 1$. The z set of variables have $W \times S \times (T - t_z)$ variables. This is, once more, due to the ending time being dependent to the start time.

For the sets u and s, the total number of variables is equal to $2 \times W \times (S^2 - S) \times (T^2 - \sum_{t=B}^{T} t)$. The travel times between zones vary according to the origin-destination vector, although there are no trips occurring from t_2 to t_1 ($t_2 > t_1$), enabling to subtract $\sum_{t=B}^{T} t$ to T^2(this is is independent from the travel time matrix). One is also able to subtract S to S^2, since there is no sense on having movements or relocations between the same station. To the set v_a corresponds a total number of variables equal to $(S^2 - S) \times$

$(T^2 - \sum_{t=B}^{T} t)$. The demand variable set d' has $S \times T$ elements, since demand is only modelled for the optimization period, $t > 0$.

Table 2: Number of elements of each MIP decision variable set

Variable set	Number of elements
$\boldsymbol{y}$	$W \times S \times (T-1)$
$\boldsymbol{z}$	$W \times S \times (T - t_z)$
$\boldsymbol{u}$	$W \times (S^2 - S) \times \left(T^2 - \sum_{t=B}^{T} t\right)$
$\boldsymbol{s}$	$W \times (S^2 - S) \times \left(T^2 - \sum_{t=B}^{T} t\right)$
$\boldsymbol{v_a}$	$(S^2 - S) \times \left(T^2 - \sum_{t=B}^{T} t\right)$
$\boldsymbol{d'}$	$S \times T$

Due to the high number of variables, it is important to understand the dimensions of the problem that allow a timely optimization. The model was tested using the optimization software Xpress-MP by FICO. Different input data files were created by changing the number of zones (S) and the number of staff (W). The cycle extension used was six time steps ($T = 6$). Additionally, to define the number of vehicles, it was considered one element of staff per 20 vehicles. Optimization tests were performed on an Intel Core i5 with 1.70 GHz of processor speed and 10 GB of RAM.

The first tests using random generated input data allowed to verify that the MIP formulation worked accordingly. Staff is correctly initiated with the previous tasks, each one starting at time steps $t < 1$, and trip-joining is being properly applied when needed to minimize costs.

Increasing the dimension of the problem, the time in seconds to reach a solution increases (see Table 3). For the problem dimensions which were considered of 30, 40 and 50 zones with 5, 10, 15 and 20 staff members, the optimization process generally reached the end in less than 7 minutes, retrieving solutions with a zero duality gap. In the case of 50 zones with 5 staff members, the optimization process did not give a zero duality gap solution in less than 420 seconds, but it reached a 0.60 gap solution in 64 seconds.

Table 3. Xpress-MP Results

zones, S	staff, W	#solution	objective	best bound	gap (%)	time (s)
30	5	4	895	895	0	57
	10	2	476	476	0	59
	15	3	88	88	0	24
	20	12	70	70	0	128
40	5	7	1210	1210	0	153
	10	12	653	653	0	88
	15	15	137	137	0	320
	20	5	116	116	0	137
50	5	3	1277	1265	0.60	64
	10	6	654	654	0	140
	15	8	125	125	0	380
	20	12	115	115	0	291

4.4 Filter

Filtering allows to send only the orders that can be physically accomplished to staff. The filter works as an interpreter between the virtually modelled system used to design staff activity and reality. The need for a filter is due to the fact that demand is an uncontrolled variable that is measured based on forecasts.

Three types of orders are defined by the assignment model for staff activity: maintenance of vehicle at a zone, movement of staff inside a carsharing vehicle, and movement of staff using public transport. The orders' plan for the considered time period is retrieved from an output of the assignment model with the following data: type of activity, staff ID, origin, destination, start time, end time. For the maintenance activity data, only the origin is specified, since it is not an activity that assumes a movement. The plan goes by time, from the first to the last planned occurrences.

1) Maintenance of vehicle at a zone

   Maintenance can begin at the scheduled time if the member of staff is free and at the zone specified in the orders' plan and if there is a vehicle needing maintenance at that zone. If not, the orders' plan is updated with the considered activity postponed by 10 minutes.

2) Movement of staff inside a carsharing vehicle

The movement of staff inside a carsharing vehicle can start at the scheduled time if the identified staff member is free and at the origin zone and there is an available vehicle to use. If the identified staff is not free and at the origin zone, the order's plan is updated by postponing this order by 10 minutes. If staff is free and at the zone, but there is no available car to be used, the considered staff member moves by public transport.

If there are conditions for the considered staff member to use an available car, it is checked if there are other members to be assigned to share the same vehicle. These need to have the same origin and destination and starting the trip (moving in a carsharing vehicle or using public transport) at the same time window (10 minutes wide). The maximum number of staff members that can possible share the same vehicle is equal to the vehicle capacity.

If the number of staff members sharing the same origin, destination, and departure time window is higher than the vehicle capacity, they are redirected to another available vehicle. If there isn't another available vehicle, they move by using public transport.

3) Movement of staff using public transport

If the specified staff member is free and at the zone and a vehicle needs maintenance at the destination, the order to perform the movement using public transport is included in the order's plan. If the referred conditions are not verified postpone the order by 10 minutes.

The process of filtering orders is repeated for each event not processed in the staff orders' list, and is described in the following lines:

For each unprocessed order in the orders' list

- Register staff member ID, order type, start time, origin, and destination;
- Count the number of vehicles needing maintenance at the origin zone of staff → $vmor$;
- Count the number of available vehicles at the origin zone of staff → $vavail$;
- Count the number of vehicles needing maintenance at destination zone of staff → $vmdest$;

If order type is maintenance **then**

If (staff member with that ID is free and at the origin) and ($vmor > 0$) **then**

- Send order to staff;
- Update staff and vehicle status;
- Mark order as sent;

Else

- Postpone order;
- Update orders' list;

End if

End if

If the order type is movement in an available vehicle **then**

If (staff member with the ID is free and at the origin) and ($vavail > 0$) **then**

- store variable $ocup = 0$ (occupancy of considered vehicle);

For each order not sent yet

If (there are other members sharing same time window, origin and destination) and ($ocup < c_v$) **then**

- Send order to staff;
- Update staff and vehicle status;
- Mark order as sent;

$ocup = ocup + 1$;

End if

End for

Else

If (staff with ID is free and at the origin) and ($vmdest > 0$) **then**

- Use public transport;
- Send order to staff;
- Update staff status;
- Mark order as sent;

Else

- Postpone order;
- Update orders' list;

End if

End if

End if

If order type is movement using public transport **then**

If (staff member with that ID is free and at the origin) **then**

- Send order to staff;
- Update staff status;
- Mark order as sent;

Else

- Postpone order;
- Update orders' list;

End if

End if

End for

4.5 Interaction with system

The real-time support tool is enabled to adjust to system parameters in real-time, improving optimization outcomes. The approach followed to include real-time adjustments is optimization over a rolling horizon. This method implies the decrease of the level of uncertainty forecasts by reducing the prospective time extent. The method consists in dividing the full daily optimization problem into time blocks. Each block is optimized by running a cyclic process. This allows to update demand and maintenance requests data between each block allowing a constant adaptation to possible changes.

The decision support tool explained previously, consisting of three main components (forecast model, assignment model and filter), needs an additional component to be able to interact with the real system, or a simulator, in the case of impossibility of using a real system. This additional component is a background database that stores previous and current system data, such as status of staff, vehicles, and client usage. The database is subdivided into three main tables: client trip log, vehicle log and staff activity log.

The **client trip log** registers the data related to all the trips performed by clients. It has two main purposes. First, having a large amount of historical client trip data can improve demand predictions. The second is that the client trip data allows the updating of vehicle data. This connection is fundamental since the assignment model is focused on the staff movements. Consequently, the tracing of clients movements need to be made by the database to allow the updating of parameters due to client vehicle use, namely location and status. The characteristics to be stored are start location, end location, start time, end time, and kilometers driven.

The **vehicle log** registers the characteristics of each vehicle at each instant. It is useful to predict maintenance requests. The characteristics to include are: status, location zone, accumulated hours of usage since last maintenance, number of users since last maintenance, total kilometers travelled, total time used, and remaining fuel.

The **staff activity log** keeps track of the staff activities. It is necessary to register all the staff activities occurring during the day, with the purpose of calculating the total costs, working hours, and other important aggregated values. The list of data needed are: staff member id, task, start time of task, end time of task, start location of task, and end location of task.

Figure 9 describes the relations in the interaction between decision support tool modules and system, by using a background database. Worth of notice is the existence of a connection between vehicle log of the background database and a maintenance requests generator. This is due to the fact that we can plan maintenance procedures by using vehicle usage data, such as time used, kilometers driven or even number of usages. This type of planned maintenance can be scheduled to low demand periods in order to minimize impacts on the service supply, and normally is performed at a service garage. Since this study is only focused on reacting to unexpected maintenance, we only consider maintenance requests originated by client reports at the time they access or try to access the vehicle or by information transmitted by vehicle sensors.

Clients can alert the system provider that there is a problem in the vehicle, normally this happens when they perform the pre-renting checkup. The most common pre-renting check-up is related to vehicle cleanliness level. Clients can also report accidents involving the vehicle during renting period, but this is a non-recurrent issue, and therefore is not analyzed by this research.

The demand for each zone is given by the forecast model. The quality of predictions has a direct effect on the assignment results. Thus, it is important to understand how many clients will look for a carsharing vehicle at each zone at each horizon. It is considered that clients use the system, if there is an available vehicle inside a walkable radius at the time that this is requested. As referred previously, service historical data can be used to produce forecasts using time series forecasting. These data is continuously complemented by the new data retrieved from the system and registered in the client trip log. If the system has not been implemented yet, and, therefore, there is no previous data, an activity based microsimulation approach supported by survey data can be used to predict the initial demand.

Having the maintenance requests and the demand for the horizon, we need the current status of staff and vehicles to run the assignment model. This information is retrieved from the background database that keeps track of system changes. After running the staff activity assignment model, the orders for the planning period pass through a filter to understand which activities can be undertaken. Finally the applicable orders for the planning period are sent to staff, changing real system status.

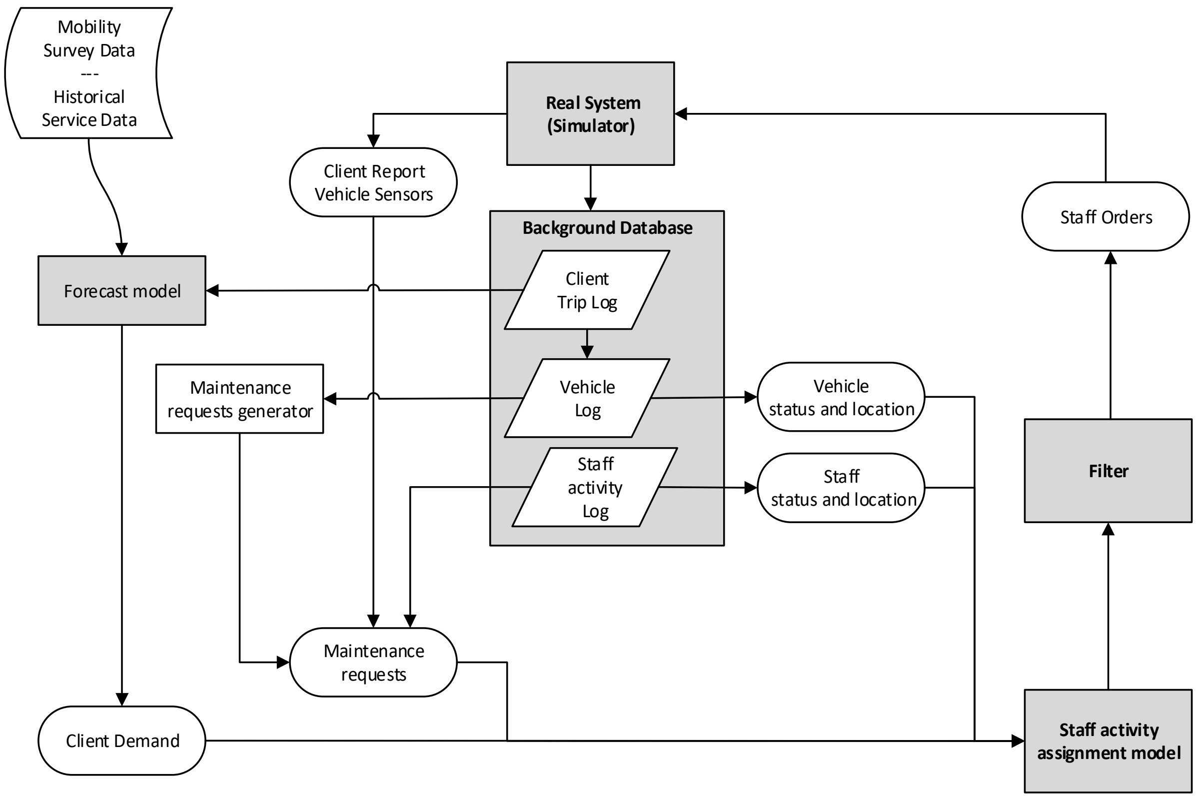


Figure 9: Interaction between real-time decision support tool modules and system

4.6 Input data

This subchapter details the characteristics of input data for a better understanding of how to prepare data to use the decision support tool.

- **Discretization of time**

The operation period is subdivided in T/p planning periods, being p the fixed duration of each planning period, and T the duration of the operation period. For each planning period is considered a horizon with an extension of n planning periods. The horizon period "rolls" one planning period forward for each cycle. For the optimization model, the horizon period is subdivided in a number of time steps (I). The extension of each time step needs to be small enough to consider changes in staff status realistic to the time durations of movements and activities, but not too small leading to an increase of the dimension of the MIP problem that needs to be solved. The relation between periods is represented in Figure 10.

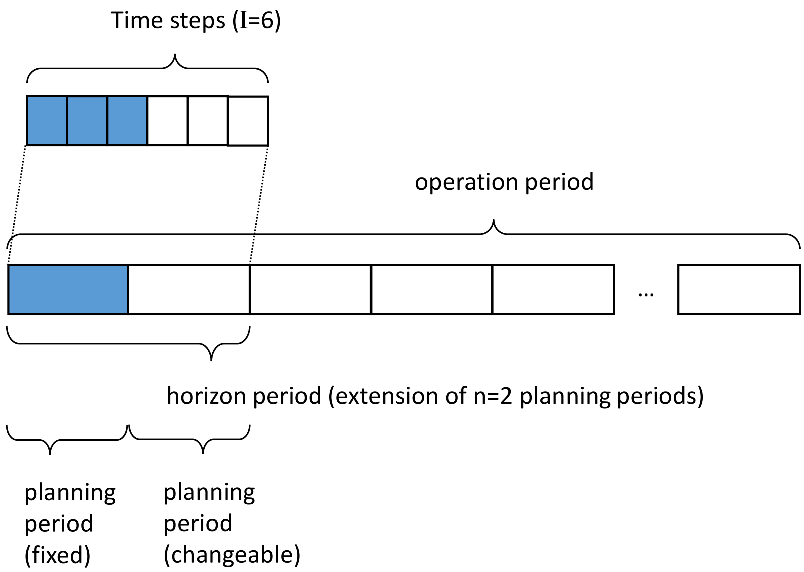


Figure 10: Representation of the relation between operation period, planning period, horizon and time steps

The staff activity assignment optimization model uses the MIP model to design the staff activity plan for each horizon of the operation period. Although, the output transmitted to the filter consists in the orders that have a starting time inside the fixed planning period. The remaining orders are considered open to be changed once the horizon is rolled and new input data is received. This allows a continuous adaptation of the staff activity plan to the changes in input data, namely system status, demand forecast and maintenance requests.

- **Discretization of space**

The division of a geographic space in zones has the objective of producing a simplification of the space inside the operating area. The discretization of space is related mainly to the use of an MIP model to produce the assignment, but it is also useful as an identification of each area during operation (for movement and statistics purposes). The number of zones, S, in pair with the number of steps, I, as explained, define a time-space network. The dimension of the time-space network affects the number of decision variables and, therefore, the optimization processing time. The size of zones and location are defined a priori and do not change during the analysis. If the desired operating area is subdivided in a large number of small areas, two approaches can be used in order to maintain a level of complexity that keep the processing time at accepted values (acceptable values are the ones that do not compromise real-time appliance). The first approach is to aggregate the smaller areas to generate the model zones. The second approach is to divide the city area in more than one operating area, considering the new smaller operating areas as the model zones. A combination between the two approaches can also be used. It is important to refer that the MIP model considers that a client can walk between any considered location and the location of any car inside the same zone. Therefore zones that have a diagonal greater than maximum walkable distance are not advisable.

- **Number of staff elements**

The number of staff elements working to produce maintenance and relocations in the system (W) need to be defined. This value influences directly the number of variables related to staff activity (y, u, z, and s variables). If in the output of the optimization process there is evidence that members of staff stay stopped all the time, it means that the staff number is excessive for the characteristics of the carsharing system.

- **Time for maintenance activity**

The duration of staff maintenance activity (t_z) needs to be established. Percentiles above the average (e.g.: the third quartile) are expected to be used. If an operation takes longer or less than the predicted value used in the MIP model, it won't erratically influence the outcome, due to the status updating after each fixed planning period. The time to complete maintenance can be established as the time to walk to a vehicle (once staff member and vehicle are in the same zone), perform maintenance and leave the vehicle ready for clients.

- **Travel times of staff**

Travel times of staff in carsharing vehicles are related to the travel times on the road network. Once the travel times are obtained for the network, we need to add a value that includes walking towards the vehicle and picking up other staff (trip joining movements).

Travel time is dependent on demand related to road usage which is, by turn, dependent on travel time. This fact is considered by the traffic assignment step of the four step transportation forecasting model. Carsharing shares the road network with other modes, and by this, there is an interdependency between the effects of the load of carsharing matrix and the load of the other modal matrices (car, bus) on the links of the network. It is assumed that the size of the carsharing transport market share for the considered urban area is insignificant when compared with the personal vehicle market share. Therefore the travel time can be determined by loading the personal vehicle demand matrix into the considered urban area network, which is represented by a set of nodes and arcs.

Each arc has a travel time associated with time of the day. Peak and off-peak travel time matrices can be used to represent the different network load conditions during the day. To calculate travel times, center of zones can be considered as the representative nodes. In a real application, the travel times can be obtained using historical data of customers and staff movements, discretized per time periods, or in a more advanced and complex way using the service vehicles as probe vehicles, taking advantage of its GPS and communication systems (Jenelius and Koutsopoulos, 2013). The travel times for using public transport is calculated based on the public transport services available.

- **Vehicle capacity**

The capacity of each vehicle in number of seats (g) corresponds to the maximum number of staff members that can be transported inside a vehicle. It is assumed that all vehicles have the same capacity. But, if this is not the case, the value used should be the minimum individual capacity of the set of vehicles used, since the assignment model is not prepared for differentiating vehicle capacity.

- **Location of staff at the beginning of operation**

The initial position of staff at the start of the operation period is a required data for simulation. We have two options: considering that all staff members start its activity at one specific zone, for instance location of company headquarters; or that each staff member starts its shift at a pre-determined zone.

- **Costs**

The costs are related to the optimization assignment model, where an objective function is minimized. The costs should be the real costs or close as possible to reality in order to result in optimize staff movements' recommendations. Four costs are considered: cost of a vehicle movement by staff, cost of a staff movement using public transport, penalty for not fulfilling or delaying one client demand request, and penalty for maintenance not fulfilled or delayed for the next time step.

The cost per minute of a carsharing vehicle movement, $c_v(i, j)$, is the cost of using a vehicle considering the distance between zone i and zone j. It can be considered the energy cost (e.g.: based on gasoline price) spent to travel between the two zones.

The cost of staff movement using public transport, $c_s(i, j)$, if associated to the use of a public transport monthly title, makes it independent on the origin and destination vector. A way of determining the unitary cost per trip is through dividing the monthly title cost by the average number of monthly utilizations of public transport per staff member.

The penalty for not fulfilling or delaying one client demand request, $c_d(i)$, is related to the average loss of profit for a not satisfied demand request. The potential profit loss can be obtained by multiplying the price per minute charged for using the service by the average time (based on historical data) of client usage for that zone and period of day.

The penalty for maintenance not fulfilled or delayed for the next time step, c_b, can be determined based on the potential profit loss of the vehicle being idle. This can be calculated based on the duration of a time step multiplied by the unitary price charged to clients for system usage.

- **Demand**

As aforementioned, the optimization model uses forecasted demand for a horizon period, although the orders that are implemented in the simulator (communicated to staff in a real system) concern to the first planning period. If there is past demand information, it can be used to predict future demand. Quantitative forecasting using time series methods can be used to perform these predictions. Trends, Seasonality and daily variation (peak and off-peak demand) need to be considered. If there isn't past demand data, activity based microsimulation approach can be used to estimate the initial demand. Both were described previously. The demand value used is the total forecast for the considered horizon, discretized per zone.

- **Maintenance requests**

Maintenance requests can result from information given from clients or based on information transmitted by vehicle sensors (e.g.: intervention to correct vehicle parking, intervention to turn off lights, intervention to close doors, intervention to close windows, intervention to enable parking brakes, simple cleaning intervention, and intervention to solve discharged battery). These are the most frequent and the ones that can be locally solved. Non-frequent maintenance tasks, such as accident assistance, heavy cleaning, and driving a vehicle to garage maintenance are not considered for the assignment process here described. If there is a report on a vehicle resulting from sensors' information or from a client report, the vehicle is signaled as needing maintenance and cannot be used until the respective maintenance procedure is performed. The information related to the number of vehicles needing maintenance and respective location is transmitted to the assignment model at the beginning of the process as input data.

- **Staff and vehicle related input data**

Staff and vehicle input data transmitted to the assignment model is captured from the "picture" of the system at the initial instant of the considered horizon. To apply to the assignment model, we need the location of vehicles that are available and needing maintenance, and detailed information about staff activity (type of activity, origin, destination, vehicles being used). Tracing the movement of vehicles from clients is not necessary to the assignment model, but is useful to determine system usage and calculate invoiced value. This activity is stored on the background database.

4.7 Performance indicators

The performance of the system needs to be measured in order to understand the changes brought to the system by the application of the tasks resulting from the assignment model output. The performance indicators used to analyze thoroughly the variables of the system related to staff, vehicle and client usage, were subdivided in: demand, supply related to vehicles, supply related to staff, economy, profit, and costs indicators.

- **Demand**

The demand related indicators express the ability of the system to capture clients and are based on accepted (T_a) and rejected (T_r) trips. The demand indicators considered were: number of accepted trips, number of rejected trips, percentage of accepted trips, average distance between car and client for accepted trips, number of accepted or rejected trips with car distance between j and $j + h$ kilometres.

i. *Number of accepted trips*

The number of accepted trips, T_a, is directly taken from the background database, and corresponds to the number of served trips.

ii. *Number of rejected trips*

The number of rejected trips are calculated having into account the potential demand. The potential demand in trips, T_p, can be estimated using a forecast model.

$$T_r = T_p - T_a$$

iii. *Percentage of accepted trips*

The percentage of accepted trips, $p(T_a)$, allow having an idea of the fulfilled demand when compared to the expected demand.

$$p(T_a) = \frac{T_a}{T_p}$$

iv. Average distance between car and client for accepted trips

When a client is served, the distance between the client and the vehicle is registered and can be used to estimate the average distance that clients have to travel, $Avg(wd)$, in order to get to a carsharing vehicle. The distance is registered by the position received from the web-based platform.

$$Avg(wd) = \frac{1}{T_a} \sum_{i=1}^{T_a} wd(i)$$

Where $wd(i)$ is the distance travelled by the client (normally walking) for trip i.

- **Vehicles**

The vehicles' indicators are related to supply and allow monitoring the level of usage of vehicles and the costs associated to it. The vehicles indicators considered were: car distance travelled, car usage time, number of car trips driven by the staff.

i. Car distance travelled

The total car distance can be processed for each vehicle and, posteriorly, aggregated to produce an overview on car usage.

$$TTCarDist = \sum_{i=1}^{V} CarDist(i)$$

Where $TTCarDist$ is the total car distance for the considered time interval, $CarDist(i)$ is the distance travelled by vehicle i for the considered time interval, and V is the total number of carsharing vehicles.

The previous values can be discriminated by staff and clients to determine the distance related to staff (u) and clients (c) movements using carsharing vehicles, respectively.

$$TTCarDist_u = \sum_{i=1}^{V} CarDist_u(i)$$

$$TTCarDist_c = \sum_{i=1}^{V} CarDist_c(i)$$

ii. Car usage time

The driving time of the vehicles can be discriminated by status, and tracked individually or aggregated for a general overview. The status of vehicles that produce movement are: used by clients (c), and used for staff movements (u). The vehicle status related to vehicles being static are: idle available (ia), idle needing maintenance (ib), and idle being maintained (ic).

$$TTCarTime_x = \sum_{i=1}^{V} CarTime_x(i)$$

Where x is equal to c, u, ia, ib or ic depending if the vehicle is used by clients, used for staff movements, idle available, idle needing maintenance or idle being maintained, respectively.

iii. Number of car trips with staff in vehicles

Another performance indicator related to vehicles is the number of car trips with staff in vehicles, $NCarTrips_u$. Having the number of car trips, we can determine the average distance and time per trip using the total car distance ($TTCarDist_u$) and the total car time ($TTCarTime_u$), respectively. Note that the number of trips by the clients is equal to the number of accepted trips described previously.

- **Staff**

The performance indicators related to staff monitor the staff activity, and are further used to calculate the costs associated to it. The staff indicators considered were: staff distance travelled, staff time per status, number of staff movements using carsharing vehicles, and number of staff movements using public transport.

i. Staff distance travelled

Staff can travel using carsharing vehicles or public transport. The total distance travelled by staff is calculated by

$$TTStaffDist = \sum_{k=1}^{W} StaffDist(k)$$

Where $TTStaffDist$ is the total distance travelled by staff for the time interval considered, $StaffDist(k)$ is the distance travelled by staff k for that interval, and W is the total number of staff members.

The distance travelled can be discriminated by mode: carsharing vehicle (u) or public transport (s)

$$TTStaffDist_u = \sum_{k=1}^{W} StaffDist_u(k)$$

$$TTStaffDist_s = \sum_{k=1}^{W} StaffDist_s(k)$$

The value of distance travelled by staff members inside a vehicle, $TTStaffDist_u$, is equal to the distance that the vehicle travelled with staff members, $TTCarDist_u$, unless there are vehicle movements with staff members travelling together inside the same vehicle.

ii. Staff time per status

The staff time per status performance indicators are related to the possible status of staff: idle (y), traveling using a carsharing vehicle (u), traveling using public transport (s), and performing maintenance (z)

$$TTStaffTime_x = \sum_{k=1}^{W} StaffTime_x(i)$$

where x is equal to y, u, s, or z depending on the status type.

Similarly to what was described for staff distance travelled inside a carsharing vehicle, the value of time travelled by staff members inside a carsharing vehicle, $TTStaffTime_u$, is equal to the time travelled by vehicles with staff members, $TTCarTime_u$, unless there are vehicle movements with staff members travelling together inside the same vehicle.

iii. Number of staff movements using carsharing vehicles

The number of staff movements inside a vehicle, $NCarStaffMov$, depends on the number of staff elements riding simultaneously inside a vehicle, and is expressed by

$$NCarStaffMov = \sum_{i=1}^{L} s(i)$$

where $L = NCarTrips_u$ and $s(i)$ is the number of staff members moving inside the car used for the considered trip.

iv. Number of staff movements using public transport

Staff can use public transport to move along the carsharing operating area when it is not viable to use a vehicle of the carsharing fleet. These trips are performed individually. The number of staff movements using public transport is designated by $NPTrips$.

- **Maintenance**

The maintenance procedures are tracked using simple performance indicators: total requests, fulfilled requests, and percentage of fulfilled requests. The maintenance indicators considered were: number of total maintenance requests, number of fulfilled maintenance requests, and percentage of fulfilled maintenance.

i. Number of total maintenance requests

The number of maintenance requests, $NMaintReq$, is an input of the assignment model used at the beginning of each horizon in order to produce the staff activity plan.

ii. Number of fulfilled maintenance requests

The number of fulfilled requests, $NMaintReqFF$, are the requests solved by staff members during the considered period.

iii. Percentage of fulfilled maintenance

The percentage of fulfilled maintenance is the relation between number of fulfilled maintenance requests and number of total maintenance requests.

$$p(MaintReqFF) = \frac{NMaintReqFF}{NMaintReq}$$

- **Financial**

The economy performance indicators show the level of savings produced by staff trip joining ability. Having more than one staff member traveling inside a vehicle leads to savings in car distance and car time. The economy indicators considered were: car distance saved and car time saved.

i. Car distance saved

The car distance saved, $CarDistS$, is equal to the difference between the total distance covered by staff movements, $TTStaffDist_u$, and the total distance travelled by cars with staff, $TTCarDist_u$.

$$CarDistS = TTStaffDist_u - TTCarDist_u$$

ii. Car time saved

The car time saved, $CarTimeS$, is the difference between the total time spent in staff movements, $TTStaffTime_u$, and the total car time with staff, $TTCarTime_u$.

$$CarTimeS = TTStaffTime_u - TTCarTime_u$$

- **Revenues and costs**

The revenues are related to the use of carsharing vehicles by the clients. There can be other sources of revenue, such as using stickers in vehicles for brand marketing, which are not considered in this study.

i. Time based revenue

It is considered that carsharing usage is charged by time, therefore

$$Revenue_{time} = p_{time} \times TTCarTime_c$$

Being p_{time} the service price per unit of time, and $TTCarTime_c$ the total car time used by clients.

ii. Time and distance based revenue

There are also services that charge by time and by distance, in those cases

$$Revenue_{time,dist} = p_{time} \times TTCarTime_c + p_{dist} \times TTCarDist_c$$

Being p_{dist} the service price per unit of distance, and $TTCarDist_c$ the total car distance used by clients.

The costs are subdivided in: cost wage of staff, cost depreciation of cars, cost of staff movement in cars, cost of staff movement using public transport, and cost related to client movement inside vehicles.

iii. Salary costs of staff

The cost related to staff wages is related to the number of staff hired.

$$C_{staffwage} = wage \times W$$

Being $wage$ the cost of staff for the period of time considered and W is the number of staff working for the carsharing system.

iv. Depreciation cost of the cars

The depreciation cost of vehicles parcel, C_{cardep}, is related to the number of vehicles.

$$C_{cardep} = Dep_{unit} \times V$$

Where, Dep_{unit} is the depreciation cost per vehicle and V the total number of vehicles in the system.

v. Cost of staff and client movement in cars

The cost of staff and client movement inside carsharing vehicles is related to the energy costs of moving the vehicles (e.g.: gasoline cost). The costs here presented are based on distance, and have into account the unitary cost of fuel per distance ($E_{unitcost}$) estimated for the urban environment.

For staff, the cost is calculated using the total distance covered by cars with staff inside, $TTCarDist_u$.

$$C_{cardist,u} = E_{unitcost} \times TTCarDist_u$$

For clients, the cost is determined by using the total distance covered by cars when used by clients, $TTCarDist_c$.

$$C_{cardist,c} = E_{unitcost} \times TTCarDist_c$$

vi. Cost of staff movement using public transport

The cost of staff moving using public transport is related to the cost of the public transport pass, and is given by

$$C_{PT} = C_{pass} \times W$$

Where, C_{pass} is the unitary cost of public transport pass per day, for the case we are considering the costs of daily operation.

Another approach is to use the average number of public transport trips carried out by a member of staff per month (N) to get a unitary cost per public transport trip ($PT_{unitcost}$), and then applied it to the number of trips using public transport ($NPTTrips$). This approach is useful to regiment the possible output of the optimization model used for the assignment.

$$PT_{unitcost} = \frac{C_{pass}}{N}$$

$$C_{PT} = PT_{unitcost} \times NPTrips$$

4.8 Simulator

A simulator was developed to test the real-time decision support tool. The system simulator emulates a free-float one-way carsharing system, allowing to test different scenarios by including the necessary algorithms to allow interaction between demand and supply. The simulator works in a hybrid way. It is time driven, to set the beginning and end of each considered planning time, and event driven to initiate and finish movements of staff, cars and clients. To reduce the level of complexity, since no animation is required, the simulator is built on top of a database (data arrays), and that, in the case of the optimization model, is additionally connected to Xpress.

4.8.1 Data arrays

The used data arrays are classified into: static input data, dynamic input data, system data, and output data.

The **static input data** consists in the sets of data that do not change during the total period of the simulation (e.g.: one day simulation). The data arrays classified as static input are: basic data, zones data, staff initial position, vehicles initial position, travel times, forecasts, and client trips (demand).

- The basic data vector includes the simulation start and end time of simulation (related to the operation period to be analyzed), the horizon period length, the planning period length (as shown in Figure 10), vehicle capacity in number of seats, maintenance activity duration, and, additionally for the optimization model of the assignment, it includes the number of time steps and its length, and the costs to be used in the MIP model.
- The zones data includes the identification of each zone, as well as its characteristics (x_{min}, x_{max}, y_{min}, y_{max}, x_{center}, and y_{center}).
- The staff initial position defines for each staff member identified by an ID, the position at the beginning of the simulation. The initial position is given by zone and the staff is considered to be at the center of the corresponding zone.
- The vehicles initial position contains for each vehicle identified by an ID, the position at the beginning of the simulation. The initial position is given by zone and the vehicles are considered to be at the center of the corresponding zone.

- The travel times are defined for each origin and destination pair of zones for cars (related to the use of carsharing vehicles) and for public transport.
- The forecast data used in the rule-based model is determined for the entire operation period and discriminated by zone, while for the optimization model forecasts are discriminated by zone and horizon.
- The client trips (demand) are ordered by time and contain the origin and destination coordinates, departure time, expected duration, and expected distance.

The **dynamic input data** of the simulator is the assignment plan retrieved from the assignment model (output of the assignment model). The assignment plan contains the information related to planed activities. Three types of activities are brought from the assignment model: maintain a vehicle (z), move inside a carsharing vehicle (u), and move by using public transport (s). The assignment plan identifies staff by its ID, the activity type, origin, destination, start time and end time.

The **system data** are the most important set of arrays for the simulation. The system data arrays include staff and vehicles ongoing activities, and arrival data related to the end of the staff and vehicle events. These arrays allow to define for each time horizon the number of available vehicles, the number of vehicles needing maintenance, and the current activity of each staff member, which is the system status information needed to feed the assignment model. System data contains information that controls the ongoing events on the simulator. These data is characterized by being temporary, and lasts until the status of the element vehicle or staff changes.

- The staff array includes the status of each staff member, which is described by the following data: staff ID, activity type, start time, end time, start zone, end zone, distance and vehicle ID (if the staff member is traveling using a vehicle). The types of activity are: “maintain a vehicle” (z), “move inside a carsharing vehicle” (u), and “move by using public transport” (s), and “stopped waiting for orders” (y).

- The vehicles array contains the status of each vehicle, which is described by: vehicle ID, status, start time, end time, start coordinates (x, y), end coordinates (x, y), expected distance and number of passengers (in the case of trip joining).
- The arrivals array keeps track of the ending of events to trigger the updating of system data. The events considered are: "arrival of vehicle used by client", "end of maintenance", "arrival of staff in a carsharing vehicle", and "arrival of staff using public transport". The stored elements are a result of the respective initiated events, and the elements stored are: type of event, end time, end coordinates (x, y), end zone, vehicle ID, and staff ID.

The **output data** is a database that serves the purpose of assessing the behavior of the system by storing the information needed to compute the performance of the system in the shape of the indicators described previously. Three data tables are used for this purpose: staff status storage, vehicle status storage, and client trips served.

- The staff and vehicle status storage data collect the data entries that were erased from the respective system data arrays once the status of the staff or of the vehicles changes. Therefore the fields in the storage database are the same as the ones used for system data.
- The client trips served array registers, for each trip ID in the static input data, the additional information related to the trip being served by the carsharing system or not (binary field), and distance to closest vehicle.

4.8.2 Structure

The simulation process initiates by building the simulation environment using the static input data (see Figure 11). The basic data vector and zones' data arrays give the information about simulation parameters and the necessary data to build the geographic space. The system data is initiated by the staff and vehicles initial positions from the respective static input data arrays. At this moment the arrivals array is empty.

4.8.2.1 Starting the simulation

For the first iteration the simulator runs the assignment model of the real-time decision tool to produce the first assignment plan to be applied in the first planning period, by using the forecast values, in number of demand requests for the respective horizon period, retrieved from the static input data. The activities of the staff for the first planning period are merged with the client trips array that are considered to be performed, in order to populate a list of upcoming events. The list is then ordered by time of occurrence. At this time there is no arrival event, since nothing has happened yet.

4.8.2.2 Processing upcoming events

The events are processed by chronological order. Three questions must be answered: “start of staff event?”, “arrival event?”, “client departure event?”. The order of the questions is not important, and the one presented in Figure 11 was used to keep the diagram reader friendly.

- If the next event is the “start of a staff event”, the simulator runs the filter of the real-time decision tool (for more information see subchapter 4.4) to check if the event is possible. If yes the event is executed, otherwise the staff activity is postponed and the list of upcoming events updated.
- If the next event is an “arrival event”, the simulator executes the event. The arrival events are updated at the time a client trip or staff event is started, as it is further discussed.
- If the next event is a “client departure”, the distance between the client and the vehicle is determined to assess if the distance between the two entities is walkable (vehicles and clients’ positions are registered in coordinates). In case the answer is positive the event is executed, otherwise demand is rejected.

4.8.2.3 Updating system arrays and adding new entries on output tables

When an event is executed (start or arrival), the system data arrays are updated and the replaced data is stored in the correspondent output data tables. The possible events are: “departure of client”, “arrival of client”, “staff starting movement”, “staff finishing movement”, “staff starting maintenance”, and “staff finishing maintenance”.

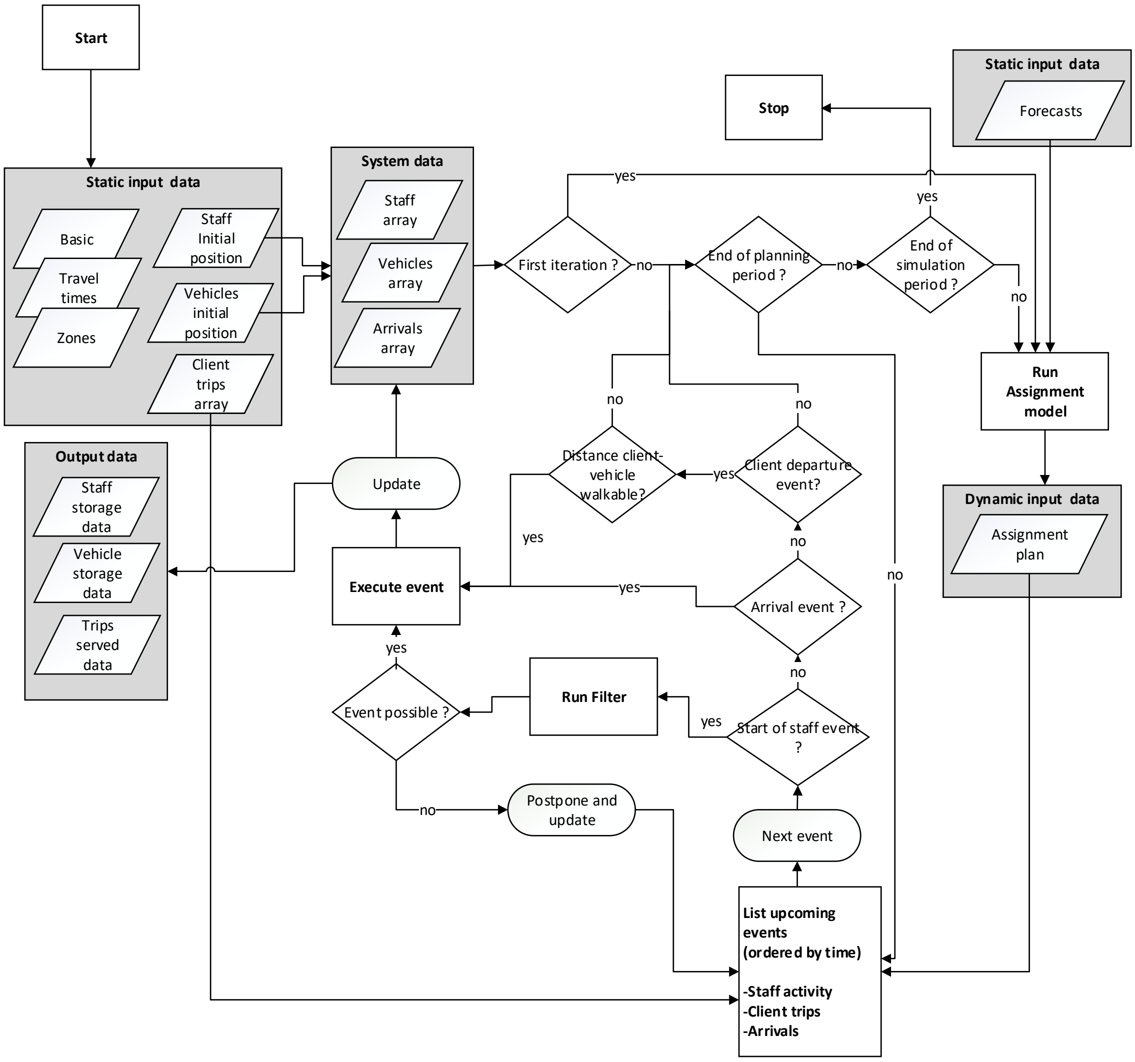


Figure 11: Simulator flow chart

- *Departure of client*

  When a client starts a trip, the vehicle system data is changed (remember that system data virtually controls what is happening inside the system). The vehicle that the client uses changes its status from "available" into "used by client" and the data related to origin, destination, duration and distance are added. At the same time, the arrivals array and output data are updated. A new entry is added to the arrivals array with the time of arrival of the vehicle and the coordinates of the location of the arrival, where the client finishes the rental period. When a new entry is added to the arrivals array, the list of upcoming events is simultaneously updated (this was not represented in Figure 11 to maintain a clean readability of the chart). Lastly, one new entry is added to the vehicles' storage table of the output data with the previous vehicle status, that is, the same data previously located at the system data.

- *Arrival of client*

  On the arrival of a client, the client and vehicle new positions are updated in the client and vehicle arrays. A Bernoulli trial with a probability p (in this work designated by maintenance generation factor) is applied to decide if the vehicle was left in a state of needing maintenance. As a consequence there are two outcomes, the status of the vehicle in the system data changes into needing maintenance or into available, depending on the Bernoulli process result. Once the status of the vehicle changes the respective values on the vehicles array of the system data are stored in the vehicle storage table of the output data.

- *Staff starting movement*

  Movements of staff are subdivided into two types: movement in a carsharing vehicle and movement by using public transport. When staff initiates a movement the mode used, zone of origin, destination, vehicle used (in the case of using a carsharing vehicle), time of departure and time of arrival are identified in the staff array of the system data, and the previous values registered in a new entry in the staff storage table of the output data. Simultaneously a new entry is added to the arrivals array and the list of upcoming events is updated. If staff is using a carsharing vehicle, the status of the vehicle used by staff changes and, consequently, the respective values in the vehicles array of the system data are updated. The previous status is stored in the vehicles storage table of the output data.

- *Staff finishing a movement*

  When staff finishes a movement the new staff position is updated, the status changes into idle, and the staff array of the system data is changed in accordance. The previous status information is stored on the staff storage table of the output data. For movements inside a carsharing vehicle, the status of the vehicle is updated to available, the vehicles array is updated, and the information related to the previous status stored in the vehicles storage table of the output data.

- *Staff starting maintenance*

  Status of the vehicle changes from needing maintenance into "being maintained" and the values of the vehicle array of the system data are updated. The assigned staff status also change into "maintaining a vehicle" and the values of the staff array are updated accordingly. The previous status of both vehicle and staff are stored in the respective tables of the output data. The event of finishing maintenance is added to the arrivals array, and the list of upcoming events is updated.

- *Staff finishing maintenance*

  When staff finishes maintenance, the status of staff changes into available, and the status of the vehicle into available, being both staff and vehicle arrays updated. The former status are stored in the staff and vehicles tables of the output data.

4.8.2.4 Assessing conditions to move to the next planning period or stop the simulation process

After processing each event two conditions are assessed. The first one marks the end of the planning period, and allows the simulator to run the assignment model once more for the new system data values and using the correspondent forecast values. This produces a new activity plan for staff, which entries are included in the list of upcoming events. The second condition marks the end of the simulation period. If the variable that controls the time clock of the simulation model reaches the simulation end time, the simulation process stops and the output data is stored in a file. Until one of these conditions is reached the simulator keeps processing each individual event on the list of upcoming events.

5 Application to the case study

5.1 Introduction

Having the real-time decision tool and the simulator defined, we can test the real-time decision tool in a virtual environment. Testing is essential to assess the performance of the real-time decision tool proposed in this thesis. The objective is to analyze the behavior of the developed tool for one day of operation by virtually emulating the interaction with a real system.

The simulation could be done by using randomly generated values. Although for this case we use realistic data. Because, in one hand, it provides a close experience of applying it to the real world, allowing to understand the difficulties that can be encountered. On the other hand, it allows taking conclusions, not only linked to the modelling process, but also related to the efficiency of applying it to the considered urban area.

The main variable to characterize for a real application site is demand. To obtain the demand data for carsharing, a survey was designed and implemented to the case study location. The survey covered socio-demographic characterization, revealed preferences, and stated preferences of the respondent in relation to the use of innovative modes of transportation, and it was firstly disseminated using the web and then complemented, for bias reduction purposes, by computer assisted personal interviews (CAPI). Another member of the InnoVshare project, pursuing a different task, used the data of the survey as an input to estimate carsharing demand. The referred work was part of another PhD thesis defended at Lisbon University [Eiró, 2015]. Since the estimated demand is used as a fundamental input to test the real-time decision optimization tool, an explanation of the new and original methodology proposed by the author is included in this document.

After the demand estimation, the preparation of data to be used in the interaction between the real-time optimization tool and the simulator is described. Then scenarios are established and results presented. In the next section we start by introducing and giving more details about the case-study area.

5.2 Case study presentation

The Lisbon Municipality is the case study for this dissertation (see Figure 12). The choice of the case location, which comes from the InnoVshare project itself, took into account the geographic market characteristics that researchers linked to carsharing success, namely high density neighborhoods, scarce parking, ability to live without a car, and mix of uses.

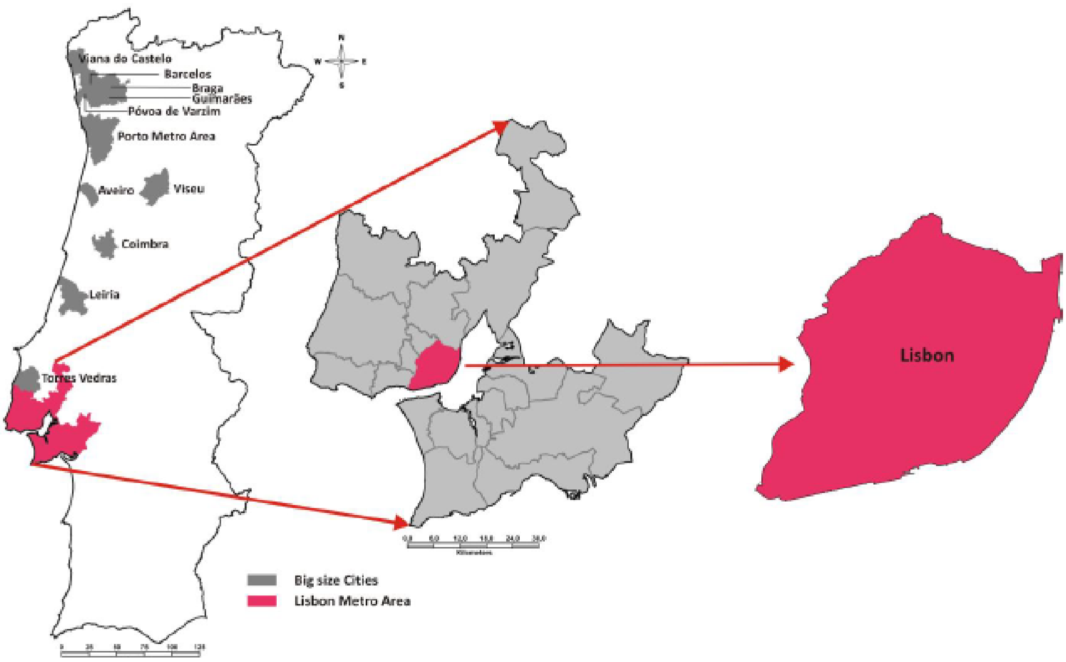


Figure 12: Lisbon and LMA location [Viegas and Martínez, 2010]

According to Celsor and Millard-Ball (2007), high density neighborhoods increase the probability of having high number of users within a walking distance of each service car. Moreover, dense neighborhoods have the necessary conditions for living without a car, due to the greater number of nearby destinations (e.g.: shopping, leisure, and working related), transit availability, and conditions to use soft modes. Scarce parking makes car ownership more expensive and less convenient, and if residents need to walk a couple of blocks to their car, they certainly would walk the same distance to a carsharing vehicle. Locations having mix of uses are able to generate non-pendular trips, which increases demand during working hours.

The choice of Lisbon municipality is also justified by the fact that two carsharing companies opted for this location to open their services. To assess the daily movements inside the Lisbon municipality, a survey is applied to its area of influence, amplifying the spatial analysis, but containing it to the limits of the Lisbon Metropolitan Area. A brief characterization of the LMA region is presented, followed by a more focused analysis of the Lisbon municipality, with the description of pertinent demographic, geographic, and mobility indicators. It is also added a descriptive analysis of the carsharing service currently available.

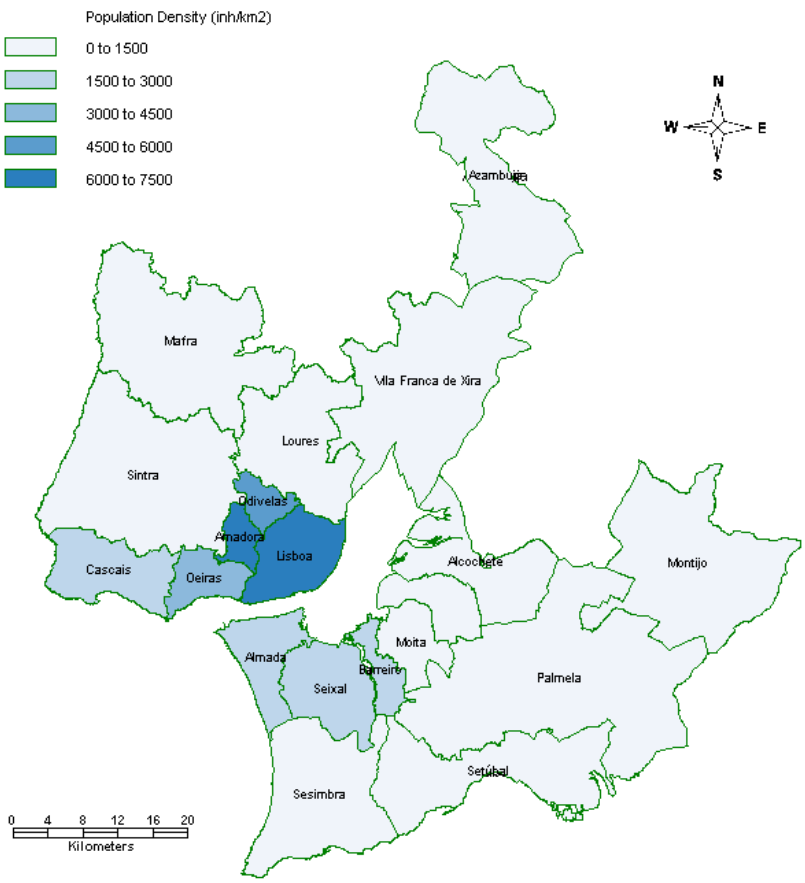


Figure 13: Population density in LMA, Census 2011 – data source [INE website]

5.2.1 Lisbon Metropolitan Area

The Lisbon Metropolitan Area is the Portuguese region with the largest economy and population. It is the home of 2.8 million inhabitants (see Table 4), around 26.7% of the Portuguese population, and the headquarters for 30% of the national companies [Julião, 2003]. The LMA is located on both sides of the Tagus River, occupying an area of 3,265 km^2. The North margin enfolds 10 municipalities (Amadora, Azambuja, Cascais, Lisboa, Loures, Mafra, Odivelas, Oeiras, Sintra and Vila Franca de Xira) and the South bank has 9 municipalities (Alcochete, Almada, Barreiro, Moita, Montijo, Palmela, Seixal, Sesimbra and Setúbal) – see Figure 13. The city of Lisbon is the core of the metropolis and the greatest pole of economic activity inside LMA. The employment and services available inside the Lisbon Municipality generate interactions with the other municipalities (see Figure 14), that are supported by a multimodal transportation network composed mainly by road, bus, rail (light and heavy), and ferry modes.

Table 4: Area, population, density, employment polarization index in LMA municipalities, Census 2011 – data source [INE website]

Municipality	Area (km2)	Population (2011)	Pop. density (inhab/km2)	Employment Polarization Index (2011)
Alcochete	128.4	17569	136.83	0.88
Almada	70.2	174030	2479.06	0.77
Amadora	23.8	175136	7358.66	0.7
Azambuja	262.7	21814	83.04	1.24
Barreiro	36.4	78764	2163.85	0.67
Cascais	97.4	206479	2119.91	0.76
Lisbon	**85.0**	**547733**	**6443.92**	**2.32**
Loures	169.3	205054	1211.19	0.76
Mafra	291.7	76685	262.89	0.71
Moita	55.3	66029	1194.01	0.5
Montijo	348.6	51222	146.94	0.81
Odivelas	26.4	144549	5475.34	0.5
Oeiras	45.9	172120	3749.89	1.11
Palmela	465.1	62831	135.09	1.03
Seixal	95.5	158269	1657.27	0.53
Sesimbra	195.5	49500	253.20	0.6
Setúbal	230.3	121185	526.20	0.93
Sintra	319.2	377835	1183.69	0.64
Vila Franca de Xira	318.1	136886	430.32	0.65
Total	3264.8	2843690	---	---

The LMA road network is well structured, being characterized by having two main road corridors in the North (A1 and A8), two from the West (A5 and IC19), two from South (A2 and A12) and two ring roads around Lisbon Municipality (CRIL and CREL). The two main roads from the south cross the river through the two existent bridges connecting Lisbon to Almada (25 de Abril bridge) and Lisbon to Alcochete (Vasco da Gama bridge). The car is being preferred as the main mode for the last decades, being the road network the object of public major investments since the eighties. Most of the main corridors described (the only exception is the 25 de Abril bridge) were built in the last three to four decades.

The bus has the greatest share in what concerns to public transport. Carris is the company that operates the urban bus services inside Lisbon municipality and it is the largest bus operator in the LMA. Other companies provide services interconnecting municipalities in LMA: Transportes Sul do Tejo, Isidoro Duarte, Mafrense, Rede Expressos, Ribatejana, Rodoviária da Estremadura, Rodoviária de Lisboa, Rodoviária do Tejo, Rodoviária do Alentejo, Barraqueiro, ScottUrb, Sulfertagus, Transportes Colectivos do Barreiro, and Vimeca.

The train is one of the oldest transport modes used by LMA inhabitants. The LMA is served by heavy and light rail transport systems. The main suburban heavy rail transport corridors of the LMA are: Azambuja line, Cascais line, Sintra line, Sado line, all operated by CP, and Fertagus line, operated by Fertagus to interconnect both margins of Tagus river using the lower deck of the 25 de Abril bridge. Lisbon and Almada have urban rail systems operating inside each municipal area. In Lisbon there is a subway system with 4 lines operated by Metropolitano de Lisboa and a Tram-train network operated by Carris. In Almada there is a Tram-train with 3 lines operated by Metro Transportes do Sul.

Transtejo and Soflusa operate the ferries that perform the fluvial crossings between the two margins of the Tagus river, linking Lisbon to Almada, Seixal, Barreiro and Alcochete. Some of the boats can carry vehicles. The ferry terminals are usually close to railway or subway stations, next to parking lots and bus terminals, promoting inter modality. Another company operating fluvial crossings in LMA is Atlantic Ferries. This company is responsible for the crossing between Tróia and Setúbal at the Sado river bay (south of the LMA).

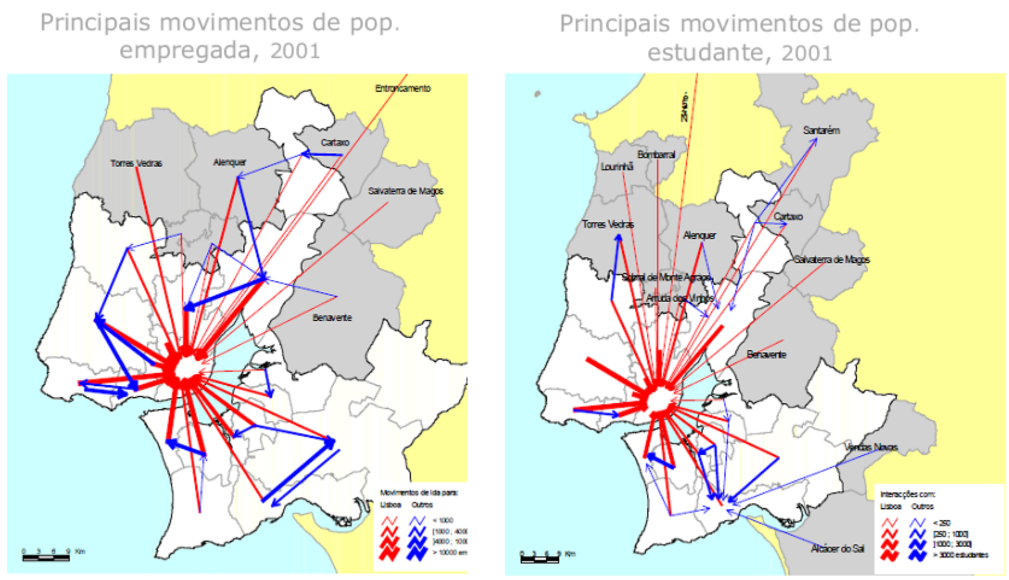


Figure 14: Main movements of the population (movements of employed population at the left and movements of students at the right) [INE, 2003]

According to census data 2011, the car is the most used transport mode (54.04%) for home-based movements in the LMA region, followed by walking (15.33%), bus (15.04%), train (7.63%) and subway (4.12%) [INE, 2012]. The ferry data was not discriminated during the Census survey.

5.2.2 Lisbon municipality

The Lisbon Municipality has 547,733 inhabitants according to Census 2011, distributed on an area of 85km^2 [INE website]. As seen in Table 5, its population has decreased 17% in 20 years, although the results between 2001 and 2011 show a certain stabilization of the population. Despite the recent trends, Lisbon is the municipality inside the LMA with the highest number of inhabitants and the highest population density. In terms of European scale, the city of Lisbon is in the 82th place in number of inhabitants, at the same level of cities like Málaga (Spain) Helsinki (Finland), Dusseldorf and Bremen (Germany), Sheffield (UK), and Copenhagen (Denmark) [Citymayors website], being the LMA the 15th larger European metropolitan area [Newgeography website].

Table 5: Comparison of population growth considering Lisbon, LMA and Portugal populations – data source [INE website]

Population	1991	2001	2011
Lisbon	663,394	564,657 (-14.9%)	547,733 (-3.0%)
LMA	2,540,276	2,682,687 (+5.6%)	2,843,690 (+6.0%)
Portugal	9,867,147	10,356,117 (+4.96%)	10,562,178 (+1.99%)

The employment, education facilities and services available in Lisbon generate traffic from the surrounding municipalities. Lisbon municipality has 96,731 companies and 44,526 societies that employ 595,242 individuals (15,9% of the country’s total), which generate a volume of business of 89 thousand million Euro (25.7% of the country’s total). In terms of education, Lisbon has 104 college level institutions with 139,761 students and 15,000 researchers [CML, 2014]. The number of commercial establishments is 17,356 which location is represented in Figure 15, being 67.2% retail businesses, and 32.8% food and beverage businesses, which employ a total of 67,375 individuals (data from 2009) [CML website].

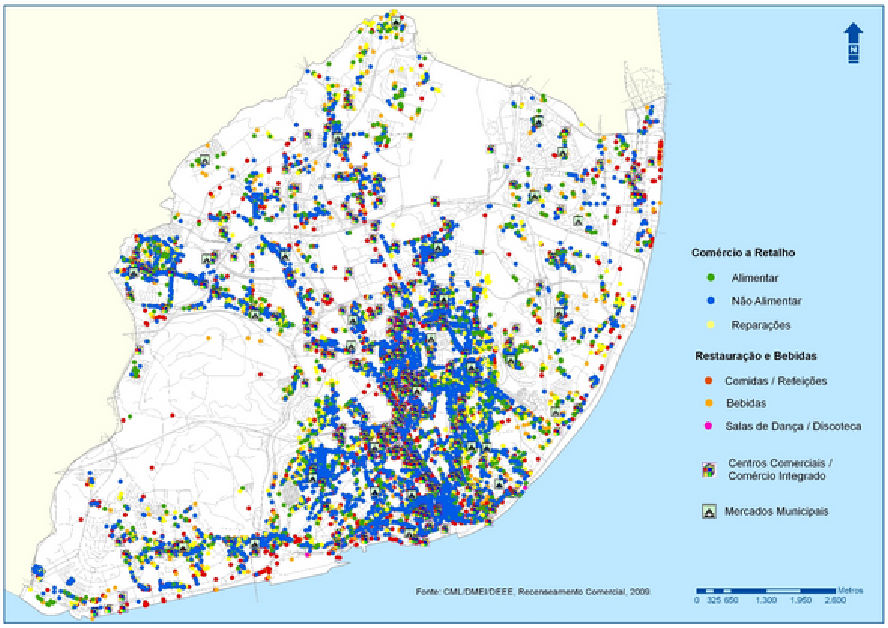


Figure 15: Location of commercial establishments in Lisbon municipality in 2009 [CML website]

The effect is the production of daily movements of people from the surrounding municipalities (see Figure 14 and Figure 16). The Census 2011 data shows that every day, only due to home-based trips, Lisbon Municipality receives 425,737 individuals, while 47,521 leave to work or study in other municipalities. This mean that there is an increase of 69% of the population during the day, only counting the movements of students and employed population [INE website].

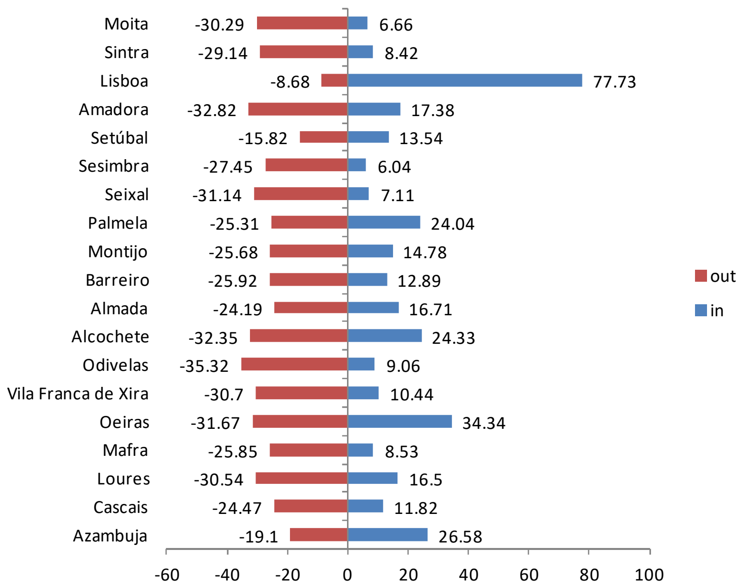


Figure 16: Proportion of the population in % that enters and leaves the municipality considering daily home-based movements - Census 2011 [INE website]

In terms of car movements, according to 2010 traffic counts, the number of cars entering and leaving Lisbon municipality per day through the main corridors is around 904,000, therefore, it can be said that more than 402,000 motorized vehicles enter every day in the city of Lisbon transporting workers, students, and visitors into the city, or just to use the inner city roads to reach other destinations, behaving as cross traffic (see Figure 17). The West side corridors are the most used ones with 46% of the motorized traffic. The North corridors deal with 30% of the motorized traffic, and the South with 24% (the 25 de Abril bridge enables the crossing of 149,000 vehicles and the Vasco da Gama bridge 64,000 vehicles per day) [INIR, 2011]. In 2004, the through traffic inside Lisbon during the morning peak represented 8% of the total traffic coming from LMA [CML, 2005].

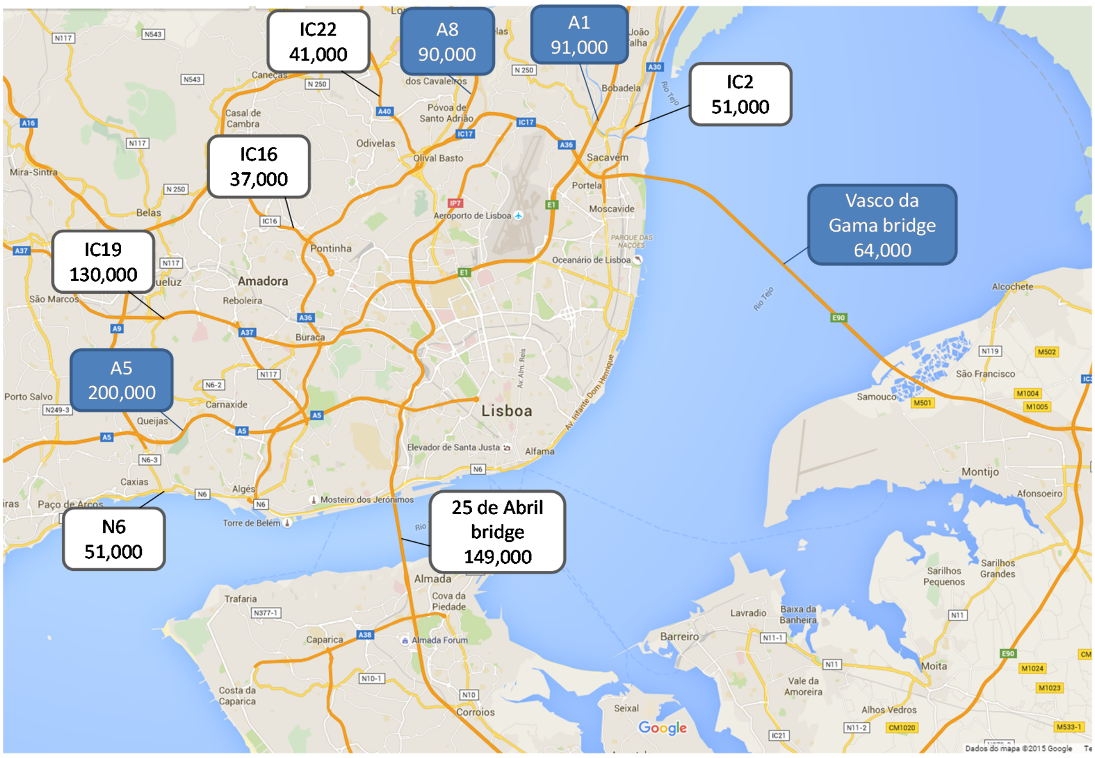


Figure 17: Motorized traffic of the main Lisbon corridors in 2010, AADT numbers in vehicles, adapted from [INIR, 2011]

According to a study done in 2004 by TIS.pt [CML, 2005], the daily migration movements coming from the AML were responsible for approximately half of the rush-hour peak traffic values inside Lisbon city roads (see Figure 18).

The intense car usage is related to car ownership. Looking at the LMA region, origin of the majority of car trips entering in Lisbon, the number of insured cars represents 27% of all light passenger cars registered in Portugal. Lisbon is the municipality with the highest number of insured cars in 2014, according to Instituto de Seguros de Portugal –

authority responsible for the regulation and supervision of insurance in Portugal. The figure indicates 291,709 vehicles, which corresponds to 533 cars per 1000 inhabitants and 3432 cars per km^2 (see Table 6). Which is somehow related to the fact that the population living inside Lisbon municipality use mainly personal transport (car, motorcycle) for home-based movements, with 48.8% of the share, putting public transport in second place, with 33.6%, followed by walking, with 13.6% of the transport share, values from Census 2011 [INE website].

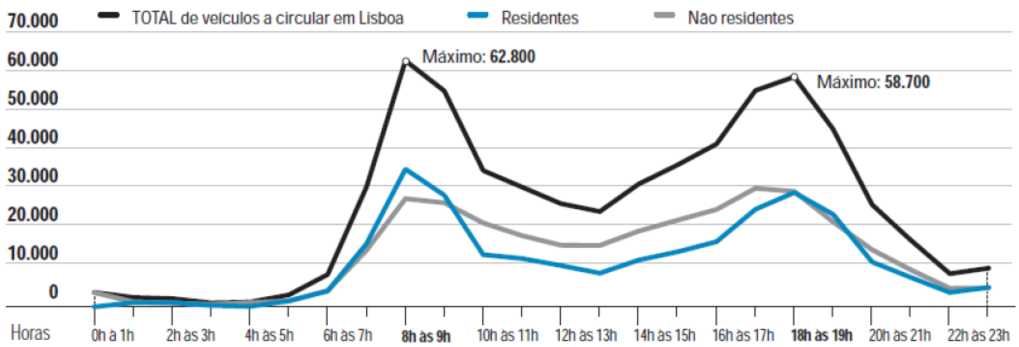


Figure 18: Vehicles moving in Lisbon Municipality [CML, 2005]

It is important to refer that the analysis of the number of insured vehicles needs some precaution since vehicles registered by owners with an address outside the Lisbon municipality can park daily inside the municipality. This is due, namely, to the migration of workers and students, who have a temporary residence and avoid the cost of redoing all official documentation (personal and vehicle).

The number of cars entering in Lisbon everyday affects parking demand levels. An exhaustive study done in 2004 indicated that the number of total parking capacity inside the municipality with public access was 203,900 vehicles, being 152,400 on-street parking and 51,500 in parking lots available to public access [CML, 2005]. Comparing this value of parking capacity with the registered insured vehicles in Lisbon and the daily number of vehicles entering the city, versus the number of people leaving Lisbon to work or study, one clearly understands that this capacity generates parking pressure.

In Figure 19, the results of a study from 2004 show the variation of the parking demand during 24 hours, discriminating Lisbon residents and non-residents. It can be seen that the minimum demand was 138,980 vehicles, and the maximum 213,500 vehicles. Meaning that more than half of the city's parking capacity is filled during the day.

Table 6: Insured number of cars per municipality in the year 2014 [ASF website]

Municipality	Number of insured cars	Insured cars per 10^3 in-hab.	Insured cars per km^2
Alcochete	8010	455.9	62.4
Almada	70672	406.1	1006.7
Amadora	66356	378.9	2788.1
Azambuja	9872	452.6	37.6
Barreiro	29920	379.9	822.0
Cascais	103443	501.0	1062.0
Lisbon	**291709**	**532.6**	**3431.9**
Loures	90455	441.1	534.3
Mafra	38103	496.9	130.6
Moita	26061	394.7	471.3
Montijo	22512	439.5	64.6
Odivelas	61471	425.3	2328.4
Oeiras	105789	614.6	2304.8
Palmela	31125	495.4	66.9
Seixal	68581	433.3	718.1
Sesimbra	23012	464.9	117.7
Setúbal	54598	450.5	237.1
Sintra	165433	437.8	518.3
Vila Franca de Xira	58297	425.9	183.3
Total	1325419	---	---

EMEL, the public parking management company, controls 45,761 public parking spaces, mainly on-street, by charging its use per time, based on a zonal tariff, to promote rotation in central areas with services and commerce as a measure to improve mobility conditions. Although special parking permits are available for residents and local commerce owners by the payment of a 12 Euro yearly fee for the first car, and an additional 30 Euro for a second car. In 2013, 50,827 residential and commercial parking permits were attributed [EMEL, 2013], a number that is higher than the parking places managed by the company.

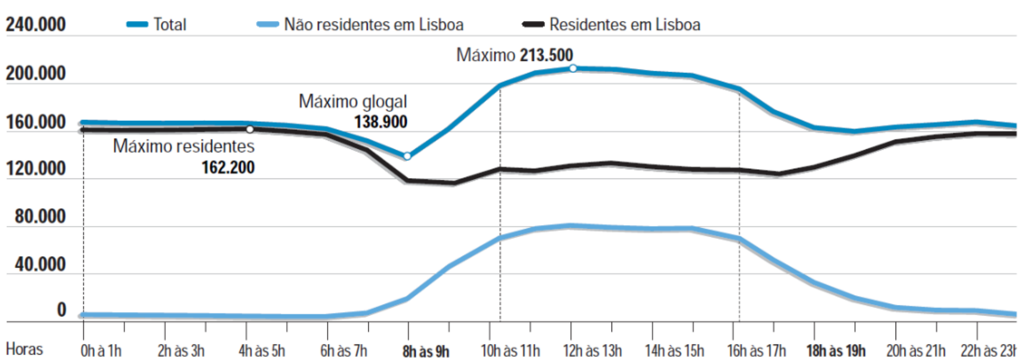


Figure 19: Parking demand in Lisbon municipality [CML, 2005]

The car is not the only available option to travel inside the city. Lisbon has three major public transport operators which together allow reaching any part of the city. Carris is the Bus and tram operator, and is responsible for the operation of urban buses, tram lines, and elevators. Metropolitano de Lisboa is the company that operates the subway system. This system has 4 radial lines, counting 45 stations inside the city of Lisbon. CP is the operator of suburban trains and it has 13 stations inside the municipality area, 7 of them with connection to the subway system. Since the beginning of 2012 these three operators joined to create a multimodal title called “navegante”. This urban monthly paid transport title allows passengers to use any of the service operators inside the city limits.

Besides public transport, Lisbon has a taxi service with a fleet of 3,445 taxis, which represents 1 taxi car per 159 Lisbon city inhabitants or 1 per 824 LMA inhabitants. Each taxi vehicle serves, on average 30 trips per day, carrying an average number of passengers equal to 1.57, and traveling an average total of 267 kilometers per day, meaning around 9 kilometers per trip [Portugal Start-Up, 2011].

The pedestrian network is being improved in order to increase the connections and safety of the individuals that chose to walk. Lisbon has already a pedestrian accessibility plan to promote improvements on the existent network until 2017 [CML, 2013]. “Uma praça em cada bairro”, translated to one square in each neighborhood is the latest initiative to fulfill this plan, which started in 2015. It consists in the execution of a set of projects in different locations of the municipality to increase pedestrian friendliness and increase urban livability [Boaventura, 2015].

The number of people using the bicycle as a mode of transportation is increasing, but it has not reach a sufficient number to be considered by the latest census survey. The Lisbon municipality is trying to promote the safer use of bicycles by investing on a cycling segregated network and plans were already presented to introduce a bikesharing service in the city center.

5.2.3 Carsharing services in Lisbon

Since Mobcarsharing had suspended its services on June (as referred in 2.4.4), the only active company providing carsharing services in Lisbon is designated by Citydrive and is promoted and supported by Mobiag, a software and service provider for carsharing operators.

The new player, Citydrive, started its operations in 2014, and, since its origin, allows one-way trips. The service is aligned with the best current practices in carsharing, and follows a similar service to the one provided by Car2go. Cars are spread in public parking places inside an operating area, and can be located by using a smartphone or computer, following the coordinates provided by the GPS tracking and communication system installed on-board the vehicles.

The operating area is subdivided by two zones: a yellow zone that covers the city of Lisbon excluding the green zone, and a green zone that is separated in two parts, one in Parque das Nações and the other including the central business district being limited by the river Tagus on the South side, Avenida de Ceuta on the West side, Avenida Gago Coutinho e Almirante Reis on the East side, and 2ª Circular on the North side. If the renting period is ended by parking a car in the green zone there are no additional costs, although if at the end of the renting period a vehicle is parked inside the yellow zone, an additional cost of 10 Euro is charged after 12 hours inside that zone without being used again.

The use of cars is charged by the minute, being 0.29 Euro per minute the price of driving time, and 0.10 Euro the price per minute while the vehicle is in standby mode, that is, parked during intermediate trip stops. The first 15 minutes of standby are free. The company establishes limits for maximum costs. The maximum charged per hour is 9.90 Euro which includes 20 kilometers, the maximum per 6 hours is 29.90 Euro with 100 kilometers included, and the maximum per day is 69.90 Euro which includes 200 kilometers. There is an additional cost of 0.29 Euro per kilometer for cases which the previous referred distance limit is exceeded.

The company has a set of additional fees that can be subdivided in irregular use penalties, administrative fees, and damage related fees. Irregular use penalties are charged in interventions to correct parking, to turn off vehicle lights, to close doors, to close windows, to activate parking brakes, to clean the vehicle, or to recover from a drained battery. The administrative fees are related to administrative costs of fines issued by authorities, to vehicle blocking or towed because of parking violations. Damage related fees are charged for animal transport, smoking inside the vehicle, losing or damaging keys, and fixing damage or replacing vehicle parts [Citydrive website, 2015].

The Citydrive service is promoted by Mobiag, a company that intends to integrate several operators under the same technological platform that manages all carsharing operations. The idea is to apply the roaming concept into carsharing networks, allowing users to be able to choose the best option without needing several membership applications. It also allows for operators to be in a broader market, and able to easily capture an interesting market share [Mobiag website, 2015].

The first vehicles of Citydrive resulted from an agreement signed in June 2014 with Opel to provide 20 Opel Adam vehicles [Mobiag website, 2015]. In September 2015, Mobiag signed a new agreement, this time with Skoda, allowing to add 20 new Skoda Fabia to the service fleet, a value that can reach 30 vehicles until the end of the year. It is important to refer that this is part of a marketing approach of a Skoda retail official seller from Lisbon to increase its sales in the technological young adopters target niche, and the vehicles will only be available for a limited time period - until the end of 2015 [Dias, 2015]. With this contribution, we can say that, currently (September 2015), Citydrive has a fleet of 40 vehicles spread around the city of Lisbon, mainly inside the green zone, which is four times higher than the fleet provided by the previous operator. The service is taking advantage of the marketing boost ignited by the visibility of vehicles parked along the streets and avenues, and this together with one of the best state of the art services will probably allow it to scale up further.

5.3 The survey

The analysis of the state of the art showed that surveys have been used as a fundamental tool to assess and understand carsharing systems, namely the way that people perceive its utility as a transport mode. Different types of surveys have been applied in the past focusing on different aspects. The level of complexity varies from characterizing the carsharing market and its potential through descriptive analysis and revealed preferences [Cervero and Tsai, 2004; Lane, 2005; Millard-Ball et al., 2005; Shaheen and Rodier, 2005; Burkhardt and Millard-Ball, 2006], to studying the potential demand by using stated preference data to calibrate discrete choice models that allow simulating user behavior at a micro level [Ciari et al., 2013].

The survey described in this subchapter is oriented to produce a synthetic population including the daily activity log of each individual, in order to characterize the mobility in the Lisbon municipality. Being part of a broader study carried out by the SCUSSE[4] research project (MIT-Portugal Program), which aimed at studying new smart transport modes and services with a strong ITS emphasis, the survey included questions designed to allow the evaluation of other innovative transport modes besides carsharing, namely carpooling, express mini-bus and shared-taxi. Therefore the final design was more complex than needed for this dissertation, hence it allowed gathering useful data for other fundamental lines of research of the InnoVshare project.

The survey was carried out between April 2011 and February 2012, being the CAPI outsourced and completed between the period of November 2011 and February 2012.

5.3.1 Web-based survey

The design of a survey is a complex and important activity. Maintaining the interest and attention of the respondent is vital to collect valuable and valid information. A careful design means having a logic structure, with the use of direct and simple questions, without repetitions, and maintaining a tight connection between the information already gathered and the next question. Avoid asking questions which do not match with the answers given before, for example, do not ask how much the respondent is paying for parking, if he/she responded that does not have a car.

The design process cannot be seen only from the respondent vantage point. Most of the times, the survey generates a good number of valid answers, but the effort put in processing the data for obtaining the first results is enormous. Therefore, the design phase needs to consider the post-processing work as well. This extra effort may compensate greatly, if one is able to decrease considerably the number of hours spent dealing with the gathered data.

The increase of the use of computers and access to the internet made the web-based survey an interesting alternative, because it is less expensive to administer and has the

[4] SCUSSE (Smart Combination of passenger transport modes and services in Urban areas for maximum System Sustainability and Efficiency) research project under the MIT-Portugal Program, which aimed to study new smart transport modes and services with a strong ITS emphasis, and their integration with the automobile and public transport in order to efficiently satisfy the increasingly complex daily activities and lifestyles of urban travelers.

potential to offer more flexibility and features than other survey methods. Web-based surveys have specific design techniques. Some are related to programming, functionality and browser compatibility, and others to online security issues. The main drawback when conducting a web-based survey is the coverage error, resulting on a biased sample. A multi-method survey approach can be used to level the biased sample to the proportions of the population [TRBNA, 2006].

The structure of the designed questionnaire had five main sections: socio-demographic data, revealed mobility data, stated preferences experiment, attribute boundary for behavioral change, and attitudes towards transport (see Figure 20).

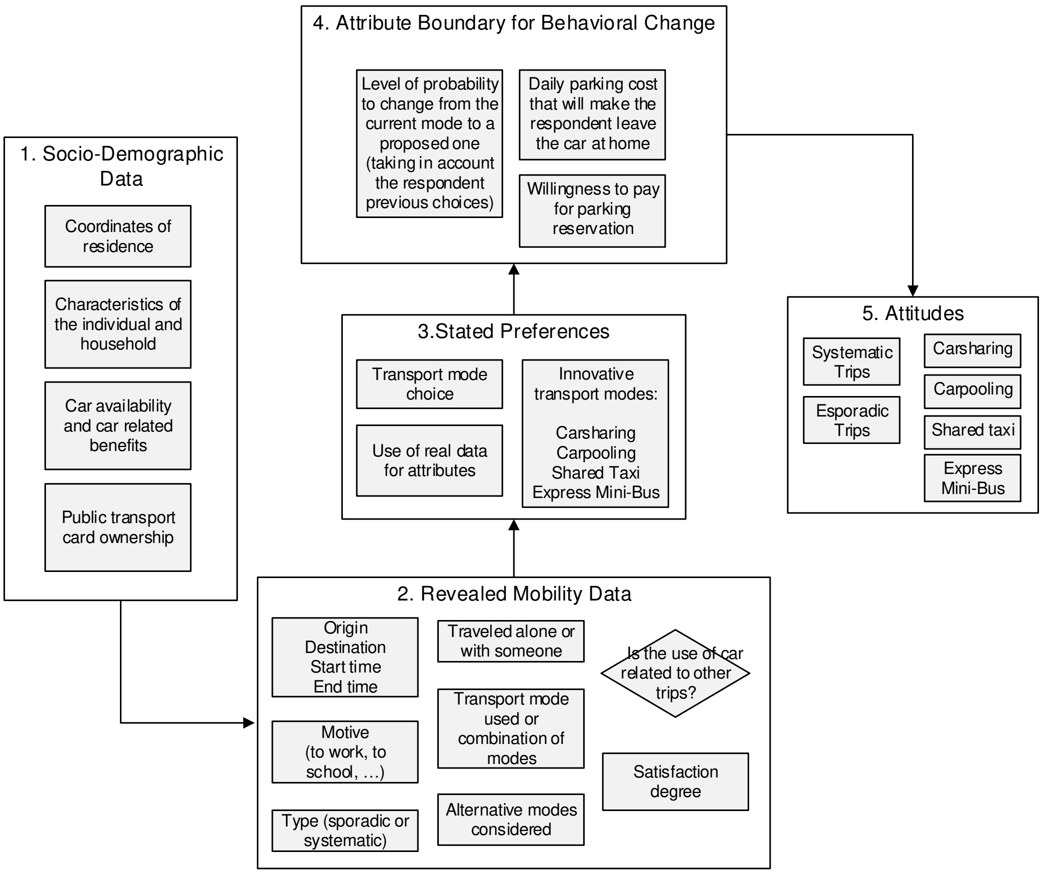


Figure 20: Structure of the survey

The socio-demographic characterization of the respondent was aimed at gathering information related to residential location, household composition, employment description, level of education, and mobility option available for daily travel (e.g. private car, public transport pass). It is important to note that only the population that lived in Lisbon Metropolitan Area with a minimum age of 18 years old were considered. Each respondent provided information about home location, birth year, gender, occupation, professional activity, educational level, household income, and household elements. The list of options available for occupation were: “full time job” specifying the type of schedule (fixed, flexible, or by shifts), “part-time employed”, “full time student”, “part-time student”, “unemployed”, “retired”, and “exerting a non-payed activity”. In terms of professional activity the respondents could choose between: “entrepreneur”, “high level corporate position” or “self-employed”, “intermediate corporate position”, “administrative position”, “service employee or salesman”, “craftsman” (workman) or “machinery operator”, “other”. In terms of educational level the options were: “basic school”, “high school”, “professional school level”, “graduated level”, and “post-graduated level”. The monthly household income was subdivided by intervals and the options were: “below 1000€”, “from 1000 to 2000€”, from “2000€ to 3500€”, “from 3500€ to 5000€”, “from 5000€ to 10000€”, and “above 10000€”. To characterize the family elements of the household, respondents specified the number of adults (between 18 and 64 years old), seniors (above 64 years old), children (below 11 years old) and teenagers (between 11 and 17 years old).

Questions were also introduced to characterize mobility related personal tools: driving license, car availability, parking availability and public transport pass ownership. For respondents that said yes, when asked if they had a driving license, questions about car availability and parking availability were provided. In terms of car availability it was asked if the respondent had a car for personal use, and the options were: “I have a vehicle for exclusive personal use”, “I have to divide it but I am the main user”, “I have to divide it and I am the secondary user”, “I do not have a car for personal use”. If the respondent had a car for personal use, it was asked if the car was owned by his/her employer and if the employer supported parking, fuel or toll fees. Questions were also included to assess how the car was usually parked close to the respondent’s home or work place. For home parking the options were: “inside the building”, “on street”, “inside a public parking lot”. For workplace parking the options were: “offered by the company”, “paid by the respondent”, and “for free”. In relation to the public transport pass, if the respondent had one, he was questioned about cost and type of pass owned.

The revealed mobility data part included questions about the respondent’s mobility choices of the previous day, requiring a detailed characterization of the trips performed and their main attributes. Each trip of the set of trips performed by the respondent were characterized. The attributes included on the query for each trip were: trip purpose, transport mode used, time, origin, destination, and if the trip is part of the daily routine or due to an abnormal activity. Origin, destination and time were specified recurring to open-ended questions. The transport mode question had the options: car; motorcycle; taxi; bus/tram; train; combination of car and train; combination of car and bus/tram; combination of car, bus/tram and train; walking; company bus; and other. In terms of trip purposes, the options presented were: to work, to school, to work with intermediate stop, to school with intermediate stop, on duty, shopping, leisure, sport or physical activity, meal, driving a person, personal matters, returning home, returning home with intermediate stop, visiting a person, and other. It was asked if the respondent did the trip alone, or with being accompanied by other people. A list was also provided for the respondent to point out what other transport modes he/she sees as an alternative for the considered trip.

A stated preference experiment, where the interviewee is subjected to three games, using four cards (see Figure 24), to choose between a private vehicle alternative, a public transport alternative or a combined private and public transport alternative, a new alternative transport mode option and an additional alternative picked up from the set of public transport and new alternative modes. The procedure to generate the preference data and how data was presented is described in Figure 25. The new alternative options considered were: carsharing, shared taxi, express minibus and carpooling. These new transport modes were briefly described, highlighting the main characteristics. The carsharing description was the following: "Carsharing is a renting service charged by the minute and kilometer. To use it you have to simply open the vehicle with your membership card, turn on the engine, drive to the nearest available parking at the destination, and close the vehicle with the membership card. The vehicle can be returned to a different place than the origin, being conditioned to an operating area. The system can be used after applying to a membership. All costs are included in the renting price (fuel, maintenance, parking and insurance). The vehicles are spread inside the main urban area (Lisbon municipality) and reservations are available". The image that complements the description suggests that the vehicles are parked on street as it would be in a free-float system.

The attribute boundary for behavioral change section provides an assessment of the degree to which the proposed alternative transport attributes may or may not change the current transport choice of the respondent. It was asked the respondents to evaluate the odds of changing from the current transport mode to an alternative one in the future, presenting a card for each mode with a set of real attributes. The respondent chooses a level from most unlikely to most likely.

The section on the attitudes towards transportation includes a set of fast questions to understand the attitudes towards sporadic and systematic trips, and the positive and negative features related to the analyzed transport alternatives. For carsharing the attributes evaluated were: I do not need to own a car, I do not have to worry about parking, I can choose the type of vehicle more adapted to my trip, availability at the closest station or at less than 750 meters away, not worrying about car ownership expenses, and not worrying about the vehicle maintenance. The options were presented using a Likert scale from 1(very negative) to 7 (very positive).

The easiness of the respondent in using the survey is a critical factor to obtain valid answers and maintain the interest in the survey for longer periods of time. In a computer based survey (online or offline), each page needs to be carefully constructed to be user friendly. The way to enter in the survey needs to be simple and easy. The use of a shortcut or a simple web address is advisable (take caution with addresses that can be mistaken by spam or viral pages). The web page has to be well-organized with the right amount of information and questions. A minimalist design is synonymous of user comfort and fast load. It is important that the respondent can see on each page the general structure of the survey and its current position. The answers to questions need to be fast and simple (use and abuse of closed answers with check lists, radio buttons or dropdown menus). The quality of the answers obtained depends on the quality of the questions asked. Therefore, it is fundamental that the questions are direct, clear and non-dubious. The use of an intelligent query is important to maintain the interest and focus of the respondent. An intelligent query is a query that continuously adapts to the information given by the respondent. This adaptation consists in considering the answers previously given to exclude or change questions that do not make sense, and also, to aid in the creation of scenarios close to the respondent's real world knowledge (for example to produce stated preference games).

The respondent experience and the quality of answers are not the only concerns to be regarded when designing a survey. The post-work is another issue that needs to be considered. The time spent in thinking, à priori, about the validation, way to storage and how to process the gathered data can be crucial to the success of the survey and save a lot of time. One basic measure is to introduce automatic validation on each page, in a way that the respondent can only move to the next page if all the answers are valid. Use textboxes to guide the respondents on the missing or non-valid answer. Use existent tools to aid the respondent in identifying geographical locations, in spite of asking for addresses. After putting the survey available to the target population, test it and check if everything is working, namely if the variables are being stored correctly and with the intended format.

The designed survey followed all the main guidelines described above and added some innovations that are highlighted on the following paragraphs.

The Google Maps API

The open-source technology Google Maps API developed by Google [Google Maps API website] is highly used by web designers to aid in showing locations and routes. It is fast and very flexible. It is built with tools that everyone is familiar with, like for example zoom, pan, insert and move marks, change the North direction and turn on/off the satellite image.

Nonetheless, this tool can also be used on the opposite way, which is, in spite of identifying a location and show it to users, it can be used for the user to identify a place and communicate it to the developer through the server.

By the experience obtained in this survey, this is simple to code, needing only a specific knowledge of Google Maps functions.

The result is a simple, fast and precise way to identify the residential location and trip ends (see Figure 21). In terms of output, it allows the automatic storage of coordinates. This is useful, not only because it considerably reduces the post-processing time required to edit and complete the working database, but also because it allows the use of the coordinates for other purposes, like automatically fill the origin of the next trip (related to the destination of the previous one), automatically put a pin on the residential location, automatically generate scenarios using information of the trips made by the respondent.

As a side note, we must say that the possibility of using Google Earth API [Google Earth API website] was also considered, but was immediately dropped when it was realized that it needed the download and installation of a plug-in by the respondent. The installation of software exceeds the respondent’s voluntary intentions and can result in early drop-offs.

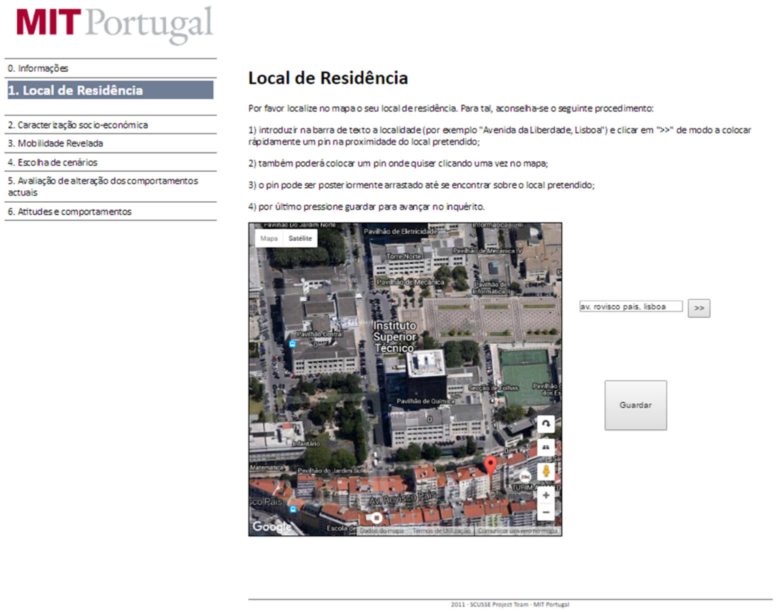


Figure 21: Identification of the residence location (web survey layout)

Trip description with the possibility to review and change

In the Revealed Mobility Data section of the survey the respondents were asked to describe the trips done during the previous week day. This can be a painful task, namely if the respondent did more than two trips (minimal number for a commuter). To ease the respondent’s experience several improvements were introduced.

One of the major concerns was to put all the questions about each trip in only one window (see Figure 22). This helps to maintain the focus of the respondent, making him know that this page is concerned to this trip with this origin and that destination. Also helps him rapidly visualize the number of questions he needs to answer.

The origin and destination information is inserted with the help of Google Maps API (explained above). For this part of the survey, it was added a button that allows the respondent to use as home location the origin or destination of the trip in question. From the second trip and beyond, the web survey automatically identifies the origin of the trip using the destination information of the previous answer (without locking the possibility to change). This reduces the time spent by the respondent in repetitive tasks.

The answers to questions with single answer are made using the options of each dropdown menu. The last question uses a checklist to permit multiple answers. This allows the rapid filling of the form and also the insertion of easy validation code routines.

After introducing the information for a trip, the query shows a page with a trip summary table where the respondent can easily visualize the important information of each trip (see Figure 23). Trips are ordered by time. In this page, the respondent has the possibility to edit the trip, erase it or add a new trip. In editing mode, the survey shows the page of the chosen trip with the information previously filled by the respondent.

In a first level validation, the web survey assures that the origin is not the same as the destination, the inserted initial time is before the end time, and that every question is answered. For a second level validation the survey recognizes if a trip is missing in the chain given by the respondent, and if so, it sends an alert message saying that “you need to add a new trip between trips x and y”.

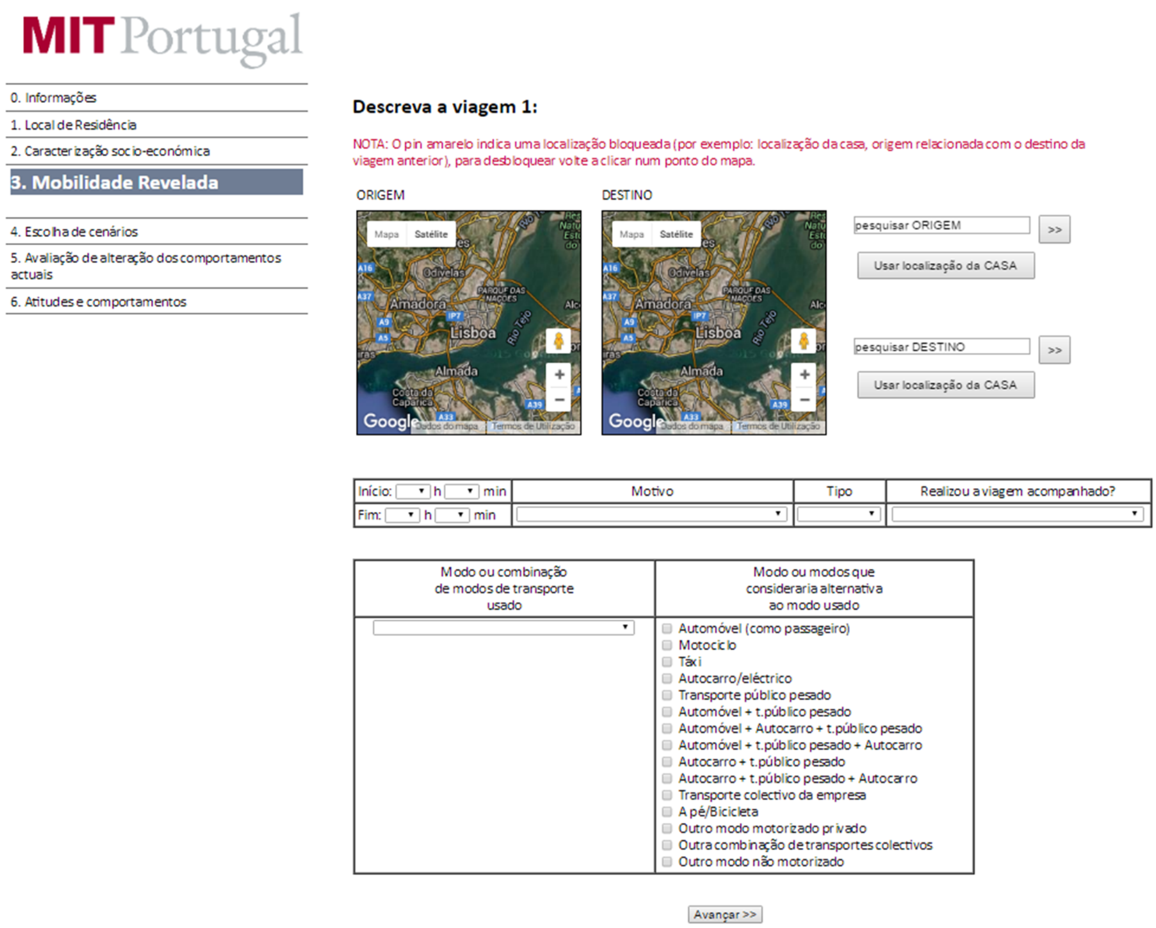


Figure 22: Trip information (web survey layout)

Viagem	Hora início	Hora fim	Origem	Destino	Motivo	Modo	
1	8:00	8:30	Santa Maria dos Olivais (Lisboa)	São João de Deus (Lisboa)	Para o trabalho	Transporte publico pesado	Editar Apagar
2	19:10	19:40	São João de Deus (Lisboa)	Santa Maria dos Olivais (Lisboa)	Regresso a casa	Autocarro/eléctrico	Editar Apagar

Acrescentar +1 viagem

Avançar >>

Figure 23: Trip summary table (web survey layout)

Generation of stated preference cards based on real data

The definition of scenarios to model the decision process of an individual can be made for hypothetic situations, without taking in consideration the real world values and respondent's experience. The use of values disconnected from reality can originate reactions like "this value is completely absurd", "this travel cost is incredibly cheap" or "the travel time is physically impossible" and can result on losing the respondent's focus or even in early drop offs. A stated preference method is more effective if values that the respondent understands are used.

This web survey used real mobility data from the study area (LMA) to generate realistic attributes for the scenarios of the stated preference alternatives. A procedure was conceived to generate the information of the cards for each modal choice game (see Figure 25).

The first action of the procedure is to select a reference trip from the set of trips defined by the user during the revealed preferences section. The reference trip is constrained to trips longer than 1,000 meters, with both extremes within the LMA, and result from a controlled draw between systematic and non-systematic trips.

For the selected reference trip, four groups of available transport modes are defined. Group1: Individual transport options (car, motorcycle); Group 2: public transport modes or combination between public transport modes and soft modes; Group 3: new transport modes (carpooling, carsharing, express minibus, and shared taxi); Group 4: aggregates the remaining options of the group 2. The transport modes inside each group take into account, not only the available alternatives for the origin and destination of the selected trip, but also the individual transport options that the user declared to have available.

The new transport alternatives presented to the respondent were carefully described through short text and bullets with the main attributes of each mode, but also with the creation of a cartoon for each mode to attract the respondent to the description of the mode before starting the stated preferences games.

Figure 24: Stated preference game with 4 cards (web survey layout)

The availability of each transport mode is estimated for each OD pair using a discrete spatial configuration formed by 281 zones for the LMA, 118 of the zones inside the Lisbon municipality [Martínez and Viegas, 2009; Viegas and Martínez, 2010]. For the new transport modes the generated rules for OD pair availability are:

- Carsharing: Trip distance shorter than 20 km and daily trip density greater than a certain threshold (200 trips/day.ha.);
- Carpooling: Only available for commuting trips between all the origin and destination pairs of the LMA;
- Shared taxi: Available between all the LMA origin and destination pairs, but with probabilities of ride matching dependent on time of the day and the traffic flow between the extreme points and the crossed areas during the travel;

- Express minibus: Trip distance greater than 5 km, daily trip density greater than a threshold (200 trips/day.ha.), or place located close to a large trip generator/attractor (i.e. shopping center, hospital).

Taking as reference the selected trip, the attributes for the different transport alternatives are estimated using forecasts from calibrated models. The models were calibrated for the referred discrete spatial configuration for the LMA. The attributes for the new modes (carsharing, carpooling, shared taxi, express minibus) are estimated based on previous research about the implementation of these modes in the LMA [Correia and Viegas, 2011; Eiró et al., 2011; Martínez et al., 2011; Viegas et al., 2008].

The selection of the transport mode for each card and game is performed independently. Each mode of the four groups previously formed has a probability of being selected. These probabilities were estimated using information from prior studies [Correia and Viegas, 2011; Martínez et al. 2011]. The objective was to obtain representative samples of each transport mode for the calibration of the stated mode choice model.

Table 7: Specification of the attributes considered in the stated preferences games by mode

Attribute	**Private car**	**Motorcycle**	**Taxi**	**Bus/tram**	**Heavy PT**	**Bus/tram + Heavy PT**	**Private car+PT**	**Walking/biking**	**Carsharing**	**Shared taxi**	**Express minibus**	**Carpooling**
Fare			x	x	x	x	x		x	x	x	
Fuel cost	x	x				x						x
Parking cost	x	x				x						x
Tolls	x	x	x			x			x	x		
Access time (destination)						x						
Access time (origin+destination)				x	x		x		x		x	x
Average time to park	x	x				x						x
In-vehicle time			x	x	x	x	x			x	x	
Travel time (walking or biking)								x				
Travel time by car	x	x				x			x			x
Waiting time			x	x	x	x	x			x	x	
# of days of the week taking carpooling												x
# of passengers on board (include driver)										x		x
# of transfers				x	x	x	x					

Then a subset of the fractional factorial design is randomly selected for the experiment. This subset includes the values that control the experiment (set of three games), affecting the previously estimated attributes to originate the values that will be presented on each card. The last step of the procedure is to fill each card with the chosen transport modes and the respective attribute values estimated by models and affected by the selected subset of the fractional factorial design.

Each transport mode was designed to present different attributes to the respondent, aggregated into three groups of attributes: time related attributes (i.e. in-vehicle travel time), cost related attributes (i.e. fuel costs), and mode specific attributes which have an impact on the selection of a transport alternative. For each transport mode, the alternatives are presented with these three groups of variables, with a summary of attributes of the same type and with the same units (i.e. travel costs in Euro and travel time in minutes). The attributes presented for each transport mode are described in Table 7.

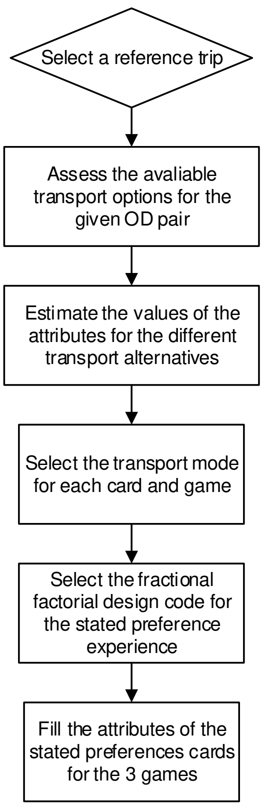


Figure 25: Generation of stated preference cards procedure

Besides the attributes for the transport modes, each game presents information about the trip in question (type of trip, origin, destination, and start time), retrieved from the selected trip (see Figure 24). Information about the weather conditions is also included.

Four types of weather were defined: hot and sunny (35ºC), cold and sunny (3ºC), average temperature with light cloudy sky (20ºC), and rain (14ºC). The weather conditions presented at each game depend on the selected subset of the fractional factorial design. The objective is to understand how the weather conditions affect the respondent's choice.

The possibility to take a break and return later

During the design process it was realized that the survey could be very extensive in some situations, and in some cases could exceed the time that the respondents were willing to spend. To avoid behaviors like “Now I do not have time to think on the question, so will give an answer just to get to the end”, two possible breaks on the query were created. These are strategically located: one at the end of the Stated Preferences part and the other before the beginning of the Attitudes section. The first break point is located after the most valuable information from the respondent. The second is before the extensive part of a series of fast Likert scale questions on the attitudes towards the modes, giving an opportunity for tired respondents to do other things before continuing.

The user is questioned if he wants to make a break, if so, he/she will be given a personal link to continue later. This link is sent automatically by email, if the email address is provided. The link is created based on an encrypted code of the database to assure that only he/she has access to his/her answers. When the user reconnects to the survey, the needed information stored in the database will be read to keep the questions adapted to this particular respondent.

Only one of the breaks can be used. This means that, if the respondent takes the first break, the second break will not appear, and if the respondent ignores the first break, the second one will appear before the last part of the survey.

5.3.2 CAPI survey

When a web-based survey is carried out there is a high probability of having a coverage error. This type of error happens when part of the population cannot be accessed by the survey. In this situation it is important to have a multi-method survey approach [TRBNA, 2006]. A targeting controlled type of survey, like for example the computer assisted personal interview (CAPI), needs to be designed to complement the penetration of the web survey and obtain a balanced sample of the population.

Firstly, it is necessary to characterize the answers received through the web-based survey to understand the obtained coverage for the target population. After filtering the web-survey entries, the result was 472 complete and valid answers. In terms of gender, the distribution of the respondents was 57% of males and 43% of females. The four main locations of residence are Lisbon (48%), Oeiras (10%), Sintra (8%) and Cascais (6%). The three main birth date intervals of the respondents are 1972-1976 (19%), 1977-1981(18%) and 1982-1986 (27%). Concerning the education level distribution, 10% have a high school degree, 3% have a middle school professional degree, 50% have a graduate degree, and 37% have a post-graduate degree. The web-survey did not get any answer from an elementary school educated person.

The comparison of the sample obtained with the population is made using data from the Portuguese CENSUS survey of 2001 [INE website]. The chosen categories of data to represent the spreading of the sample are: population per municipality, population per age cohort and population per education level.

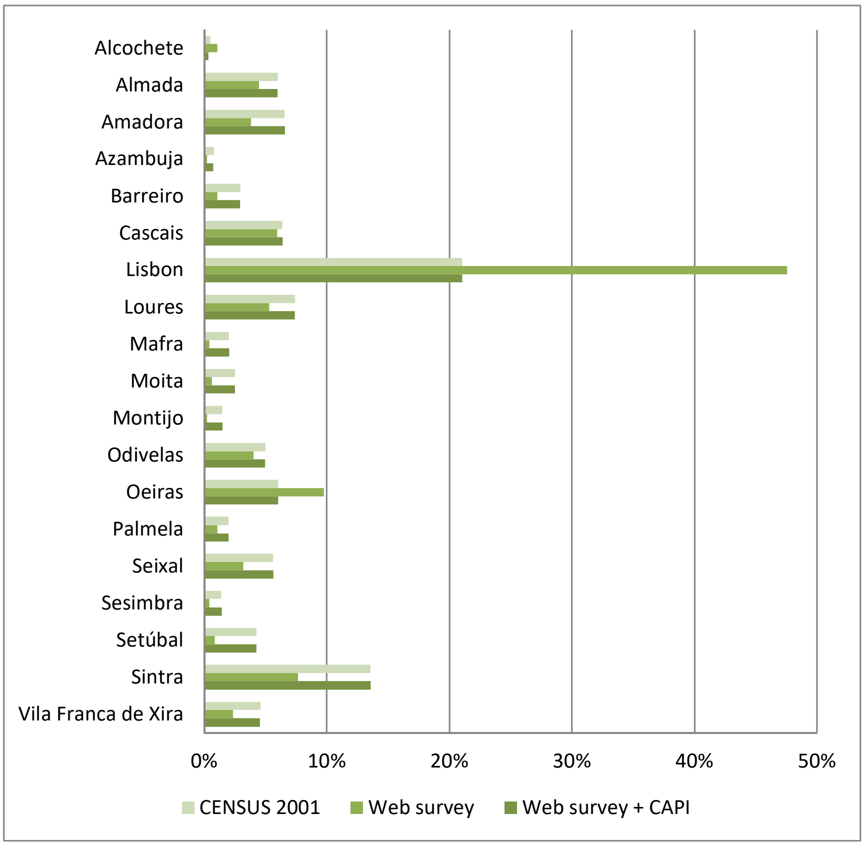


Figure 26: Population per municipality for the Lisbon Metropolitan Area

Regarding to the population distribution per municipality (see Figure 26), we can see that Lisbon, Oeiras and Alcochete are overly represented on the Web-survey sample; Cascais is almost levelled; and the remaining municipalities are under-represented. In terms of age (Figure 27), we verify a good coverage of the respondents from 18 to 35 years old. The coverage is less effective as the age of the respondent increases. This is understandable if we compare it to studies of internet users by age for Europe [Arch, 2008]. Concerning to the level of education (Figure 28), respondents with a graduation, post-graduation and middle/professional level are over-represented. The part of the population that has high, elementary or middle school level is under-represented. The survey does not have any entry for elementary and middle school levels.

As referred previously, a Web-survey originates a biased sample of the population. This is due to various facts, but namely because only a subgroup of the population in the analysis have access to the internet and consequently to the web-survey.

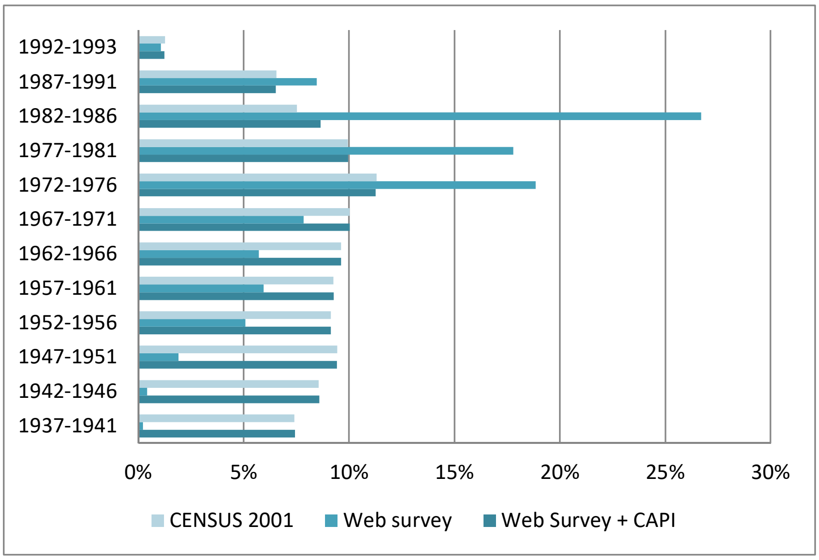


Figure 27: Population per birth year intervals for the Lisbon Metropolitan Area

A way to unbias the sample is by using interviewers equipped with internet access computers that go to the respondents' houses to perform the interview and fill the web-survey for them. The respondent selection process can be done by a previous phone call that confirms the selected attributes and schedules the interview.

The design process establishes the attributes required for each respondent to guarantee a good fitness of the sample at a minimum cost (the CAPI survey is an expensive tool).

In this case, the level of fitness of the optimization process is evaluated using the population per municipality, population per birth year and population per education level.

With the addition of 1,000 CAPI interviews to the web-survey sample, with the attributes (municipality, birth date interval, and level of education) well defined, we eliminate the sample bias. There is only the need to assure that the CAPI is done according to the design specifications.

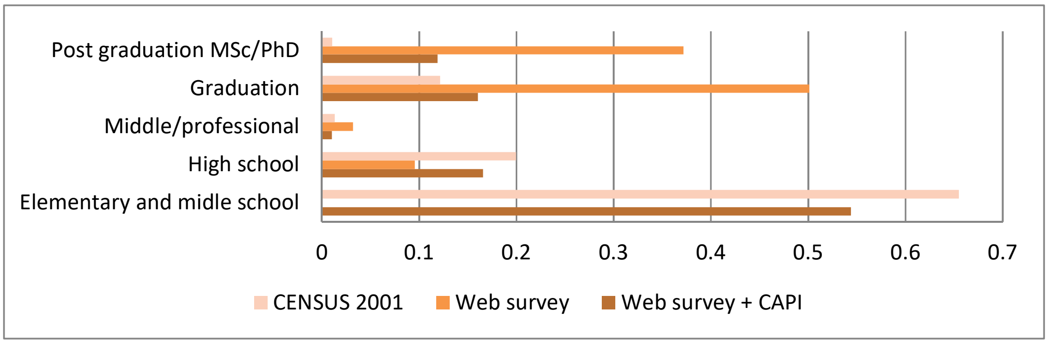


Figure 28: Population per education level for the Lisbon Metropolitan Area

5.3.3 Filtering the collected data

The data obtained was filtered according to criteria that enables to eliminate invalid entries. The database has repeated entries, showing that some entities were testing the code of the survey to see its capabilities, others gave random answers not declaring their real information. The criteria for validating the survey entries are:

1. *Reaching the end of the survey*. The first action was to select the entries of the database which reached the end of the survey. The database recorded information each time the user moved into the next survey page. Entries with incomplete information, showing that the respondent did not reach the end were eliminated.

2. *Time of answer*. The entries generated from responses that took less than 5 min were discarded. The same to the answers with more than 4 trips in revealed preferences filled in less than 5 minutes

3. *Repeated answers in stated preferences*. The stated preferences part of the survey is subdivided in 6 web pages (systematic trips, sporadic trips, carsharing, shared taxi, express mini-bus, and carpooling), where the user needs to give in a scale

from 1 to 7 is opinion related to certain attributes. The entries with more than 4 pages with the same answer were excluded.

4. *Valid postal code.* It is certain that some people give an error when writing the postal code. The postal codes (first 4 numbers) where compared to the location of the house given by the use of Google maps API. The ones that did not match were analyzed to see if it was an error and not a false postal code given on purpose.
5. *Trip speed.* The speed of each trip was calculated using the Cartesian distance and the time between origin and destination of each trip. Entries with values of speeds above 200km/h were ignored. This speed limit value allows the possibility to include errors in time perceived.
6. *A normal trip chain.* It was verified if the chain of trips of each entry did not had a gap. Therefore, entries that do not have compatible origins and destinations, that is where one or more movements are missing in the chain of trips, are discarded.
7. *Trips with zero data.* The trips that had no data inside were eliminated from the database.

From the database filtering resulted 1495 entries. The entries were compared in proportion with data from the Census 2011 [INE website]. The sample of 1495 individuals represents a little more than 0.05% of the target population, when compared with the Census 2011. The proportion male/female obtained from the sample was 40%/60%, which is close to the proportion of the target population. According to Census 2011 the LMA has 48% males and 52% females. The three types of data used to design the CAPI survey are now recalled to assess the sample after the described filtering process.

Analyzing the population distributed per municipality, it can be seen that the number of survey entries for people living in the city of Lisbon are higher, in proportion, that the Census 2001 used as reference to calibrate the CAPI (see Figure 29). The reason for this over-representation of Lisbon in the filtered sample is that, when performing the CAPI survey, the web survey continued open allowing other Lisbon inhabitants to continue answering to it.

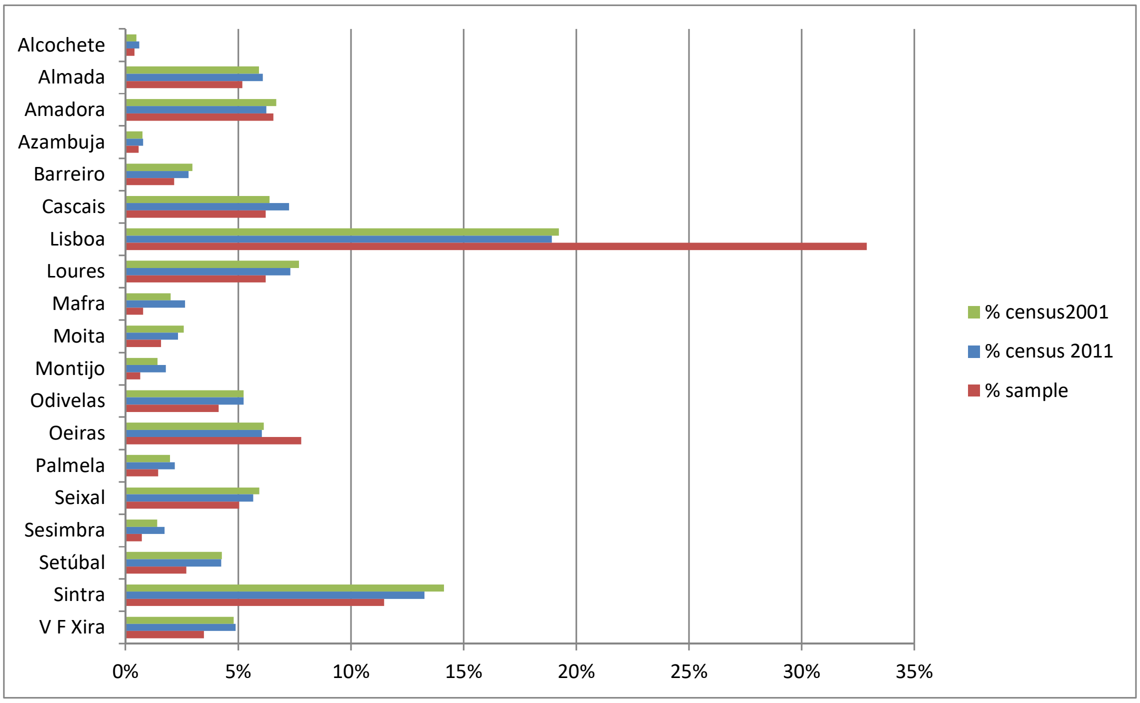


Figure 29: Population per municipality (sample after filtering/census 2011)

In the population per age intervals, it is visible a difference between the sample and the census proportions for age cohort 1992-1993 (see Figure 30). Census 2011 proportion is 64% higher than the data retrieved by the survey. This is due to the fact that the survey was unable to capture enough 18 and 19 years old inhabitants.

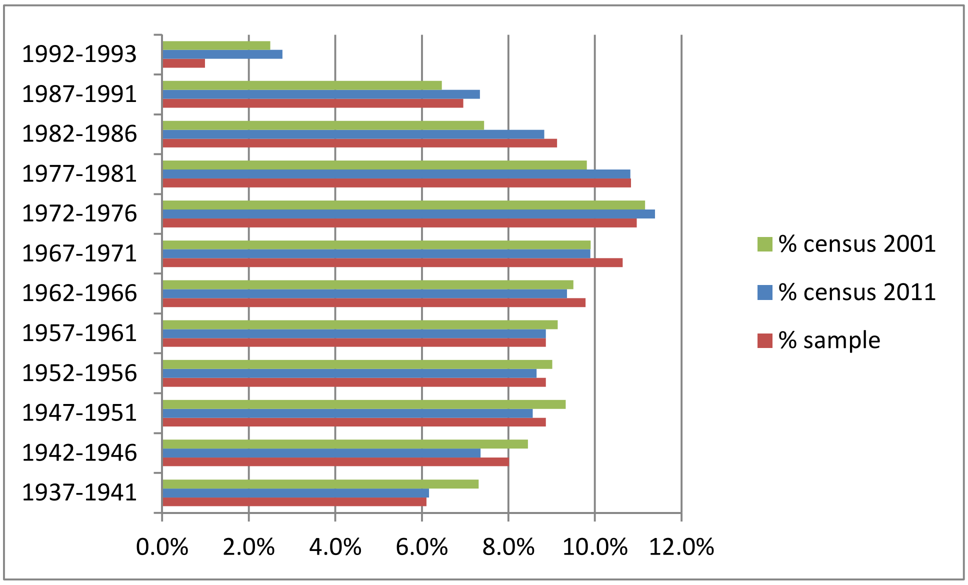


Figure 30: Population per birth year intervals (sample after filtering/census 2011)

The method used to publicize the web survey had an impact on the educational level proportions. The survey was advertised at our university communication channels which provided an overrepresentation of people with post-graduation and graduation degrees (see Figure 31). The CAPI survey balanced in an acceptable manner the number of answers of inhabitants with elementary, middle and high school educational levels. Since previous studies showed that the most likely users of carsharing are highly educated people, the overrepresentation of graduated and over-graduated inhabitants in the sample can be seen as an advantage.

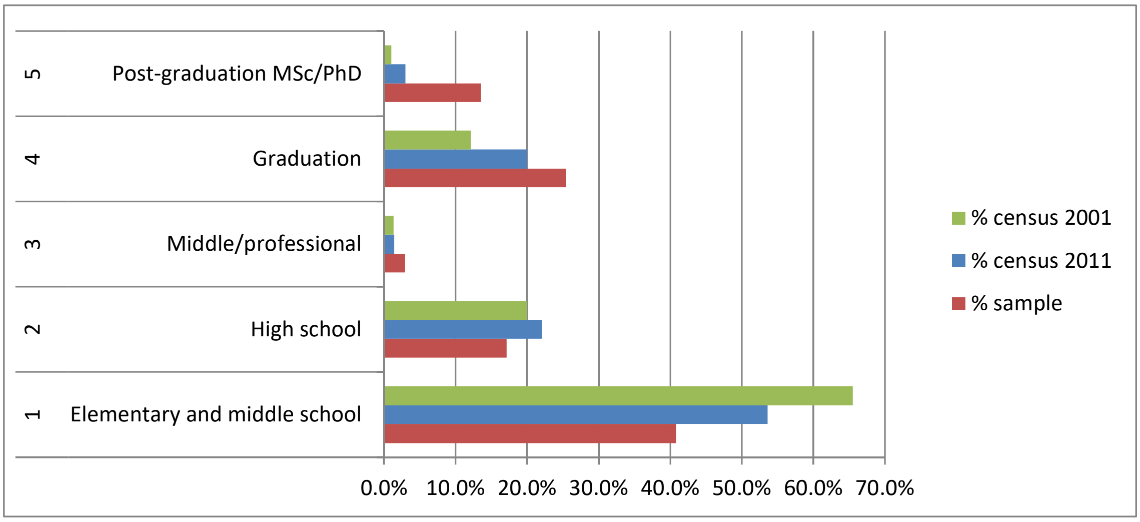


Figure 31: Population per education level (sample after filtering/census 2011)

5.4 Estimation of carsharing demand

To estimate the carsharing demand we use the activity based microsimulation approach generally described previously. As a remark, the process is subdivided in four steps: generating the synthetic population; generating the activity log for each individual; calibrating a discrete choice model that gives the probability of using each mode; and defining carsharing demand by filtering target market trips and modelling individual mobility choices. The three first steps were undertaken by another member of the InnoVshare project and are thoroughly described by Eiró (2015). Using the resulting data and the discrete choice model calibrated, the carsharing demand was estimated using a static approach, during the last step.

5.4.1 Synthetic Population

The synthetic population with a detailed set of attributes of the individuals is the basis of the process of demand estimation. The attributes considered were aimed to identify the individual (age, gender, marital status, educational level, etc.) and associate it to a household and house location. The generation process followed a methodology used by Martínez and Viegas (2009) to estimate household data, and updated by Lopes et al. (2014). The referred methodology is based on iterative proportional fitting process [Birkin and Clarke, 1988]. It allows obtaining a synthetic population from aggregated data, which is an advantage since a seed population is not available (the national statistics institute do not publish microdata results of the census survey due to data privacy protection).

Table 8: Attribute data sources [Eiró, 2015]

Attributes	Data source
Age	Census 2001
Gender	Census 2001
Marital Status	Census 2001
Education level	Census 2001
Employment status (active, student, other, retired)	Census 2001
Income	SOTUR
Driving license	SCUSSE
Number of cars	ACAP
Car ownership	SCUSSE
Motorcycle ownership	SOTUR
Public transport pass ownership	SOTUR
Parking at home	SOTUR
Parking at work	SOTUR

Table 9: Comparison between aggregate model results and Census 2001 and 2011 [Eiró, 2015; INE website]

Number of	Model	Census 2001	Census 2011
Population (inhabitants)	2,700,474	2,682,687	2,843,690
Households	1,013,102	1,014,259	1,157,163
Individuals per household	2.67	2.64	2.46

Table 10: Population and household spatial distribution, difference between model and Census 2001 and 2011 [Eiró, 2015; INE website]

Municipality	Population			Households		
	Census 2001	Census 2011	Model	Census 2001	Census 2011	Model
Alcochete	0.48%	0.62%	0.61%	0.48%	0.59%	0.59%
Almada	5.99%	6.12%	6.02%	6.01%	6.22%	6.00%
Amadora	6.56%	6.16%	5.41%	6.64%	6.35%	5.44%
Azambuja	0.78%	0.77%	0.77%	0.73%	0.71%	0.79%
Barreiro	2.95%	2.77%	3.38%	2.96%	2.87%	3.30%
Cascais	6.36%	7.26%	6.33%	6.21%	7.10%	6.27%
Lisboa	21.05%	19.26%	21.91%	23.14%	21.10%	24.29%
Loures	7.42%	7.21%	7.75%	7.00%	6.96%	7.30%
Mafra	2.03%	2.70%	1.98%	1.98%	2.50%	1.92%
Moita	2.51%	2.32%	2.08%	2.36%	2.26%	1.99%
Montijo	1.46%	1.80%	1.44%	1.46%	1.78%	1.40%
Odivelas	4.99%	5.08%	4.60%	4.82%	5.00%	4.40%
Oeiras	6.04%	6.05%	6.01%	6.09%	6.19%	6.03%
Palmela	1.99%	2.21%	2.08%	1.87%	2.05%	1.97%
Seixal	5.60%	5.57%	5.81%	5.28%	5.39%	5.42%
Sesimbra	1.40%	1.74%	1.30%	1.31%	1.67%	1.20%
Setúbal	4.25%	4.26%	4.15%	4.22%	4.18%	4.05%
Sintra	13.56%	13.29%	14.03%	13.03%	12.47%	13.44%
Vila Franca de Xira	4.58%	4.81%	4.33%	4.40%	4.62%	4.19%

The input for the synthetic population generation process had different data sources, as described by Eiró (2015) (see Table 8). Age, gender, marital status, educational level, and employment status aggregated data for the LMA were retrieved from the Census 2001 survey. The information related to Income, motorized vehicle ownership (car and motorcycle), public transport pass ownership, availability and type of parking at home and work were retrieved from the SOTUR[5] project survey, that was aimed to analyze residential choices (past and current) and stated neighborhood preferences and its connection to the accessibility levels and mobility patterns. Silva and Martínez (2011) include more details

[5] SOTUR (Strategic Options for integrating Transportation innovations and Urban Revitalization overview) research project under the MIT-Portugal Program, which aimed to define innovative solutions sufficiently attractive to private investment and that could simultaneously contribute to urban development patterns with the capacity to leverage innovative transport solutions.

about the SOTUR survey. The data related to the number of cars was taken from the Portuguese Automobile Association statistics [ACAP website]. The data related to driving license and car ownership was taken from the revealed preferences part of the survey described previously, that was part of the SCUSSE project.

The output that resulted from applying the referred methodology is a synthetic population where each element (or person) was characterized by the following attributes: age, gender, marital status, education level, employment status, income, driving license possession, number of cars, car ownership, motorcycle ownership, public transport pass ownership, parking at home, and parking at work. The synthetic population aggregated data was found to be well adjusted to the aggregated data from Census 2001, despite of slightly overestimating the number of inhabitants. A good adjustment was also verified for Census 2011 since, there isn't a significant difference between the two census survey data (see Table 9 and Table 10). This is confirmed when comparing some of the generated attributes with Census 2011 data (see Table 11).

Table 11: General attributes data, difference between model and Census 2011 [Eiró, 2015; INE website]

		Census 2011	Model	Absolute difference
Gender	male	47.82%	47.73%	0.08%
	female	52.18%	52.27%	-0.08%
Marital status	married	68.28%	68.77%	-0.49%
	divorced	6.26%	5.73%	0.53%
	separated	1.81%	1.85%	-0.05%
	single	11.91%	11.69%	0.22%
	widower	11.74%	11.96%	-0.22%
Education level	no education	19.09%	19.38%	-0.29%
	basic school	36.39%	37.11%	-0.72%
	middle school	10.55%	10.12%	0.43%
	high school	19.14%	18.82%	0.33%
	college	13.94%	14.56%	-0.62%
Employment status	active	52.17%	51.77%	0.39%
	student (≤15y.o.)	14.86%	15.06%	-0.20%
	student (>15y.o.)	6.61%	6.28%	0.33%
	retired	18.07%	18.64%	-0.57%
	other	8.29%	8.25%	0.04%

5.4.2 Individual activity logs

A synthetic activity based mobility generator was used to estimate stochastic activity agendas for the synthetic population with outputs adjusted to the aggregate statistical data available. The method used is described in Eiró (2015).

The generator distinguishes mandatory trips from non-mandatory trips. Mandatory trips are home-based trips related to work or study. Non-mandatory trips are trips taken for other purposes, such as personal duties, well-being (e.g.: sport, leisure), social (e.g.: visiting family or friends), and meal. These options were considered on the design of the SCUSSE survey revealed preferences.

The individuals of the generated synthetic population were classified into individuals with and without mandatory trips. Individuals with mandatory trips can have non-mandatory trips, although the constraining effect of the mandatory trips in the trip chain is taken into account when establishing other types of activities. These cannot overlap the existing ones.

To pre-determine the set of work related trips, it was used a synthetic travel simulation model calibrated for the LMA, developed by Viegas and Martínez (2010). The model resorts to a fuzzy theory methodology to extrapolate mobility survey sample data into a "virtual reality" where all trips of the population are represented. Based on trip generation rates for each type of land-use and transport network characteristics, it generates origin and destination points, transport mode used, and starting time of each performed trip. For individuals that were students at a school, a gravitational model was developed to select a school. The attraction of schools was determined based on the distance from the home or work of the head of the household. The criteria used for university students was different, being the selection considered to be related with the number of students of each institution. The higher the number, the most likely to be chosen. The start and ending time of university student activity was randomly generated considering the probabilities associated to it.

Using the generated volume of trips for the synthetic population categorized by trip purpose and time of day, the statistical distribution of activities by type and period of the day were generated. Aggregation of data was used to guarantee statistical significance. The fifteen different trip purposes considered by the survey were aggregated into five new categories: mandatory (work or study), personal, well-being, social and meal. The

24 hours period was also discretized in five time intervals: 7h to 10h, 10h to 16h30, 16h30 to 19h, 19h to 0h, and 0h to 7h. The number of non-mandatory trips, due also to statistical significance, varied from zero to more than five. The age strata was also considered in discretized intervals: 18-25, 25-35, 35-65, and more than 65 years of age. The Euclidean travel distance to work or study place was considered to categorize mandatory trips, which were subdivided in five intervals: 0 to 2 kilometers, 2 to 5 kilometers, 5 to 10 kilometers, 10 to 25 kilometers, and more than 25 kilometers. Using the SCUSSE survey data combined with data from other sources, probabilities were established associated with the generation of non-mandatory activities and mandatory activities for individuals with mandatory trips, and probabilities were also defined associated with the generation of non-mandatory activities for individuals without mandatory trips. The data was organized in tables [Eiró, 2015]:

- probability distribution of the number of activities for people with mandatory trips – it provides the probability of having a certain number of activities, having in account the age stratum and the Euclidean distance to work or study place, for people with mandatory trips;
- probability distribution of the number of activities for people without mandatory trips – it gives the probability of the number of activities per age stratum for people without mandatory trips;
- probability distribution of the type of activity (non-mandatory) and time of day for people with mandatory trips per age strata – for each age stratum of individuals with mandatory trips, it delivers the probability of an activity per type, time of day and Euclidean distance to work or study place;
- probability distribution of the type of activity and time of day for people without mandatory trips – it provides, for individuals without mandatory trips, the probability of an activity per type, time of day and age stratum;
- average and standard deviation of travel distance of each type of activity at a time of day – it provides the average and standard deviation of travel distance for trips associated to activities, considering type of activity and time of day;
- probability distribution of the start hour of the day of each activity – it gives the probability of the starting hour of an activity, considering type of activity (including university);

- probability distribution of the duration of the activity – it provides the probability of the duration of an activity, considering the activity type (including university)
- coefficients to define the equivalent area of each type of activity according to the area of different establishments – it gives the proportionally equivalent area by type of activity, considering different land uses (schools, office spaces, dwellings, hospitals, hotels, restaurants and bars, commercial);
- mean and standard deviation of maximum level travel time budgets according to the number of activities – it provides the mean and standard deviation of the maximum travel time budget of each person according to the number of extra activities (non-mandatory activities).

Having the synthetic population, the mandatory activities data and the probabilities related to activities, a two stage model was used to generate the non-mandatory activities.

The first stage defines the number of non-mandatory activities, the starting time, duration, the maximum travel distance, by fitting all activities into a possible agenda. It begins with the classification of individuals, according to mandatory trip travel distance and age stratum. The mandatory trips are added to the person agenda. Then the number of non-mandatory trips is generated randomly using the probabilities previously set (dependent on the person classification). Once the number of activities is defined, the type of activity and time of day is generated. The time of day is dependent on the class of person and constrained by the already generated activities. If no mandatory trips are generated, the existing activities are stored and the algorithm advances to the next person. The next step is to probabilistically select the duration and maximum travel distance of each activity on the individuals' log. Afterwards the exact starting time is defined. Compatibility conditions are able to reduce or re-initiate the process until the activities can fit into the person's agenda.

The second stage starts with the activity agenda defined on the first stage, generates the destinations of the non-mandatory activities, and validates the potential travel times based on the pre-established travel budget. The destinations are dependent on the land-use characteristics of a grid's spatial units. The model chooses one grid unit from all the units within the maximum acceptable distance plus a pre-defined tolerance. The location chosen guarantees that the potential travel time does not go above a threshold obtained by dividing the maximum travel time budget by the number of the person's activities plus a pre-set tolerance value. Algorithmic conditions guarantee that the total travel time is inside the budget range.

At the end, each person's agenda is defined with the trips originated by the activities interrelated in time and space. If home location was the reference point of a certain activity (besides the first in the day), then it was considered that two trips could be performed in the time window between the current and next activity, in order to simulate the possibility of returning home.

The activity based mobility generator was able to reproduce the real data available, as it can be seen on the extensive analysis made by Eiró (2015). Table 12 and Table 13 allows to understand the differences on the distribution of trips by purpose and time of day, between the SCUSSE survey and the developed activity generator.

Table 12: Distribution of trips by purpose and time of day - SCUSSE survey [Eiró, 2015]

Purpose	7h-10h	10h-16h30	16h30-19h	19h-24h	0h-7h
work/study	69.16%	17.88%	3.38%	1.53%	8.05%
personal	28.89%	56.78%	9.44%	1.96%	2.92%
well-being	9.41%	62.27%	14.77%	12.43%	1.13%
social	25.35%	57.47%	9.20%	7.98%	0.00%
meal	0.00%	80.46%	0.00%	19.54%	0.00%
return home	1.87%	31.18%	39.02%	27.06%	0.87%

Table 13: Distribution of trips by purpose and time of day – Activity generator [Eiró, 2015]

Purpose	7h-10h	10h-16h30	16h30-19h	19h-24h	0h-7h
work/study	53.33%	16.10%	2.01%	1.98%	26.58%
personal	24.86%	51.49%	15.64%	6.86%	1.15%
well-being	9.41%	40.95%	19.74%	26.96%	2.95%
social	32.92%	37.43%	25.35%	4.31%	0.00%
meal	0.13%	56.49%	4.73%	38.23%	0.42%
return home	2.29%	31.54%	42.14%	19.34%	4.70%

At the end of this process we have the synthetic population with socio-economic characteristics defined, the ordered activity agendas of each person, and the correspondent trip chain, namely specifying origin, destination, start time, and duration time of activity at the destination.

5.4.3 Discrete choice model

A discrete choice model was calibrated to determine the choice of the passenger. Eiró (2015) calibrated a model aimed at assessing the choice of new shared transport mode alternatives, such as carsharing (CS) and express minibus, while integrating the traditional transport options available.

Table 14: Alternative specific constants and coefficients of the calibrated discrete choice model, adapted from [Eiró, 2015]

Attributes	C	MT	TX	W	B	HV	C+HV	B+HV	CS
ASC	0.000	0.000	-3.650 ***	-1.940 ***	-0.232	0.000	-1.550 ***	-0.730 ***	-2.250 ***
Socio demographic attributes									
Age [25-35]	-	-	-	-	-	0.796 ***	0.796 ***	-	0.796 ***
Age [35-65]	-	-	-	-0.381 ***	-	-0.381 ***	-	-	-
Age [+65]	-	-	-	-	0.429 ***	-	-	-	-
Income (thousand €)	-	-	-	-	-0.010 ***	-	-0.010 ***	-	-
BSc, MSc or PhD degree	-	-	-	0.728 ***	-	-	-	-	0.728 ***
Land-use, car, and public transport pass									
No parking at home	-	-	0.238 *	-	-	-	-	-	0.238 *
No parking at destination	-	-	0.238 *	-	-	-	-	-	0.238 *
Own car	-	-	-	-	-	-	-	-	-0.457 ***
Public transport pass	-	-	-	-1.500 ***	0.930 ***	0.930 ***	0.930 ***	0.930 ***	-
Parking pressure [0-1]	-0.116 ***	-	-	-	-	-	-	-	-
Entropy	-	-	-5.270 **	-	-	-	-	-	-
Transport operation attributes									
Fuel cost (€)	-0.317 ***	-0.317 ***	-	-	-	-	-0.317 ***	-	-
Toll (€)	-0.317 ***	-0.317 ***	-	-	-	-	-	-	-
Parking cost (€)	-0.268 ***	-	-	-	-	-	-0.268 ***	-	-
Travel time private (min)	-0.031 ***	-0.031 ***	-0.031 ***	-	-	-	-0.031 ***	-	-0.031 ***
Travel time public (min)	-	-	-	-0.005 **	-0.029 ***	-0.015 **	-0.015 **	-0.015 **	-
Access time (min)	-	-	-	-	-0.084 ***	-0.084 ***	-0.084 ***	-0.084 ***	-0.129 ***
Tariff (€)	-	-	-0.153 ***	-	-0.523 ***	-0.523 ***	-0.523 ***	-0.523 ***	-0.283 ***
Transfers	-	-	-	-	-0.237 **	-0.197 ***	-0.197 ***	-0.197 ***	-
Waiting time (min)	-	-	-0.044 ***	-	-0.044 ***	-0.065 ***	-0.044 ***	-0.044 ***	-

***significant at the 99% level, ** significant at the 95% level, * significant at the 90% level.

The traditional transport modes considered were: private car (C), motorcycle (MT), taxi (TX), bus (B), walk (W), heavy public transport – subway and rail (HV), private transport + heavy public transport ($C + HV$), bus + heavy public transport ($B + HV$). The model was calibrated using the revealed and stated preferences data obtained from SCUSSE survey. A multinomial logit model represented the best adjustment with an adjusted-ρ^2 of 0.358 and a final log-likelihood of -2500.638 [Eiró, 2015].

In a multinomial logit model, the probability of an alternative i being chosen by individual q is equal to:

$$P_{i,q} = \frac{e^{V_{i,q}}}{\sum_{j=1}^{J} e^{V_{i,q}}}$$

where $V_{i,q}$ is the deterministic component of the utility of the alternative i for individual q, and J is the number of alternatives considered.

Since the utility of each mode is not influenced by the utility of the other modes, the discrete choice model can be applied to situations where carsharing is the only new alternative mode present in the set of available modes. The alternative specific constants (ASC) and the coefficients of the utility functions for each transport mode are presented in Table 14 (the ASC and coefficients obtained by the author for express minibus are not included, since they are not used in this work). From the attributes it is important to refer that the parking pressure is the ratio between estimated demand and supply of parking in a specific area and time period of the day, and entropy is an indicator of mixed land uses and was determined based on the work of Cervero and Kockelman (1997).

5.4.4 Carsharing demand

The data obtained previously (synthetic population, individual activity agendas with trip chain characteristics, and discrete choice mode) is used to define the carsharing demand for Lisbon municipality. The estimation of the carsharing demand resorts to an emulation of individuals' choice, using static parameters to calculate the probabilities of each mode. The parameters used were obtained from the databases which were the basis of the discrete choice model calibration, referred previously.

Eiró (2015) used an agent based approach to dynamically estimate parameters related to operation, and, using this information, proceeded to determine the choice of the individual for each trip associated to the activity log. Rules were added to the mode choice procedure, due to the fact that in some circumstances individuals may not fully perceive the utility of each available alternative. One example is that if a person drives a car from home to work in the morning, this person will have a higher probability of using this transport mode for the remaining trips until returning home, whilst if the car has not been used in the morning then private transport cannot be available throughout the day.

In this dissertation the modal choice process is simplified (see Figure 33). The approach is still simulating the transport mode option at the individual level, although it uses operation parameters obtained, a priori, for the existent transport modes from public transport data and from loading an LMA OD matrix in a calibrated macrosimulation model [Viegas and Martínez, 2010]. The tariff for carsharing was obtained from the citydrive website [Citydrive website, 2015], 0.29€ per minute. The travel time is the same as for the private vehicle and obtained from macrosimulation. For the access time it was used an optimistic value of 10 minutes.

The total number of trips that resulted from the activities generated for all individuals of the synthetic population was 5,976,378. The first task was to filter these trips in order to get the total carsharing potential market. Since the carsharing operating area will have as its maximum area the region encompassed by the municipality borders, the trips considered for the carsharing target market are the trips performed by individuals with a driver's license, with origin and destination inside the Lisbon municipality, excluding short distance trips. The reasons are simple: individuals without a driver's license cannot use the service, and short distance trips (less than 700 meters [6]) that can easily be done by walking are clearly not the target of the carsharing service. The application of this first filtering resulted in 628,443 trips (see Figure 32).

The trips filtered represent the total potential carsharing market for a hypothetic scenario, in which, every person with a driver's license that performs trips with more than 700 meters distance and with trip ends inside the Lisbon municipality, uses carsharing.

[6] Trips with origin and destination inside the same grid cell were excluded. These have distances below $500\sqrt{2}$ meters, once each grid cell is a square with 500 meters side.

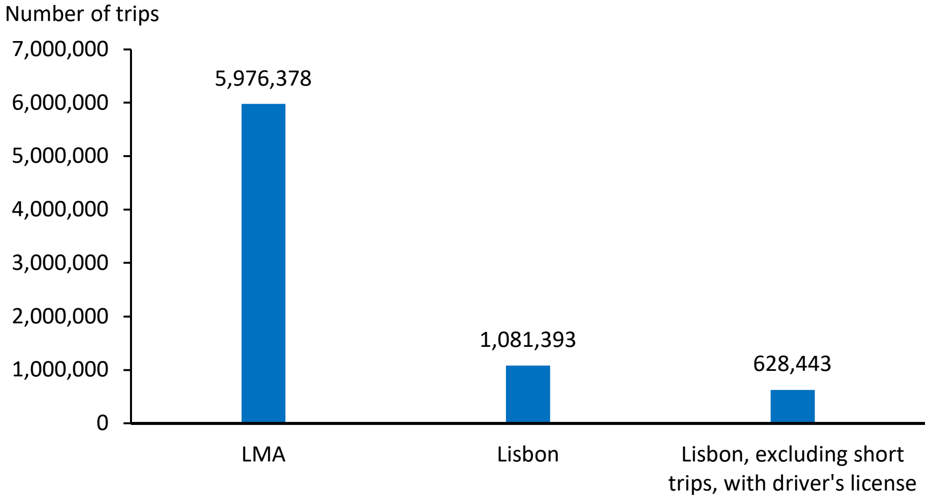


Figure 32: Number of trips that resulted from the filtering process

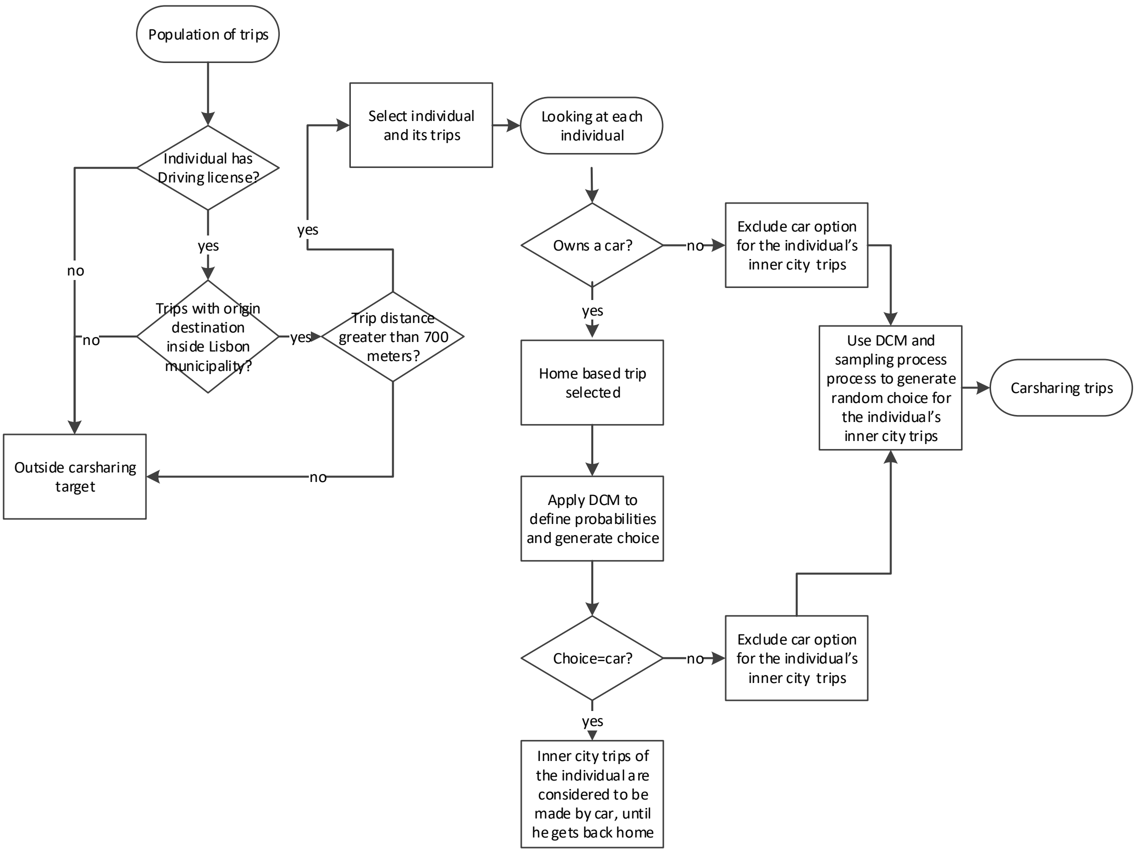


Figure 33: Overall procedure for obtaining carsharing demand

The discrete choice model presented previously is applied to determine the probabilities of each transport mode. Once the probabilities are determined, a random choice is generated by using a discrete distribution sampling process.

For each trip q of the 628,443 trips of the filtered sample, the probability for each transport alternative i of the total K alternatives available, $P_{i,q}$, is calculated using the expression in 5.4.3. Since we are not varying q and being X a discrete random variable

$$P(X = i) = P_{i,q} = p(i), \forall i \in K$$

And the cumulative distribution function F can be determined by,

$$F(j) = \sum_{i \leq j} p(i)\,, \forall i, j \in K$$

A sliced interval can be created between 0 and 1,

$$([0, F(1)], [F(1), F(2)], [F(2), F(3)], \dots, [F(K-1), 1])$$

Then we generate a random value, r, using a Uniform (0,1) distribution, and by seeing in which subinterval r it falls into, we get the chosen alternative for trip q, which is equal to a, being $r \in [F(a-1), F(a)]$.

For example, having three modes with the probabilities $p(1) = 0.2; p(2) = 0.7; p(3) = 0.1$ it generates the intervals $([0; 0.2], [0.2; 0.9], [0.9; 1])$. If the generated random value $r = 0.55$, then the choice is 2.

Some individuals can have a biased view of the utilities concerning to the available modes, namely if owing a car. For these individuals choosing a car for the first trip, when leaving home, affects the mode choice for the remaining trips of the individual's agenda. To emulate this behavior, the process evaluates the choice of the individual for the trip originated at home, and if the car is chosen, it will be considered the mode for the remaining trips until the individual gets home again. This is a simplified assumption that does not take into account the weight of the other trips of the individual's trip log and, moreover, it does not consider the possibility of transporting other people inside the vehicle. This simplification allowed to contain the complexity of the process. It is important to remember that the resulting carsharing demand data is simply used as an input to test the decision support tool.

The choice had into account the modes available in each zone. Walking was considered "not available" for Euclidean distances above three kilometers. The availability of modes and its parameters were assessed using previous studies data, namely CML (2005) and Eiró (2015). The application of the discrete choice model attributed 26,025 trips to carsharing, which represents 4.1% of the Lisbon inner trips from people with driver's license, excluding short trips. This is the potential demand considering that the choice for carsharing can be explained by the attributes considered in the DCM (age of individual, educational level, parking at home, parking at destination, car ownership, travel time, access time to a carsharing vehicle, tariff for using the carsharing system).

Geographic Information Systems (GIS) software was used to analyze the demand. This analysis uses a grid covering the Lisbon municipality area. Each cell is a square with 500 meters wide, wrapping an area of 250 000 square meters. The Airport runways and the middle of Monsanto forest park are the gaps on the grid, since these areas of the municipality are not urbanized. In Figure 34, we can see that the demand as origin and demand as destination are mainly concentrated in the business center, namely in the vicinities of the Liberdade, Fontes Pereira de Melo, and República avenues. The similar pattern between the two figures is an indicator that the resulting movements of vehicles tend to balance the geographic distribution of system vehicles. Figure 35 characterizes the most profitable areas (considering that the service is paid by the minute). On the left side it can be seen that the most profitable areas are centered on the axle composed by the three avenues referred previously. Though, the zones that give origin to longer trips are actually in the outskirts of the city, namely on the west, north and east side.

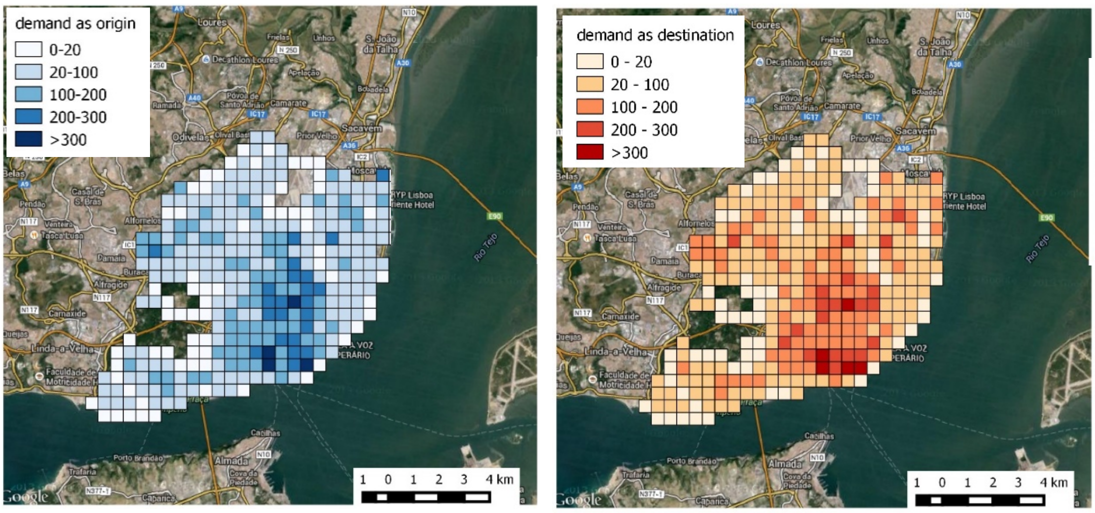


Figure 34: Geographical distribution of demand requests - demand as origin and destination for one day period

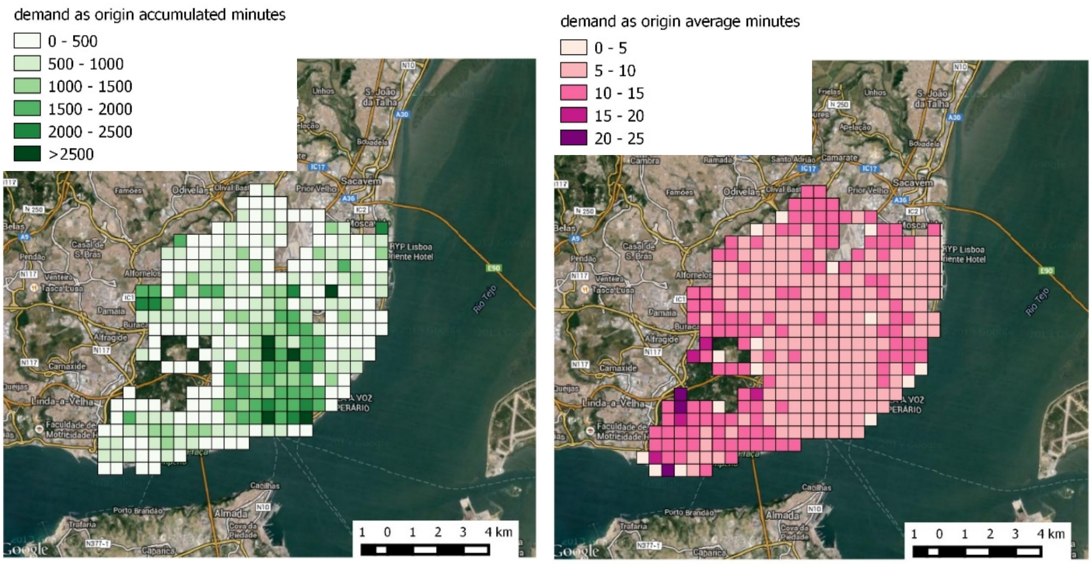


Figure 35: Geographical distribution of demand requests – demand as origin accumulated minutes and demand as origin average minutes for one day period

The difference between demand requests as destination and demand requests as origin, gives a preview of the zones that will be unbalanced if no relocations are performed, see Figure 36 . The zones where the demand as destination outdo the demand as origin will have an excess of vehicles, while the zones where the demand as origin exceeds the demand as destination will have a vehicles shortage, on average. These values allow to have a view of the imbalance that result from one day of operation, although the geographical distribution changes during the day due to the movements of individuals identified as potential carsharing users.

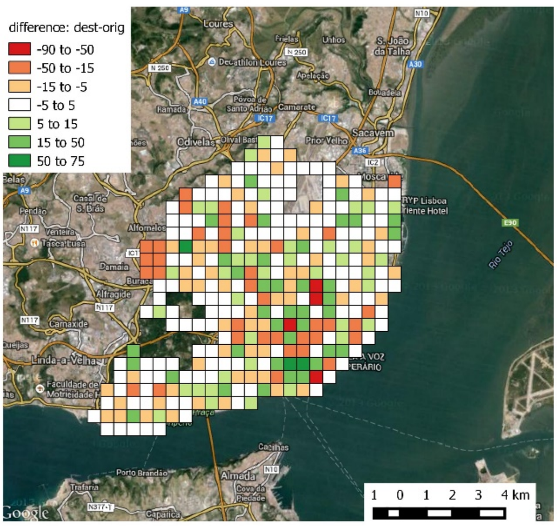


Figure 36: Geographical distribution of the difference between demand as destination and demand as origin requests for one day period

5.5 Simulations

5.5.1 Input data

Once the demand for the study area is determined we can define the data needed for the simulation, that is, the static input data described in 4.8.1. The static input data is the data that needs to be determined previous to the application of the simulator. It is subdivided in basic data, zones data, staff and vehicles initial positions, travel times, client trips and demand forecasts.

5.5.1.1 Basic data

The basic data refers to the parameters that need to be defined before applying the simulation with the real-time decision tool. It includes the start and end time of the simulation, the horizon (rolling-horizon) and planning period durations, the vehicle capacity, the duration of a maintenance activity, and the costs and revenues for the optimization model and performance indicators.

The start and end time of the simulation of staff movements matches the operation period of the staff. It is considered that the working period of staff starts at 8h00 and ends at 20h00. The lengths adopted for the horizon and planning period were 60 and 30 minutes, respectively (see Figure 10).

It is considered that every vehicle used is equal, therefore, the capacity (in number of seats) is also equal for every vehicle of the system. The maximum number of staff members that can share a vehicle was considered to be four.

The duration of a maintenance activity includes the time to perform the maintenance activity. In this case, of using the real-time decision tool in a simulation environment, 30 minutes is the value adopted as the prediction for both the maintenance activity duration for planning staff activities, and the maintenance time used in the simulation. In a real application, we can use 30 minutes for planning staff activities and wait until staff communicates the end of maintenance operation to the manager.

The costs and revenue values are used in the optimization model and to calculate some of the performance indicators. Starting with the profit, the price value for using the service is the same as the company Citydrive, which is 0.29 Euro per minute (see 5.2.3). The salary cost for the staff is 3.5 Euro per hour, which corresponds to a monthly wage of 560

Euro, 30 Euro higher than the minimum wage established by the Portuguese law for the year 2016 [DN, 2015] (the monthly wage was determined by considering a working period of 40 hours per week).

According to Carfax Website (2016), a new vehicle depreciates its price around 15 to 20% per year on the first four years. The AA Website (2016) states that the average new car has a residual value of around 40% of its price after 3 years, which means that the value depreciates on average 20% yearly on the first three years. For this study, it is considered that the cars costed 15,000 Euro each when new, and will be used in the system for an average of three years, having a depreciation of 20% per year. This leads to a depreciation rate of 8.22 Euro/day.

The fuel cost was considered to be 0.09 Euro per kilometer, for system car usage by staff and clients. This value considers that the car consumes 6.9 liters of petrol per 100 kilometers in an urban environment (e.g.: Opel Adam with 1400 cc engine), and a price of 1.31 Euro per liter of unleaded petrol 95 (average price in Portugal in January, 4th 2016 [DGEG website, 2016]).

Parking the vehicle inside the city of Lisbon has a cost. According to the parking regulation for the municipality, a carsharing vehicle using conventional fuel can have unlimited parking at any area by paying 50 Euro per month (the municipality includes a beneficiation of 20 Euro for the first year and 10 Euro for the second year, not considered in this study; electric vehicles don't pay any parking fee), which corresponds to 1.67 Euro per day [CML, 2014(b)].

It is considered that the carsharing company provides a monthly transit pass for every employee to be used in service. The monthly multimodal individual title covering the city of Lisbon, named “navegante”, costs 35.65 Euro [Transportes de Lisboa, 2015]. This value is subdivided by day. Considering a 30 days period, the resulting cost is 1.19 Euro per day and per staff.

The probability of an arrival leading to a maintenance procedure, and consequently leaving the vehicle unavailable is considered to be 0.5% (this is the probability used in the Bernoulli process referred previously).

5.5.1.2 Zones

As a base to define the zones we use a grid composed of 500 meter width square cells that covers the entire city of Lisbon. This grid was obtained from filtering the Lisbon Municipality from the grid used to define the individual activity logs. The resulting grid was already used in Figure 34, Figure 35 and Figure 36 to characterize the geographical distribution of requests). It excludes the Monsanto green area and the airport runways. The uncovered Monsanto area does not have population and the airport area is restricted to airport operations, therefore carsharing activities are not considered in these areas. The total number of cells (322) gives an over detailed space discretization for the operation control, and consequently leads to a high number of decision variables in the real-time decision support tool, namely for the MIP model. The zones defined are squares with a walkable distance size composed by the cells from the grid previously defined, resulting in 46 zones for the operating area (see Figure 37). Using the grid cells eases the data aggregation. Each zone aggregates 9 grid cells, having a 1500 meters side, which results in a walkable range between a client and a vehicle, if both are inside the same zone (in situations that a client is on a vertex and the vehicle on the opposite vertex the distance to travel is 2121 meters).

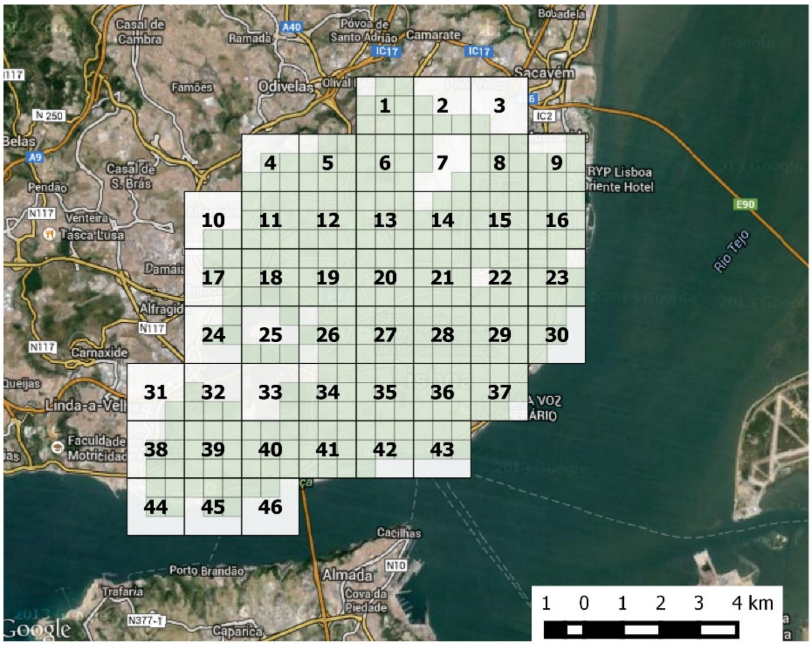


Figure 37: Defined Zones with the grid cells in the background

5.5.1.3 Staff and vehicles initial positions

It is considered that staff departs at the beginning of the operation period from the same zone, considered to be the staff headquarters. The chosen zone is zone 28, located at the area of Avenidas Novas. The choice is justified by the fact that this zone is: central to the operating area; well served by public transport including stations for all the subway lines and the major bus lines; close to the main central road arteries Avenida da República, Almirante Reis, Fontes Pereira de Melo, and João XXI; and, the zone with the highest demand according to the estimations (see Table 15).

The vehicles initial positions were determined using a process with two stages. First, vehicles were distributed by the zones according to the demand as origin for the entire operation period, which was considered the distribution for the beginning of the day (0 hours). Then, a warm up period followed. The movements of clients between 0h00 and 8h00 were simulated to get the positions of vehicles close to what most likely would be found by the staff when starting the working period (from 8h00 to 20h00).

Table 15: Proportion of the number of departure and arrivals per zone

Zone	departs	arrivals	Zone	departs	arrivals	Zone	departs	arrivals
1	1.04%	1.04%	**16**	2.28%	2.28%	**31**	0.05%	0.00%
2	0.28%	0.43%	**17**	2.28%	1.38%	**32**	0.24%	0.66%
3	0.00%	0.00%	**18**	1.94%	1.94%	**33**	0.00%	0.00%
4	1.00%	1.00%	**19**	2.18%	2.37%	**34**	3.51%	2.94%
5	2.09%	1.52%	**20**	3.61%	3.80%	**35**	6.88%	6.74%
6	1.71%	2.28%	**21**	5.17%	4.93%	**36**	6.36%	6.64%
7	0.38%	0.43%	**22**	2.09%	2.13%	**37**	2.09%	2.51%
8	1.80%	2.28%	**23**	1.04%	1.19%	**38**	0.81%	0.57%
9	2.28%	1.66%	**24**	0.62%	0.33%	**39**	2.09%	2.32%
10	1.19%	0.81%	**25**	0.00%	0.05%	**40**	2.42%	2.32%
11	2.47%	2.99%	**26**	1.33%	1.66%	**41**	1.80%	2.04%
12	3.46%	3.70%	**27**	5.60%	5.50%	**42**	3.56%	3.04%
13	1.76%	1.99%	**28**	8.02%	6.78%	**43**	3.89%	4.22%
14	2.32%	2.37%	**29**	3.23%	3.51%	**44**	0.19%	0.09%
15	2.89%	3.65%	**30**	0.90%	0.85%	**45**	0.62%	0.71%
						46	0.57%	0.33%

5.5.1.4 Travel times

The travel times for clients are associated with the trips characteristics obtained from the estimation of carsharing demand. For staff, the travel times are established for each pair of zones. It is considered that each zone is represented by one of the possible 9 grid cells that can be inside its limit. Note that the grid cells were established by Eiró (2015) to estimate the individual activity logs. The car travel times are obtained by applying a sinuosity index and the car average speed to the Euclidean distance of each pair of representative cells. The sinuosity index represents the proportion of the short path distance in the Euclidean distance between the pair of zones. Both car sinuosity and car speed were determined by the simulation of the traffic in the network. In this study, there is no distinction between peak and off-peak situations.

The travel times using public transport (alternative mode) are considered to be two times higher than the travel times by car, and they include moving to the station or stop and waiting time. The moving time in public transport depends on the mode chosen by the staff member, and this simplification allows the definition of a time window after which the staff member is supposed to be at the destination.

For the simulation the same estimated travel times are used to plan the activities (assignment mode) and to perform movements.

5.5.1.5 Client trips

The real demand, represented by the characteristics of the trips of the clients to be simulated, is directly retrieved from the data gathered as explained on section 5.4. The process of carsharing demand estimation leads, as referred, to 26,025 trips for carsharing which is a value too high for a carsharing system that is being implemented [Jorge et al., 2014]. The value results from the optimistic considerations made by Eiró (2015) when defining the discrete choice model, namely that every individual has perfect knowledge of the existence of a carsharing system. And is also a result from the consideration made for its application in this dissertation that there is always an available vehicle at a walking distance from the potential client (perfect level of service). This leads to the maximum potential demand.

The reality is not so optimistic. When a carsharing system is starting up there are factors that influence demand, such as the potential market not knowing of the existence of such a system or not understanding its benefits, and also the system not having enough supply affecting its reliability and visibility. The demand is highly dependent on the supply of vehicles.

Taking into consideration the difficulties of a new carsharing system entering the market (not having enough vehicles, not having enough visibility), conservative scenarios are analyzed, in which the simulated demand is only part of the potential demand previously obtained. Demand requests were randomly chosen from the potential demand by using Bernoulli trials with a probability of 8% of success, which returns a number of trips close to the demand considered by Jorge et al. (2014). The result was a daily number of 2108 trips, with 1648 trips starting in the period between 8h and 20h. Besides using 8% of the demand, 15% (about two times higher), and 25% (about three times higher) were used as well for sensitivity analysis purposes. The demand is obtained by using these percentages as probabilities in the Bernoulli process. Applying the 15% share resulted in a total of 3929 trips, from which 3034 start in the time interval between 8h and 20h. The 25% probability in the Bernoulli process, resulted in a total of 6414 trips, from which 4912 trips start in the period between 8h and 20h.

5.5.1.6 Demand forecasts

The demand forecasts are calculated using a homogeneous Poisson process. It is considered that the inter-arrival times of clients, X_i, are independent and identically distributed following an exponential distribution with parameter λ. The cumulative distribution function for the exponential distribution is

$$F(x) = 1 - e^{-\lambda x}$$

Considering a uniformly distributed random number U_i on $[0,1]$, it can be said that $U_i = F(x)$, resulting in:

$$X_i = \frac{-1}{\lambda} \ln(1 - U_i)$$

Once U_i and $1 - U_i$ are both uniformly distributed random numbers on [0,1], this expression can be simplified to:

$$X_i = \frac{-1}{\lambda} \ln(U_i)$$

Therefore the random variable T_j, the time for the j^{th} event, is equal to $T_j = \sum_{i=1}^{j} X_i$.

The generation of arrival events for a rate of λ arrivals per hour in an interval [0,T] is a simple algorithmic process, consisting in:

1) Initialization of first arrival event $t = -\ln(U_0)/\lambda$, for n=0 (the t initialized is the time of the first arrival S_1);
2) While $t < T$, do $n = n + 1$, $S_n = t$, and $t = t - \ln(U_n)/\lambda$.

To apply the Poisson generation process we used the estimated and reduced carsharing demand data retrieved from the processes described in 5.4. From these data, average hourly vehicle departure and arrival rates are defined for each zone, and for each of the twelve hours operation period. Based on this information we apply the described process separately for vehicle departures and arrivals, in order to generate the necessary forecasts.

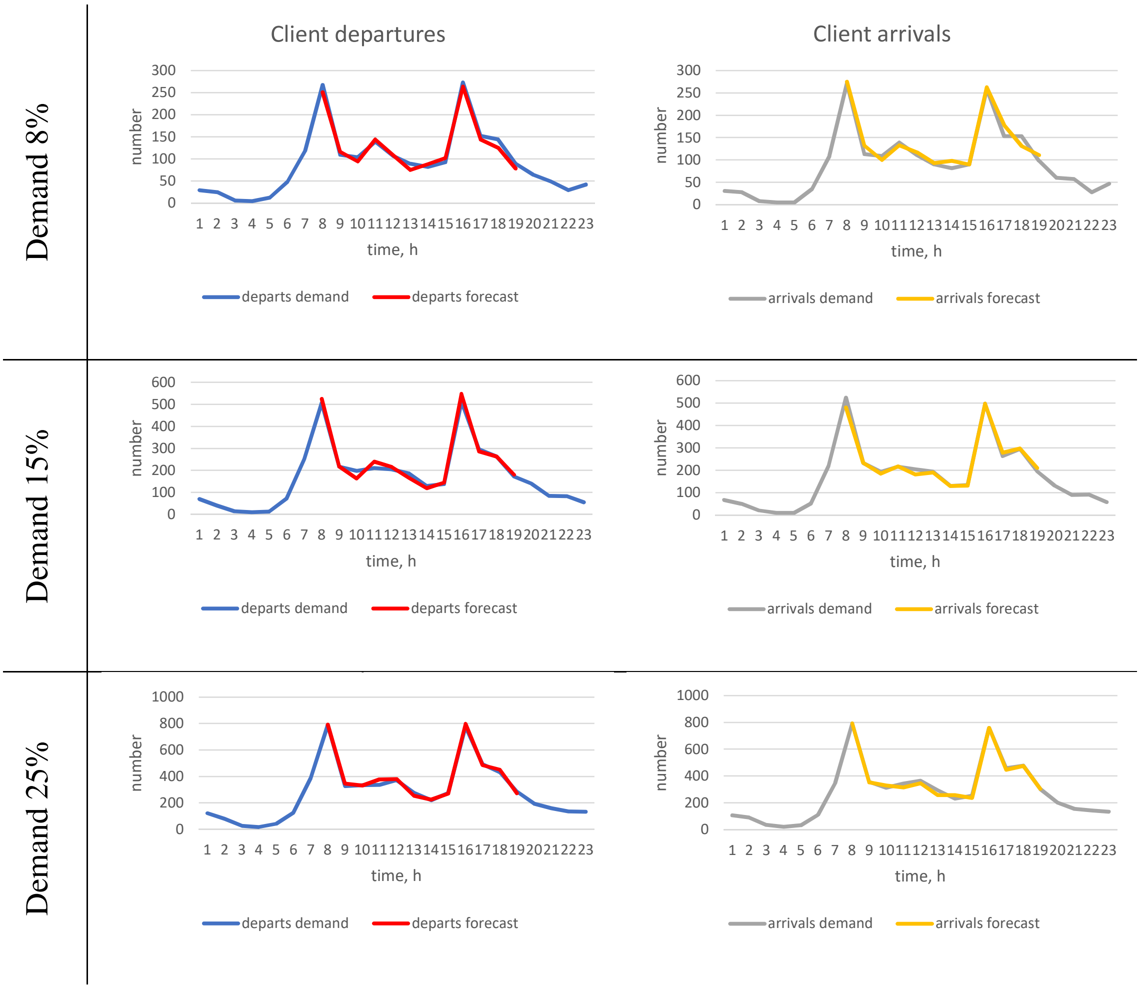


Figure 38: Client arrivals and departures – comparison between demand (number of client trips) and forecasts using the stochastic process for, 8, 15, and 25% of the demand along one day period

The forecasts were performed for the period of operation that is established to be between 8h and 20h. As it can be seen in Figure 38, the hourly forecast values are well adjusted to the hourly number of simulated trips (the “real” demand). Both arrivals and departure graphs are similar due to the fact that every considered trip starts and ends inside the operating area.

To consider the forecast uncertainty and avoid the generation of unnecessary relocation movements, we use 80% of the forecasted value of demand departures and arrivals as a reference for relocation needs. This reduction also accommodates the arrivals leading to unavailability of vehicles due to the need of maintenance (not all forecasted arrivals lead to available vehicles due to that process).

5.5.1.7 Minimum and maximum stock limits (rule-based model)

The rule-based model uses minimum and maximum stock thresholds for establishing zones that are in need of vehicles and zones which have a number of vehicles that are considered to be in excess. The determination of these limits uses the forecasted demand of arrivals and departures, and follows the process described in 4.3.1. The obtained values are presented in Table 16. The random element of Bernoulli trials (see 5.5.1.6) should be taking in account when comparing thresholds from different demand levels, namely for zones with low demand.

Table 16: Minimum and maximum thresholds of vehicle stocks per zone

Demand	**8%**		**15%**		**25%**	
zone	min	max	min	max	min	max
1	1	2	0	1	1	3
2	0	0	0	1	0	1
3	0	0	0	0	0	0
4	1	2	0	1	0	1
5	1	2	2	5	1	3
6	0	1	1	3	1	1
7	0	1	0	1	0	1
8	0	0	1	2	1	3
9	1	1	0	1	1	3
10	0	1	1	2	1	3
11	0	1	1	1	1	3
12	0	1	2	6	2	6
13	1	2	1	2	2	5
14	1	2	1	2	1	2
15	0	1	2	5	2	6
16	1	2	1	2	1	3
17	1	2	1	3	2	7
18	1	2	2	5	2	4
19	0	1	1	2	0	1
20	1	3	2	4	3	7
21	2	5	2	4	2	6
22	1	1	1	2	1	2
23	0	1	0	1	2	3

Demand	**8%**		**15%**		**25%**	
zone	min	max	min	max	min	max
24	0	0	0	1	0	1
25	0	0	0	0	0	0
26	0	0	1	3	1	3
27	1	2	2	5	2	5
28	2	4	3	6	4	9
29	1	2	1	2	2	4
30	1	2	1	3	1	5
31	0	0	0	0	0	0
32	0	0	0	0	0	1
33	0	0	0	0	0	1
34	1	3	1	2	1	2
35	1	2	2	5	3	8
36	1	2	2	4	2	4
37	1	2	1	2	1	3
38	0	1	0	1	1	2
39	0	1	1	3	1	3
40	1	2	2	6	1	3
41	0	1	1	2	1	3
42	1	3	2	3	1	3
43	1	3	1	3	2	6
44	0	1	0	1	0	0
45	0	1	0	1	0	1
46	0	1	0	1	1	1

5.5.2 Considered scenarios

A total of 272 scenarios were simulated in order to test the real-time decision support tool. Three levels of demand were used: starting by the 8% demand level (reduction obtained from demand determined in 5.4), that results in a similar value of trips to the one considered by Jorge et al. (2014), followed by a demand level two times higher, and a level three times higher. The number of cars considered in each scenario had a lower and an upper limit. The lower limit allows to have a fulfilled demand above 50%, and the upper limit is the subsequent increment of 100 cars that satisfies more than 95% of demand (previous simulation tests were performed to perceive the best scenarios to be analyzed). With this being said, the number of vehicles considered for the 8% demand level are 50, 100, 150, 200, 300 and 400; for the 15% demand level are 100, 150, 200, 300, 400 and 500; and for the 25% demand level are 150, 200, 300, 400, 500 and 600.

A base model was additionally developed to gather the system performance indicators if staff operations are not used in the system, that is, only the movements of clients are considered. And it uses the scenarios described before.

For the rule-based and the optimization models of the real-time decision support tool, staff members were added. The number of staff considered for the rule-based and optimization model are related to the number of vehicles, varying from 1 staff member per 10 vehicles to 1 member per 80 vehicles. For 50 vehicles, we tested only the case of having 5 staff members; for 100 vehicles, it was tested 5 and 10 staff members; for 150 and 200 vehicles, it was used 5, 10 and 15 staff members; for 300, 400, and 500 vehicles, it was adopted 5, 10, 15 and 20 staff members; and for 600 vehicles, the number of staff members tested were 5, 10, 15, 20 and 25. In all cases two scenarios were tested with maintenance calls, by using a maintenance generation factor of 0.5% (see 4.8.2.3) and without maintenance calls (maintenance generation factor equal to 0%). All scenarios are summarized in Table 17.

Table 17: Overview of simulated scenarios

Demand	Number of cars	Number of staff	Maintenance gen. factor	Models	Total Sims
8%	50	5	0 and 0.5	-Base	6×2
(reference)	100	5, 10		-Rule-	17×2
	150	5, 10, 15		based	17×2
	200	5, 10, 15		-Optimal	=
	300	5, 10, 15, 20			80
	400	5, 10, 15, 20			
15%	100	5, 10	0 and 0.5	-Base	6×2
(2×)	150	5, 10, 15		-Rule-	20×2
	200	5, 10, 15		based	20×2
	300	5, 10, 15, 20		-Optimal	=
	400	5, 10, 15, 20			92
	500	5, 10, 15, 20			
25%	150	5, 10, 15	0 and 0.5	-Base	6×2
(3×)	200	5, 10, 15		-Rule-	22×2
	300	5, 10, 15, 20		based	22×2
	400	5, 10, 15, 20		-Optimal	=
	500	5, 10, 15, 20			100
	600	5, 10, 15, 20, 25			

5.5.3 Results

After running the simulations for all scenarios described previously, we get the performance and comparative results for the real-time decision support tool. The introduction of a base scenario (whereby only client trips are simulated) allows to understand the difference between having a system running freely, that is, without any interference of staff, and a system with staff activity resulting from the use of the real-time decision support tool.

First we analyze the results obtained for the base model, in which there is no staff activity, hence, only movements of clients are considered. Then we analyze the results for the application of the real-time decision support tool, making a comparison between the rule-based and the optimal assignment models.

5.5.3.1 Base model

Through the analysis of the data related to revenues and costs, we can verify that the revenues increase with the increase of the number of vehicles. This increment is rapidly absorbed by vehicles' fixed costs, making the overall balance (difference between revenue and costs) decrease after an initial growth. This leads to optimum values for the number of vehicles on the fleet.

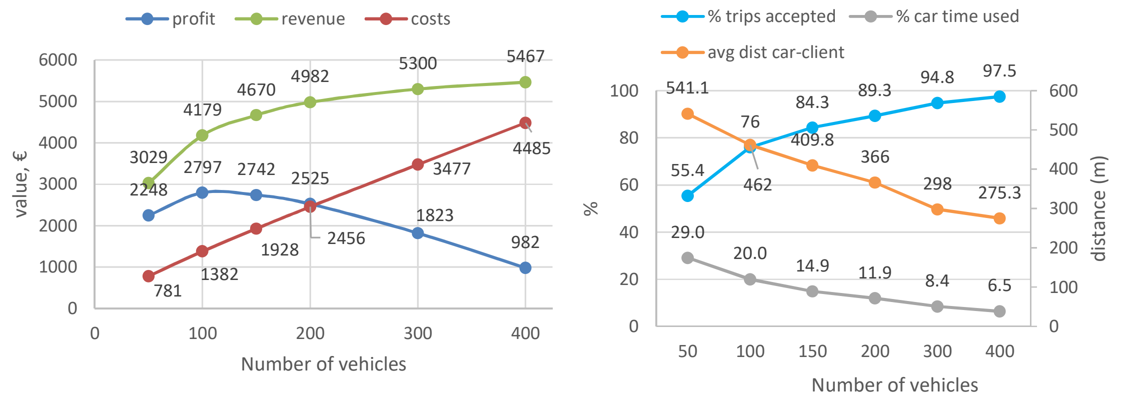
Base model without maintenance requests

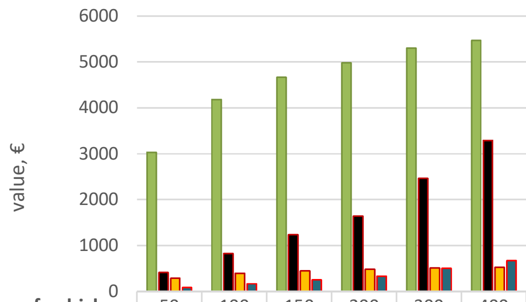
Analyzing the base model without maintenance requests, meaning considering an ideal operation day with clients delivering vehicles without flaws we got the following results.

For the case of 8% of the demand, the fleet that leads to higher profits is composed of 100 vehicles, leading to a profit of 2797 Euro (for the 12 hours of operation simulated). The vehicles' utilization time is 20%, the proportion of trips accepted is 76% of the total demand requests simulated, and the average distance between client and vehicle is 462 meters for the accepted trips (see Figure 39). Looking at the results for 15% of the demand and 100 vehicles, which is the same size of vehicle fleet, the profit value increases to 4940 Euro (see Figure 40), with the fulfilled demand reducing to 63.9% and the car usage increasing to 31.4%. Meaning that, if no staff is used and for the ideal situation of not having maintenance needs, the utilization of a fleet of 100 vehicles can produce a profit between 3000 and 5000 Euro, for demand levels ranging between 8 and 15% of the value deduced in 5.4.4., by increasing the usage of vehicles.

The maximum profit value obtained for the level of demand of 15% was 5626 Euro for a fleet composed by 200 vehicles. As it can be seen in Figure 40, this corresponds to a vehicle utilization rate of 20.1%, a proportion of trips accepted equal to 81.4%, and an average distance between car and client of 388.3 meters for the accepted trips.

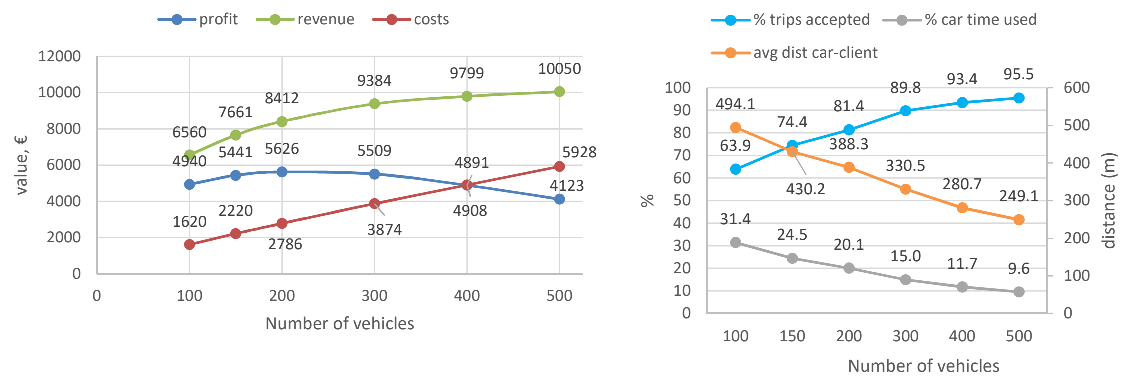
A fleet size of 300 vehicles leads to the maximum profit value for the 25% level of demand, which is equal to 9456 Euro. This fleet size results in a car time usage of 21.9%, 84.3 % of trips accepted, and an average distance between car and client of 338.7, for accepted trips (see Figure 41).

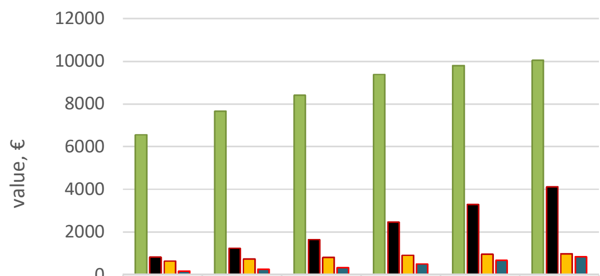




number of vehicles	50	100	150	200	300	400
revenue	3029	4179	4670	4982	5300	5467
car depreciation cost	411	822	1233	1644	2466	3288
client movement cost	287	393	444	478	510	529
parking cost	84	167	251	334	501	668

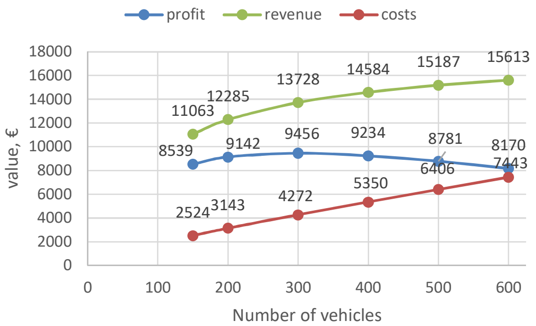
Figure 39: Main results from applying the base model to the 8% demand level scenario

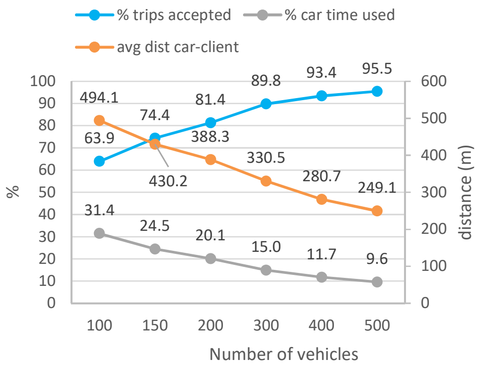


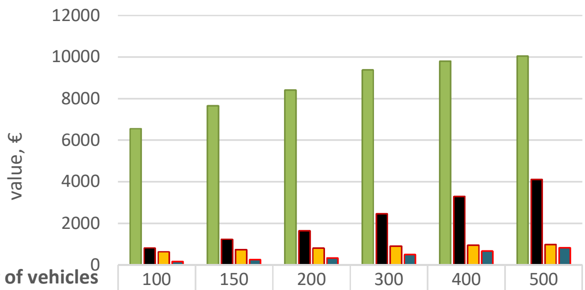


number of vehicles	100	150	200	300	400	500
revenue	6560	7661	8412	9384	9799	10050
car depreciation cost	822	1233	1644	2466	3288	4110
client movement cost	631	736	808	907	952	983
parking cost	167	251	334	501	668	835

Figure 40: Main results from applying the base model to the 15% demand level scenarios







number of vehicles	100	150	200	300	400	500
revenue	6560	7661	8412	9384	9799	10050
car depreciation cost	822	1233	1644	2466	3288	4110
client movement cost	631	736	808	907	952	983
parking cost	167	251	334	501	668	835

Figure 41: Main results from applying the base model to the 25% demand level scenarios

Base model with maintenance requests

In the scenarios of the base model no staff is available, therefore, when introducing maintenance requests, the vehicles needing maintenance become unavailable until the end of the simulation period. This could be normal if maintenance was performed during the night (low demand period), although if nothing is done to restore the availability of vehicles, the number of vehicles with problems transfers for the next day, lessening the quality of service.

The number of maintenance requests are dependent on the number of served trips, since the simulator applies a 0.5% chance of a vehicle delivered by a client having a need of maintenance by the staff. The main results are summarized in Table 18, Table 19, Table 20, Figure 42, Figure 43, and Figure 44.

Comparing the results of the base scenario with and without maintenance requests we can say that there is a difference in the financial balance resulting on the impact of having unavailable vehicles. The profit decreases with having unavailable vehicles. Although the impact of the unavailability decreases with the increase of the number of vehicles in the fleet, which dilutes the weight of unavailability time in vehicle total time. In Figure 43, it can be seen that the impact of the unavailability for a fleet of 200 vehicles is an exception to what was said before. This is due to the fact that 6 of the 9 unavailable vehicles are located in the top three demanding zones, and the unavailable time is higher than in other situations. This is due to the random generation of maintenance requests. In this case the number of broken trip chains are higher than average, leading to more unserved trips.

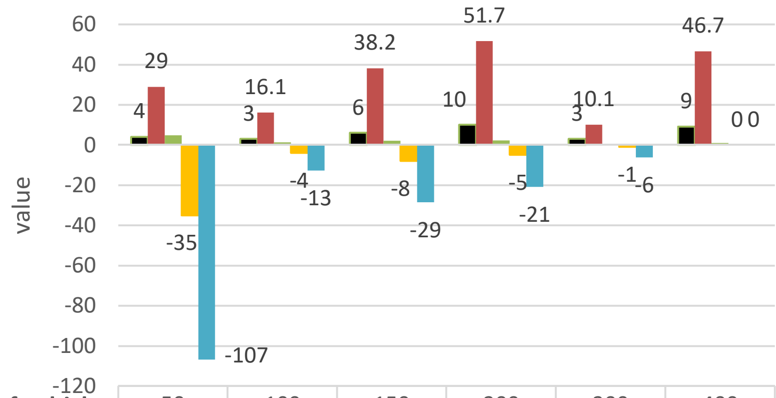
It needs to be reminded that the increase on demand generally leads to an increase on the number of maintenance requests, due to the augment of the number of client trips. This is a consequence of randomly generating maintenance requests by using a generation factor.

The profit losses here presented increase for the next days if nothing is done, so it is highly advisable to have staff to solve the vehicle issue that is inhibiting its availability.

The use of the real-time decision support tool allows adding staff activity to improve the system in two possible ways: by allowing relocation movements of vehicles, and by solving maintenance problems which cause the unavailability of vehicles. In the following we present an analysis of the main results from using the real-time decision support tool, subdivided according to the assignment model used: rule-based model and optimization model (as explained in section 4.3). This analysis uses the scenarios with maintenance requests, which are more realistic.

Table 18: Results of base scenario with and without maintenance requests for 8% demand

# vehicles	Request generator	# maint. requests	Profit (€)	Revenues (€)	Costs (€)	Car depreciation cost	Client mov. cost (€)	Parking cost (€)	% trips accepted	% car time used	Avg dist. car-client (m)
50	0	0	2247.99	3029.34	781.35	411	286.85	83.5	55.4	29.0	541.1
50	0.5	4	2141.16	2911.02	769.86	411	275.36	83.5	53.3	27.9	544.2
100	0	0	2797.09	4179.48	1382.39	822	393.39	167	76	20.0	462
100	0.5	3	2784.39	4165.56	1381.17	822	392.17	167	75.7	20.0	461.9
150	0	0	2742.44	4670.16	1927.72	1233	444.22	250.5	84.3	14.9	409.8
150	0.5	6	2713.84	4638.84	1925.00	1233	441.50	250.5	83.8	14.8	416.9
200	0	0	2525.33	4981.62	2456.29	1644	478.29	334	89.3	11.9	366
200	0.5	10	2504.40	4957.26	2452.86	1644	474.86	334	89	11.9	368.4
300	0	0	1822.61	5300.04	3477.43	2466	510.43	501	94.8	8.4	298
300	0.5	3	1816.36	5293.08	3476.72	2466	509.72	501	94.8	8.4	298.6
400	0	0	982.46	5467.08	4484.62	3288	528.62	668	97.5	6.5	275.3
400	0.5	9	982.46	5467.08	4484.62	3288	528.62	668	97.5	6.5	277.2



number of vehicles	50	100	150	200	300	400
# maint. requests	4	3	6	10	3	9
unavailable time, h	29	16.1	38.2	51.7	10.1	46.7
unavailable time, %	4.83	1.34	2.12	2.15	0.28	0.97
trips accepted diff.	-35	-4	-8	-5	-1	0
profit difference, €	-107	-13	-29	-21	-6	0

Figure 42: Effects of vehicle unavailability on profit – 8% demand

Table 19: Results of base scenario with and without maintenance requests for 15% demand

# vehicles	Request generator	# maint. requests	Profit (€)	Revenues (€)	Costs (€)	Car depreciation cost	Client mov. cost (€)	Parking cost (€)	% trips accepted	% car time used	Avg dist. car-client (m)
100	0	0	4940.03	6559.99	1619.96	822	630.96	167	63.9	31.4	494.1
100	0.5	8	4857.14	6465.87	1608.73	822	619.73	167	63.1	31.0	501.2
150	0	0	5441.32	7661.19	2219.87	1233	736.37	250.5	74.4	24.5	430.2
150	0.5	14	5391.30	7606.79	2215.49	1233	731.99	250.5	73.8	24.3	435.1
200	0	0	5625.81	8411.54	2785.73	1644	807.73	334	81.4	20.1	388.3
200	0.5	14	5489.25	8260.99	2771.74	1644	793.74	334	79.9	19.8	389.2
300	0	0	5509.49	9383.67	3874.18	2466	907.18	501	89.8	15.0	330.5
300	0.5	12	5457.08	9326.12	3869.04	2466	902.04	501	89.3	14.9	337.2
400	0	0	4890.83	9799.09	4908.26	3288	952.26	668	93.4	11.7	280.7
400	0.5	14	4868.76	9774.94	4906.18	3288	950.18	668	93.1	11.7	286.8
500	0	0	4122.70	10050.47	5927.77	4110	982.77	835	95.5	9.6	249.1
500	0.5	12	4113.81	10040.61	5926.80	4110	981.80	835	95.4	9.5	251.4

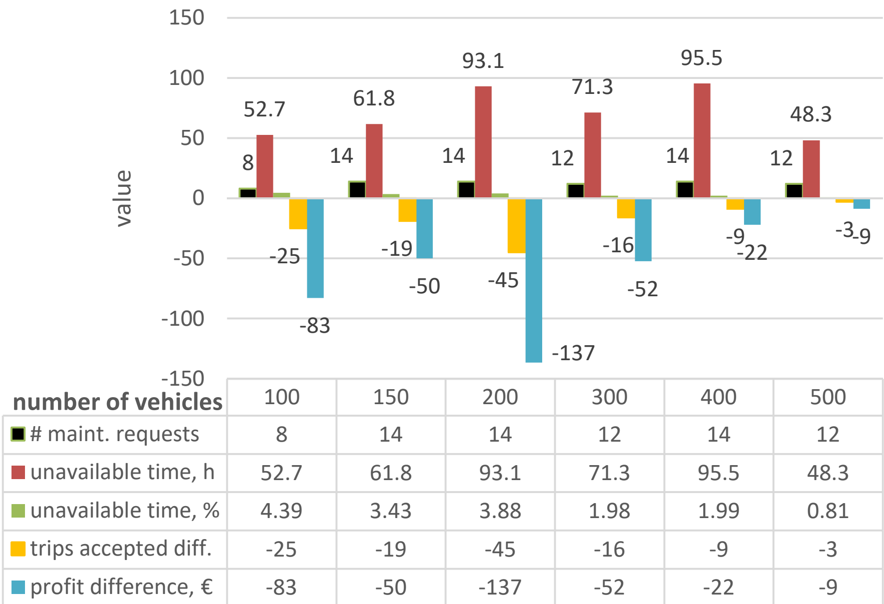
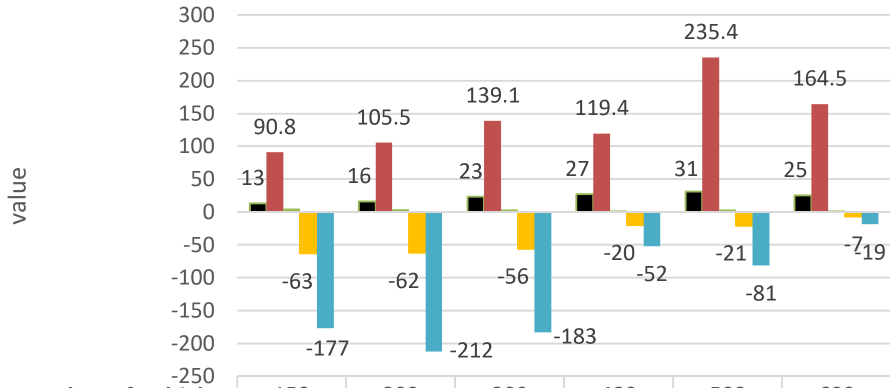


Figure 43: Effects of vehicle unavailability on profit – 15% demand

Table 20: Results of base scenario with and without maintenance requests for 25% demand

# vehicles	Request generator	# maint. requests	Profit (€)	Revenues (€)	Costs (€)	Car depreciation cost	Client mov. cost (€)	Parking cost (€)	% trips accepted	% car time used	Avg dist. car-client (m)
150	0	0	8539.33	11063.4	2524.05	1233	1040.55	250.5	69.6	35.3	444.6
150	0.5	13	8362.47	10868.6	2506.11	1233	1022.61	250.5	68.3	34.7	455.7
200	0	0	9142.01	12285.3	3143.27	1644	1165.27	334	76.2	29.4	396.9
200	0.5	16	8929.62	12047.2	3117.59	1644	1139.59	334	74.9	28.8	401.2
300	0	0	9455.79	13728.1	4272.30	2466	1305.30	501	84.3	21.9	338.7
300	0.5	23	9272.52	13526.8	4254.25	2466	1287.25	501	83.2	21.6	343.8
400	0	0	9234.46	14584.0	5349.50	3288	1393.50	668	89	17.5	300.3
400	0.5	27	9182.33	14527.3	5344.93	3288	1388.93	668	88.6	17.4	303.5
500	0	0	8780.71	15186.8	6406.09	4110	1461.09	835	92	14.5	269.9
500	0.5	31	8699.49	15093.4	6393.88	4110	1448.88	835	91.6	14.4	275.7
600	0	0	8170.37	15613.5	7443.11	4932	1509.11	1002	94.3	12.5	248.3
600	0.5	25	8151.54	15592.2	7440.66	4932	1506.66	1002	94.1	12.4	252.4



number of vehicles	150	200	300	400	500	600
# maint. requests	13	16	23	27	31	25
unavailable time, h	90.8	105.5	139.1	119.4	235.4	164.5
unavailable time, %	5.04	4.40	3.86	2.49	3.92	2.28
trips accepted diff.	-63	-62	-56	-20	-21	-7
profit difference, €	-177	-212	-183	-52	-81	-19

Figure 44: Effects of vehicle unavailability on profit – 25% demand

5.5.3.2 Rule-based model

The rule-based assignment model allows a simple and fast plan of the staff activities as it was explained in section 4.3.1. Analyzing the balance between revenues and costs, it can be seen that, for the demand levels of 8% and 15%, the profits are lower for scenarios with staff members than the base scenarios with zero staff members. The revenues increase due to the efficiency of relocation movements and also due to the rapid fixing of vehicle unavailability, however this is not sufficient to overtake the costs, namely due to the salaries of the staff members and to the costs of relocating the vehicles (see Figure 45 and Figure 46).

With the increase of the demand level to three times higher (25%), the increase of demand due to relocations, and the reduction of vehicle downtime promoted by maintenance activities, there is a positive profit variation for the scenarios with 5 elements of staff and a fleet of 200 and 300 vehicles (see Table 23 and Figure 47). For a fleet of 200 vehicles, the increase in profit is 5 Euro and for a fleet of 300 vehicles, the increase is 21 Euro. The increase in profit is not higher than 0.2%.

Since staff is needed to perform maintenance requests and consequently to reduce the unavailability time of vehicles, the best option is to have between 1 and 5 elements of staff, even if this leads to a lower profit. It is important that these staff members give priority to solving maintenance requests, as it was defined for the rule-based model. Considering the scenarios with 5 elements of staff, the number of vehicles that lead to the maximum profit are 100 for the 8% demand level, 200 vehicles for the 15% demand level, and 300 vehicles for the 25% demand level. It is relevant to note that for the 25% demand level, having 300 vehicles and 5 elements of staff actually leads to better results than having no staff at all (see Table 21, Table 22, and Table 23).

Table 21: Profit values, revenues and costs for the scenarios with maintenance requests - rule-based model and 8% demand level

	8% demand level						
	Staff\Cars	**50**	**100**	**150**	**200**	**300**	**400**
Profit	0	2141.16	2784.39	2713.84	2504.40	1816.36	982.46
	5	2071.41	2584.03	2541.60	2328.04	1663.38	781.99
	10	--	2410.30	2370.90	2161.57	1434.70	567.48
	15	--	--	2152.43	1918.03	1204.55	345.88
	20	--	--	--	--	999.82	138.26
Revenues	0	2911.02	4165.56	4638.84	4957.26	5293.08	5467.08
	5	+176.12	+38.56	+77.16	+73.05	+88.93	+33.26
	10	--	+116.52	+144.23	+140.35	+80.24	+37.88
	15	--	--	+145.7	+112.52	+68.51	+32.62
	20	--	--	--	--	+74.92	+39.77
Costs	0	769.86	1381.17	1925	2452.86	3476.72	4484.62
	5	+245.87	+238.92	+249.4	+249.41	+241.91	+233.73
	10	--	+490.61	+487.17	+483.18	+461.9	+452.86
	15	--	--	+707.11	+698.89	+680.32	+669.2
	20	--	--	--	--	+891.46	+883.97

Figure 45: Rule-based model - profit, revenues and costs for the scenarios with maintenance requests, and 8% of demand level, considering 0, 5, 10, 15 and 20 staff members

Table 22: Profit values, revenues and costs for the scenarios with maintenance requests - rule-based model and 15% demand level

		15% demand level					
	Staff\Cars	**100**	**150**	**200**	**300**	**400**	**500**
Profit	0	4857.14	5391.3	5489.25	5457.08	4868.76	4113.81
	5	4718.42	5241.42	5402.24	5261.34	4739.08	3937.03
	10	4719.06	5072.08	5249.99	5066.23	4528.57	3709.73
	15	--	4920.21	5011.99	4821.57	4296.56	3496.88
	20	--	--	--	4638.19	4067.12	3287.2
Revenues	0	6465.87	7606.79	8260.99	9326.12	9774.94	10040.61
	5	+103.75	+93.3	+168.94	+50.11	+124.53	+58.16
	10	+364.98	+176.98	+265.27	+92.06	+133.23	+48.15
	15	--	+267.74	+262.63	+68.32	+116.11	+50.8
	20	--	--	--	+105.2	+100.49	+58.59
Costs	0	1608.73	2215.49	2771.74	3869.04	4906.18	5926.8
	5	+242.47	+243.18	+255.95	+245.85	+254.21	+234.94
	10	+503.06	+496.2	+504.53	+482.91	+473.42	+452.23
	15	--	+738.83	+739.89	+703.83	+688.31	+667.73
	20	--	--	--	+924.09	+902.13	+885.2

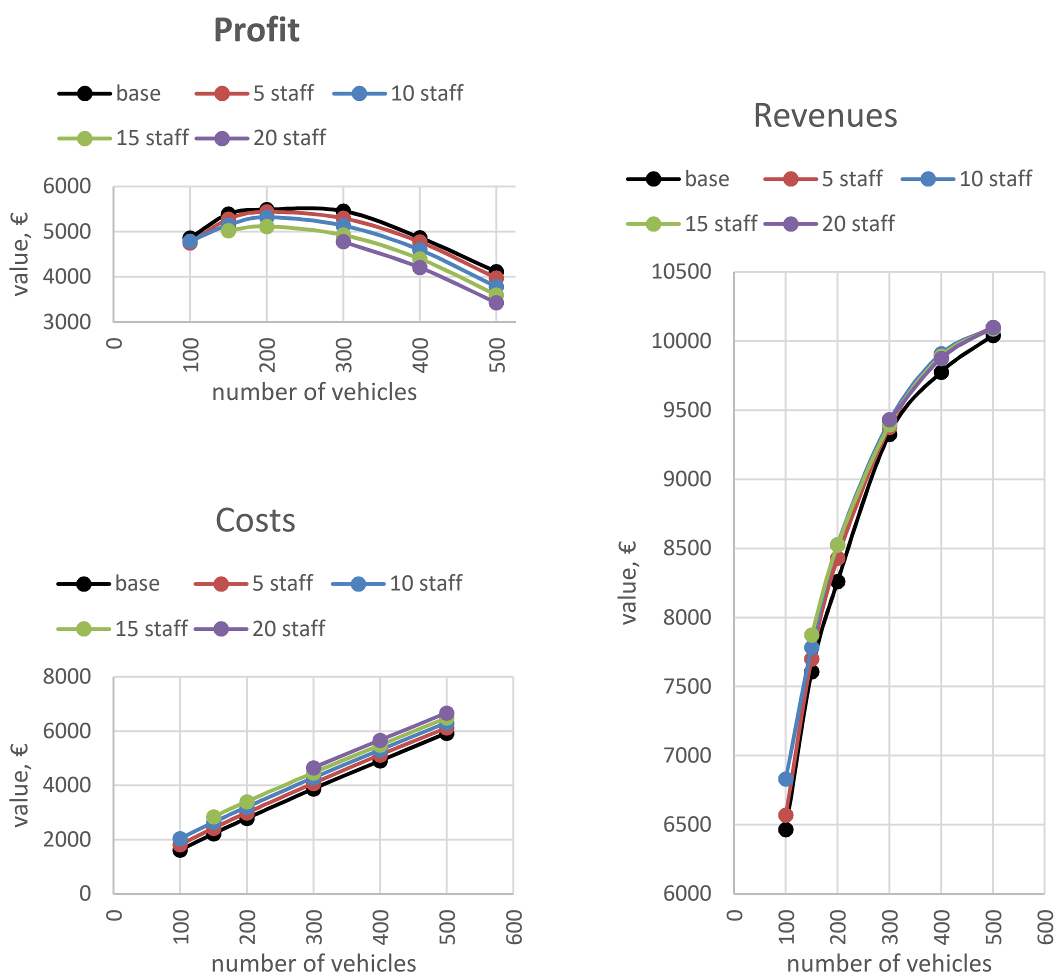


Figure 46: Rule-based model - profit, revenues and costs for the scenarios with maintenance requests, and 15% of demand level, considering 0, 5, 10, 15 and 20 staff members

Table 23: Profit values, revenues and costs for the scenarios with maintenance requests - rule-based model and 25% demand level

		25% demand level					
	Staff\Cars	**150**	**200**	**300**	**400**	**500**	**600**
Profit	0	8362.47	8929.62	9272.52	9182.33	8699.49	8151.54
	5	8262.95	8934.39	9293.51	9037.08	8596.24	7995.69
	10	8094.68	8821.87	9103.44	8905.04	8421.94	7826
	15	8055.5	8592.05	9011.75	8674.38	8230.11	7611.76
	20	--	--	8755.59	8460.04	8011.12	7396.55
Revenues	0	10868.58	12047.21	13526.77	14527.26	15093.37	15592.2
	5	+143.6	+267.67	+286.1	+96.35	+147.09	+87.97
	10	+227.17	+411.37	+343.21	+221.6	+222.26	+160.45
	15	+450.7	+420.17	+507.12	+226.96	+253.85	+163.48
	20	--	--	+478.06	+230.25	+247.51	+163.22
Costs	0	2506.11	3117.59	4254.25	5344.93	6393.88	7440.66
	5	+243.12	+262.91	+265.12	+241.61	+250.34	+243.81
	10	+494.96	+519.12	+512.29	+498.89	+499.82	+485.99
	15	+757.67	+757.74	+767.89	+734.91	+723.23	+703.26
	20	--	--	+994.99	+952.54	+935.88	+918.21

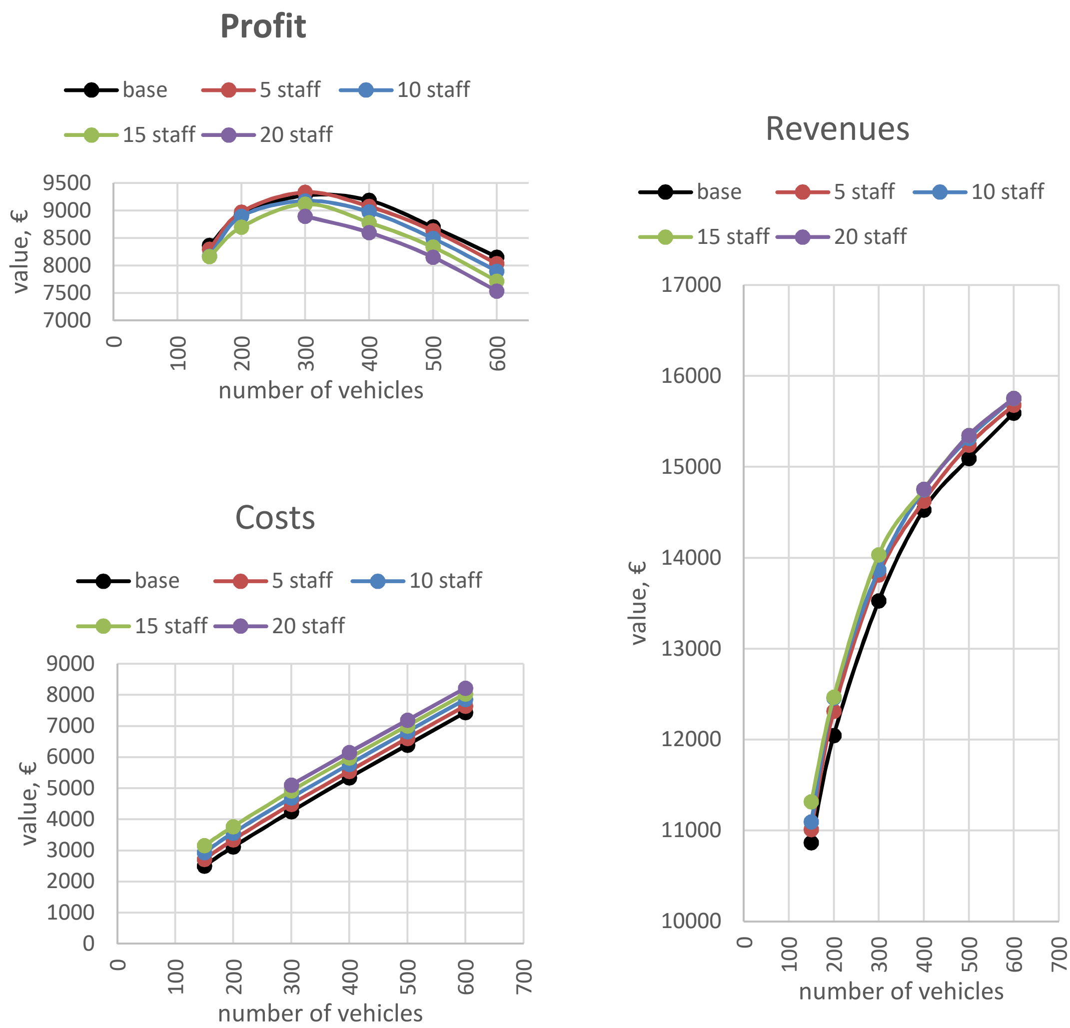


Figure 47: Rule-based model - profit, revenues and costs for the scenarios with maintenance requests, and 25% of demand level, considering 0, 5, 10, 15 and 20 staff members

5.5.3.1 Optimization model

The optimization model was formulated with the purpose that the use of optimal staff activity plans would benefit the profit return, since optimization is not available for the rule-based model. Similarly to what was verified for the utilization of the rule-based model, the profit results of using staff elements moving according to a plan coming from the optimization model in a scenario where the level of demand is 8% or 15% are lower than the profit obtained for the situation of having no staff, for all scenarios considered (any number of vehicles and any number of staff - see Figure 48). On the other hand, the profit is higher than the base model for the scenarios of 200 vehicles with 5 and 10 elements of staff, and 300 vehicles with 5 members of staff, for a 25% demand level (see Figure 50).

The more profitable configurations that include staff members (staff is important to maintain vehicle availability, as stated before) are: 100 vehicles with 5 elements of staff for the 8% demand level; 200 vehicles with 5 elements of staff for 15% demand level; and 300 vehicles with 5 elements of staff for the 25% demand level (see Table 24, Table 25, and Table 26).

Table 24: Profit values, revenues and costs for the scenarios with maintenance requests - optimization model and 8% demand level

		8% demand level					
	Staff\Cars	**50**	**100**	**150**	**200**	**300**	**400**
Profit	0	2141.16	2784.39	2713.84	2504.40	1816.36	982.46
	5	2036.36	2610.59	2567.36	2354.59	1648.16	760.28
	10	--	2409.89	2382.96	2139.67	1454.17	567.81
	15	--	--	2201.90	1954.41	1214.12	357.26
	20	--	--	--	--	1016.53	129.78
Revenues	0	2911.02	4165.56	4638.84	4957.26	5293.08	5467.08
	5	+149.64	+72.89	+127.02	+111.36	+88.74	+19.14
	10	--	+139.2	+189.66	+144.42	+130.5	+59.16
	15	--	--	+236.64	+191.4	+104.4	+71.34
	20	--	--	--	--	+135.72	+59.16
Costs	0	769.86	1381.17	1925	2452.86	3476.72	4484.62
	5	+254.44	+246.69	+273.5	+261.17	+256.94	+241.32
	10	--	+513.7	+520.54	+509.15	+492.69	+473.81
	15	--	--	+748.58	+741.39	+706.64	+696.54
	20	--	--	--	--	+935.55	+911.84

Figure 48: Optimization model - profit, revenues and costs for the scenarios with maintenance requests, and 8% of demand level, considering 0, 5, 10, 15 and 20 staff members

Table 25: Profit values, revenues and costs for the scenarios with maintenance requests - optimization model and 15% demand level

		15% demand level					
	Staff\Cars	**100**	**150**	**200**	**300**	**400**	**500**
Profit	0	4857.14	5391.3	5489.25	5457.08	4868.76	4113.81
	5	4830.73	5290.79	5412.58	5269	4706.77	3924.06
	10	4678.88	5147.75	5258	5035.98	4480.66	3710.7
	15	--	4915.19	5057.53	4830.45	4274.59	3465.08
	20	--	--	--	4617.44	4081.02	3285.67
Revenues	0	6465.87	7606.79	8260.99	9326.12	9774.94	10040.61
	5	+246.54	+168.7	+200.33	+82.48	+98.77	+65.72
	10	+342.69	+280.04	+292.57	+77.7	+104.44	+78.33
	15	--	+265.09	+325.55	+107.6	+126.69	+46.7
	20	--	--	--	+122.77	+165.75	+101.45
Costs	0	1608.73	2215.49	2771.74	3869.04	4906.18	5926.8
	5	+272.95	+269.21	+277.	+270.56	+260.76	+255.47
	10	+520.94	+523.59	+523.82	+498.8	+492.54	+481.43
	15	--	+741.21	+757.27	+734.23	+720.86	+695.43
	20	--	--	--	+962.41	+953.49	+929.59

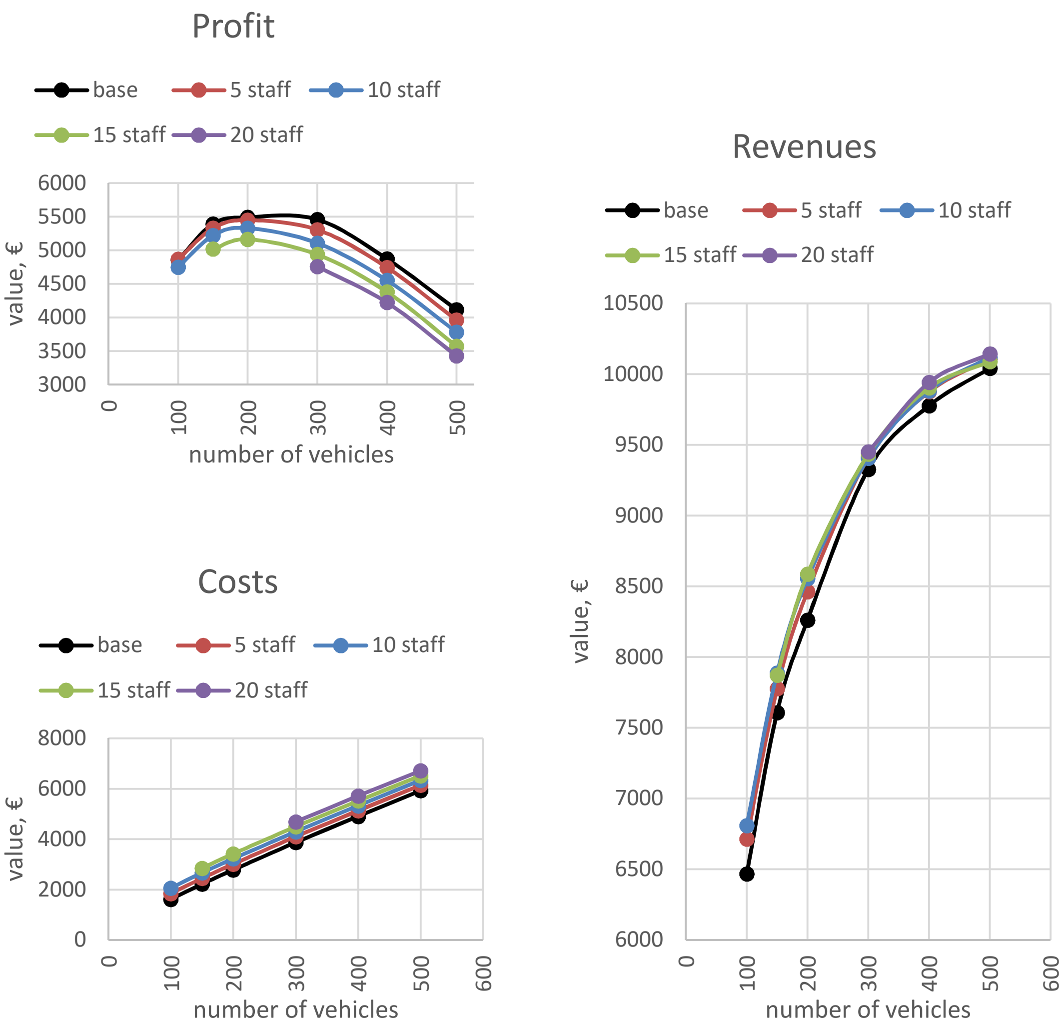


Figure 49: Optimization model - profit, revenues and costs for the scenarios with maintenance requests, and 15% of demand level, considering 0, 5, 10, 15 and 20 staff members

Table 26: Profit values, revenues and costs for the scenarios with maintenance requests - optimization model and 25% demand level

	25% demand level						
	Staff\Cars	**150**	**200**	**300**	**400**	**500**	**600**
Profit	0	8362.47	8929.62	9272.52	9182.33	8699.49	8151.54
	5	8293.85	8948.52	9304.14	9104.42	8643.47	7990.29
	10	8163.92	8864.66	9136.8	8932.62	8453.33	7806.25
	15	8067.99	8541.72	8950.63	8715.67	8202.83	7596.36
	20	--	--	8641.2	8513.06	7991.33	7374.19
Revenues	0	10868.58	12047.21	13526.77	14527.26	15093.37	15592.2
	5	+197.69	+295.23	+309.45	+195.09	+225.14	+111.08
	10	+324.2	+485.08	+407.09	+296.28	+287.2	+169.01
	15	+463.08	+365.04	+460.07	+317.86	+258.73	+176.86
	20	--	--	+355.84	+314.19	+287.17	+208.42
Costs	0	2506.11	3117.59	4254.25	5344.93	6393.88	7440.66
	5	+266.31	+276.33	+243.48	+273.01	+281.16	+272.33
	10	+522.75	+550.03	+542.81	+545.98	+533.36	+514.3
	15	+757.56	+752.93	+781.96	+784.52	+755.39	+732.04
	20	--	--	+987.16	+983.46	+995.33	+985.77

Figure 50: Optimization model - profit, revenues and costs for the scenarios with maintenance requests, and 25% of demand level, considering 0, 5, 10, 15 and 20 staff members

5.5.3.2 Comparison between the rule-based and the optimization model

The first aspect to acknowledge during the simulation running was that the rule-based model retrieved the staff activity plan almost instantaneously, while the optimization model took more time. The duration of the optimization model is dependent on the number of decision variables, as explained in 4.3.2.

As it was seen, the use of staff in the carsharing system normally reduces the value of profits, due to the fact that the increase of costs associated to staff salaries are not compensated by the increment of profits generated by the ability to maintain and relocate vehicles. Let us now analyze in detail why this happens while at the same time we perform a comparison between the rule-based and optimization models of the real-time decision support tool. To produce such analyses we use the scenarios that produce the best profit values for the base conditions (no intervention of staff), and then compare it to the results of having 5 members of staff working in the system (which are the ones that result in more profit). Table 27 shows the values of the performance indicators obtained for the referred scenarios: 8% of demand with 100 vehicles, 15% of demand with 200 vehicles and 25% of demand with 300 vehicles. All the scenarios consider a 0.5% maintenance generation factor.

The introduction of staff members results in a reduction of the profits relatively to the base scenarios for the demand levels 8% and 15%, and an increase for the 25% demand level scenario (this is one of the exceptions aforementioned)

In terms of costs, the introduction of staff members has two fixed components: the salary of 3.5 Euro per hour that increases the costs by 210 Euro for a set of 5 staff members working for 12 hours, and the 1.19 Euro daily parcel of the monthly pass per staff member that increases the cost by 5.95 Euro. The fixed parcel of having 5 members of staff is then 215.95 Euro per operation day. Additionally there is a variable costs parcel related to the movement of staff in vehicles for relocation or maintenance purposes, which ranges from 16 to 43 Euro for the scenarios in Table 27.

The benefit of having staff activity is that it increases the revenue due to relocation of vehicles from places where they are not needed to places with demand as origin, and also by making cars available after maintenance operations.

Table 27: Performance indicators for the simulations of one day of operation using 8% of demand with 100 vehicles, 15% of demand with 200 vehicles, 25% of demand with 300 vehicles, and maintenance requests

	8% demand			15% demand			25% demand		
Model	base	rule-based	optim.	base	rule-based	optim.	base	rule-based	optim.
Number of cars	100	100	100	200	200	200	300	300	300
Number of staff	0	5	5	0	5	5	0	5	5
Profit (€)	2784.4	2584.0	2610.6	5489.2	5402.2	5412.3	9272.5	9293.5	9304.1
Revenues (€)	4165.6	4204.1	4238.4	8261.0	8429.9	8461.3	13526.8	13812.9	13836.9
Costs (€)	1381.2	1620.1	1627.9	2771.7	3027.7	3048.7	4254.2	4519.4	4532.7
- car depreciation	822	822	822	1644	1644	1644	2466	2466	2466
- parking cost	167	167	167	334	334	334	501	501	501
- staff wage	--	210	210	--	210	210	--	210	210
- staff movements PT	--	5.95	5.95	--	5.95	5.95	--	5.95	5.95
- client movements in car	392.2	398.2	398.7	793.7	812.8	812.7	1287.2	1318.1	1320.6
- staff movements cars	--	16.9	24.2	--	21.0	42.1	--	18.3	29.2
Number of accepted trips	1248	1262	1270	2424	2475	2486	4086	4153	4169
Number of rejected trips	400	386	378	609	559	548	825	759	743
% accepted trips	75.7	76.6	77.1	79.9	81.6	81.9	83.2	84.5	84.9
Num. of accepted trips per car	12.5	12.6	12.7	12.1	12.4	12.4	13.6	13.8	13.9
Average dist. car client (m)	461.9	470.6	469.3	389.2	392.7	376.8	343.8	338.3	338.6
Total maintenance requests	3	6	11	14	10	21	23	23	21
Number of fulfilled maint. req.	--	6	10	--	10	17	--	23	15
Car downtime (h) - (corresponding %)	16.1 (1.3)	6.3 (0.5)	15 (1.3)	93.1 (3.9)	14.9 (0.6)	46.4 (1.9)	139.1 (3.9)	27 (0.8)	40.9 (1.1)
Car time mov. clients (h) - (corresponding %)	239.4 (20.0)	241.6 (20.1)	243.6 (20.3)	474.8 (19.8)	484.5 (20.2)	486.3 (20.3)	777.4 (21.6)	793.8 (22.1)	795.2 (22.1)
Car time mov. staff (h) - (corresponding %)	-- (..)	9.2 (0.8)	6.7 (0.6)	-- (--)	8.8 (0.4)	11.2 (0.5)	-- (--)	7.5 (0.2)	8.2 (0.2)
Car time idle available (h) - (corresponding %)	944.5 (78.7)	943 (78.6)	934.7 (77.9)	1832.1 (76.3)	1891.8 (78.8)	1856.2 (77.3)	2683.5 (74.5)	2771.7 (77.0)	2755.8 (76.5)
Total car distance (km)	4357.4	4612.7	4699	8819.3	9263.8	9497.7	14302.8	14849.1	14997.6
- with clients	4357.4	4424.6	4430.4	8819.3	9030.7	9030.3	14302.8	14645.8	14673.1
- with staff	--	188.1	268.6	--	233.2	467.4	--	203.2	324.4
Staff time maintaining (h) - (corresponding %)	-- (--)	3 (5.0)	5 (8.3)	-- (--)	5 (8.3)	8.5 (14.2)	-- (--)	10.8 (18.0)	7.2 (9.2)
Staff time moving in car (h) - (corresponding %)	-- (--)	9.2 (15.3)	8.2 (13.6)	-- (--)	8.8 (14.7)	12.8 (21.3)	-- (--)	7.5 (12.5)	10 (17.0)
Staff time moving in PT (h) - (corresponding %)	-- (--)	20.7 (34.4)	25.7 (42.8)	-- (--)	17.3 (28.9)	29 (48.3)	-- (--)	18 (30.0)	27.3 (42.8)
Staff time idle (h) - (corresponding %)	-- (--)	27.2 (45.3)	21.2 (35.3)	-- (--)	28.8 (48.1)	9.7 (16.2)	-- (--)	23.7 (39.5)	15.5 (31.1)
Number of car trips with staff	--	55	48	--	50	67	--	42	60
Number of staff PT trips	--	59	72	--	50	87	--	53	81
Num. of trip join passengers	--	--	9	--	--	10	--	--	11
- car distance saved (km)	--	--	58.8	--	--	82.3	--	--	83.7
- car time saved (h)	--	--	1.5	--	--	1.7	--	--	1.8

However for the 8% and 15% demand level scenarios this is not enough to overtake the costs increase. For the 8% demand scenario with 100 vehicles, the increase of revenues of having 5 members of staff are: 38.56 Euro for the rule-based model, and 72.89 Euro for the optimization model. For the 15% demand level scenario with 200 vehicles, the increase in revenues are: 168.94 Euro for the rule-based model, and 200.33 Euro for the optimization model.

The 25% demand level with 300 vehicles, is one of the exceptions referred before, where the staff activity slightly increases the profit. The increase in revenues is 286.10 Euro for the rule-based model and 310.10 Euro for the optimization model, which, in both cases, allows overtaking the fixed costs of staff.

The consideration of more staff members leads to a gradual decrease of profit, as it can be seen in Figure 45 to Figure 50, and Table 21 to Table 26. For example, the profit for the 8% demand level with 100 vehicles, decreases from 2584.03 to 2410.3 Euro for the rule-based model, and 2610.59 to 2409.89 Euro for the optimization model, when increasing the number of staff elements from 5 to 10 elements.

The results obtained using the rule-based model assignment are close to the ones obtained for the optimization model, meaning that the quality of results from the rule-based model are close to optimal. Looking at the profit, costs and revenues, we can see that they do not differ much. For the optimization model, considering 8% of demand level with 100 vehicles, the increase of profit relatively to the rule-based model is 26.56 Euro, for the scenario with 15% demand level with 200 vehicles the difference is 10.04 Euro, and for the scenario with 25% of demand and 300 vehicles the increase in profit is 10.63 Euro (see Table 27).

There are some other differences between both assignment models which need to be highlighted. The main difference is that the rule-based model gives first priority to maintenance requests while the optimization model defines staff activity plans based on an objective function designed with the aim to optimize the profit. This has impacts on the performance indicators, namely on the proportion of fulfilled maintenance requests and the vehicle downtime. The number of fulfilled maintenance requests for the rule-based model is higher, lowering the downtime of vehicles, when compared with the optimization model. For example, the proportion of fulfilled maintenance requests for the scenarios on Table 27 varies from 71% to 91% for the optimization model, and is equal to 100% for the rule-based model. The car downtime varies from 0.5 to 0.8% of the total car time for the rule-based model, and 1.1 to 1.9% for the optimization model.

Giving priority to maintenance leads to higher values of vehicle availability, but not necessarily to an increase of the number of accepted trips, since vehicles might not be available at the right places. The simplicity of the rule-based model by establishing relocation movements using stock limits defined for the entire day also contributes to having less accepted trips than the optimization model. For the 8% demand level, the rule-based model has less 8 accepted trips than the optimization model, for the 15% demand the difference on accepted trips is 11, and for 25% demand level the referred difference is 16 trips (see Table 27).

The optimization model is based on forecasts for the horizon period (equal to one hour for the application to the case study) and decides if it is more profitable doing relocations or performing maintenance, resulting in more movements of staff to perform relocation of vehicles. Since forecasts can be different from what happens in reality, the vehicles relocated not always result in trips served, and consequently in an increase of revenues. This is visible for the 8% demand level case scenario where base and optimization models have similar car downtime (time that the vehicle is unavailable to clients due to maintenance request) allowing to discard the contribution of maintenance on the number of accepted trips. For the referred scenario, there are 48 vehicle movements, and the increase in accepted trips relatively to the base model is 22.

For the other scenarios of Table 27, the reduction of car downtime has a joined effect with relocations, increasing the number of accepted trips and diluting the previously described effect related to forecasts. For the 15% demand level the number of vehicle movements is 67 and the increment on the number of accepted trips is equal to 62; and for the 25% demand level, the number of car movements is equal to 60 and the increase on accepted trips is 83. In 5.5.3.3, an analysis is made for the scenarios that do not have maintenance requests to isolate the effectiveness of the relocations.

Trip joining was considered to be an advantage to the movement of staff. It allowed staff moving in a car with the same origin and destination to share the same vehicle, and this way, saving fuel and money. During the simulation process it was verified that the economy savings due to trip joining were not significant. For the case of 8% demand level, the saving of 58.8 kilometers corresponds to 5.29 Euro, which is 0.1% of the total revenues. For the case of 15% of demand there were savings of 82.3 kilometers, correspond to 7.41 Euro (0.09% of the total revenues). And for the of 25% demand level situation, there were savings of 83.7 kilometers, which correspond to 7.53 Euro, 0.05% of the total revenues (see Table 27).

5.5.3.3 On the importance of operator-based relocations

The scientific research outputs preconize operator-based relocations as a mechanism to solve imbalance problems on vehicle stocks in one-way carsharing systems, assuming the need of including staff members to move vehicles within the system (see referred papers in 3.3).

During the previous analysis it has been seen that the revenues obtained with the introduction of staff activity were in general not enough to surpass the costs or resulted in profits slightly higher than the scenarios without staff. In that analysis staff had to simultaneously take care of maintenance and relocations. To understand what would happen if staff members were only focused on relocations, we can analyze the scenarios without maintenance requests (maintenance request generator factor equal to zero).

For these scenarios the number of vehicle movements resulting from staff are directly associated to relocations, with the exception of the optimization model, where vehicle movements can, in some cases, be associated to joined movements of staff inside the same vehicle if it represents a favorable situation for the objective function (see 4.3.2). To simplify the current analysis it is assumed that for the optimization model the car movements with multiple staff members end up in relocations. As a consequence, the resulting value is then equal or higher than the simulated relocations.

Analyzing the scenarios without maintenance requests, the movement of vehicles performed by 5 members of staff are not enough to increase the profits in relation to the base scenario (see Table 28). The maximum number of vehicle movements verified for these scenarios is 66, for the 8% demand level rule-based model and for the 15% demand level optimization model scenarios. For the 8% demand level with the rule-based model scenario, the 66 movements are converted in 11 additional accepted trips, while for the 15% demand level with the optimization model scenario, the same number of vehicle movements by the staff is converted into 28 additional accepted trips. Ideally, if all 66 movements were converted in accepted trips, the increase in revenues would be around

215 Euro, for the average client car usage pattern (each simulated client trip results on average in a revenue of 3.26 Euro, after discounting the fuel cost), which is 1 Euro lower than the fixed cost of having 5 members of staff (approximately 216 Euro per operation day).

Table 28: Performance indicators for the simulations of one day of operation using 8% of demand with 100 vehicles, 15% of demand with 200 vehicles, 25% of demand with 300 vehicles, and without maintenance requests

	8% demand			**15% demand**			**25% demand**		
Model	base	rule-based	optim.	base	rule-based	optim.	base	rule-based	optim.
Number of cars	100	100	100	200	200	200	300	300	300
Number of staff	0	5	5	0	5	5	0	5	5
Profit (€/day)	2797.1	2579.6	2624.0	5625.8	5405.4	5440.4	9455.8	9306.7	9330.4
Revenues (€/day)	4179.5	4201.1	4266.5	8411.5	8436.2	8494.4	13728.1	13834.9	13872.7
Costs (€/day)	1382.4	1621.5	1642.5	2785.7	3030.8	3054.0	4272.3	4528.2	4542.4
Number of accepted trips	1252	1263	1280	2469	2481	2497	4142	4168	4181
Number of rejected trips	396	385	368	564	553	537	769	744	731
% accepted trips	76	76.6	77.7	81.4	81.8	82.3	84.3	84.9	85.1
Num. of accepted trips per car									
Car time mov. clients (h)	240.2	241.4	245.2	483.4	484.8	488.2	789	795.1	797.3
Avg client trip time (min/trip)	12	12	12	12	12	12	12	12	12
Car distance with clients (km)	4371	4419.6	4493.2	8974.8	9014.5	9080.4	14503.3	14672	14708.3
Avg car dist with client (km/trip)	3.5	3.5	3.5	3.6	3.6	3.6	3.5	3.5	3.5
Number of car trips with staff	--	66	57	--	62	66	--	61	58
Car time mov. staff (h)	--	11	9.5	--	11	11.3	--	10.8	9.7
Avg. time car staff mov. (min/mov.)	--	10	10	--	10.6	10.3	--	10.6	10
Car distance with staff (km)	--	208.7	368.2	--	283.6	476.1	--	275.7	396.4
Avg car dist. with staff (km/staff)	--	3.2	6.5	--	4.6	7.2	--	4.5	6.8
Num. of trip join passengers	--	--	23	--	--	13	--	--	23
- car distance saved (km)	--	--	94.3	--	--	78	--	--	110.2
- car time saved (h)	--	--	2.3	--	--	2.2	--	--	2.5

Realistically the maximum possible number of relocations per staff per hour can be considered to be between 2 and 3. The staff member needs to move towards the vehicle, drive it to the new location, park and leave it there. Considering a maximum of two relocations per hour per staff, for 12 hours of operation, each staff member would possible perform 24 relocation movements. Assuming the average cost for staff relocation equal to 0.72 Euro (consisting in 8 kilometer per movement with a fuel cost of 0.09 Euro per kilometer) and the average revenue for accepted trip equal to 3.16 Euro (based on the average time and distance of client trips, respectively 12 minutes and 3.5km), values based on the simulated demand level scenarios, we can estimate the maximum possible profit increase considering 5, 10, 15 and 20 elements of staff (see Table 29).

Table 29: Possible profit increase from relocations for ideal conditions considering that all relocations are converted in accepted trips, and staff does not perform any other task besides relocations.

Number of staff	5	10	15	20
Number of relocations	120	240	360	480
Possible profit from clients (€)	+379.2	+758.4	+1137.6	+1516.8
Salary costs (€)	-210	-420	-630	-840
Public transport costs (€)	-6	-12	-18	-24
Relocation movement cost (€)	-86.4	-172.8	-259.2	-345.6
Possible profit variation (€)	+76.8	+153.6	+230.4	+307.2

In ideal conditions of every car being used by clients after being relocated and staff having no other activity besides relocation, allowing 2 vehicle relocation movements per hour per staff, the potential increase in profit varies from 77 Euro for 5 elements of staff to 307 Euro for 20 elements of staff per 12 hours of operation. This would represent a profit increase from 2.7% to 11.0% for the 8% demand level, 1.4% to 5.5% for the 15% demand level, and 0.8% to 3.2% for the 25% demand level (see Table 30). The impact of the potential increments is eliminated as the demand increases, due to the fact that relocation revenues are limited by the number of staff elements.

Table 30: Proportion of profit increase for the considered scenarios by adding the relocation potential profit for ideal conditions to the base scenario

		Number of cars	Base Profit (€)	5	10	15	20
Potential profit increase (€)				+76.8	+153.6	+230.4	+307.2
Demand level	8%	100	2797.1	+2.7%	+5.5%	+8.2%	+11.0%
	15%	200	5625.8	+1.4%	+2.7%	+4.1%	+5.5%
	25%	300	9455.8	+0.8%	+1.6%	+2.4%	+3.2%

For the results presented in Table 29 and Table 30, it was assumed that all relocation movements were converted in accepted trips. In a real situation this is unlikely to happen.

Analyzing the potential of having each staff member relocating two vehicles per hour, it was verified that the minimum proportion of accepted trips has to be above 80% in order to produce profit (see Table 31).

Table 31: Trips and percentage of successful relocations to positive profit variation

Number of staff	5	10	15	20
Number of relocations	120	240	360	480
Wage cost (€)	-210	-420	-630	-840
Public transport cost (€)	-6	-12	-18	-24
Relocation movement cost (€)	-86.4	-172.8	-259.2	-345.6
Number of additional trips to positive profit variation	>95	>191	>287	>385
Minimum % of successful relocations to assure positive variation (€)	80%			

Let us analyze what happens in the simulated reality. Considering all the simulated scenarios presented in 5.5.2 without maintenance requests, the percentage of relocations that are converted into accepted trips is on average less than 65%, varying from 63.5% for a level of accepted trips between 60 and 70% to an average of 39.6% for a level of accepted trips between 90 and 100% (see Table 32). The percentage of accepted trips corresponds to the proportion of trips accepted when compared to the total potential demand. As expected the number of successful relocations decrease when the accepted demand gets close to the potential total demand, since there is no more demand gap to explore. These values were determined using all the scenario results considered that had no maintenance requests.

Table 32: Average and standard deviation of the proportion of successful relocations for different levels of the proportion of accepted trips

	% of successful relocations	
%accepted trips	Average	Standard deviation
60-70	63.5	44.1
70-80	43.3	14.7
80-90	41.5	11.9
90-100	39.6	17.7

In summary, providing relocation movements in a system with similar characteristics to the one that was simulated would very unlikely have a positive influence on the profit of the system, since its benefits can only support the costs in less likely favorable conditions. But, since the integration of staff is necessary to solve the problems that induce unavailability of vehicles (to guarantee that the referred unavailability does not escalate with time increasing its unwanted effects) relocations can be added to fill staff activity time and to improve service quality.

The question that arises is why this was not concluded by other researchers. From the research publications analyzed in the state of the art (see 3.3), only Kek et al (2009) and Jorge et al. (2014), perform detailed analysis through simulation of the operator-based relocations potential.

Kek et al. (2009), presented a decision support system to optimize the staff activity. The focus of the study was to mitigate the problems of zero-vehicle time (the time that stations had no vehicles available to users) and full-port time (the time with no available parking spaces to drop the vehicle). Relocation and maintenance activities were used to improve the system performance indicators and, therefore, to provide higher customer service levels keeping lower operational costs. The full-port time performance indicator is not applicable to a free-float carsharing system, since a client can park the vehicle at any available parking space of the operating area.

The system was applied to a monthly demand data sample of 1235 trips from the ICVS carsharing company operating in Singapore (one-way and station-based). This corresponds to an average of 41 trips per day for a 30 day month period, meaning that the system had a small scale. The support tool that they proposed did not work in real-time, instead it used a MIP model to optimize blocks of 8 hour subdivided by 15 minutes intervals to retrieve optimized staff activity.

It seems that the authors were not assessing profit, even though they developed tools to do it. First the objective function only looks to the minimization of costs of staff, although it considers a cost for rejecting demand. Then the outputs that minimized costs were used to extract parameters for defining typical activity plans (one for weekdays and another for weekends), and not applied straight to the simulator. The activity plans aimed to an improvement of the two performance indicators, which are not perceived as being directly associated to profit. Since the characteristics of the existent ICVS system used as base of comparison are not described, as well as the absolute results, due to data confidentiality, nothing can be concluded in what respects to the significance of the described improvements. Either way, the profit is referred in the conclusions as an “intangible benefit” [Kek et al., 2009], though there is no evidence in the contents of the publication leading to this statement.

Jorge et al. (2014) applied a relocation optimization model to the same case study of this thesis (city of Lisbon), using a different demand sample, that has a number of potential trips and minutes similar to the 8% demand level scenarios (due to the demand reduction made in 5.5.1.5). The authors used a mathematical model that maximizes the profit of running a one-way carsharing system by applying optimized relocations assuming exact knowledge of future demand. They also proposed real-time rule-based relocation policies in a simulator. Both models were compared to the results of a base model without relocations, which resulted from applying the optimization of station locations using the trip selection approach presented by Correia and Antunes (2012). From the three different station network size scenarios analyzed in Jorge et al. (2014), the one that can be used to compare with the present research work is the scenario with full demand attended leading to 69 stations (every zone with demand has a station). The system is station-based which requires to have a stock of parking spaces. The parking places increase the fixed costs of running the system when compared to the situation of having free-float and the parking cost paid by vehicle. The cost per parking space, considered by the authors, was 2 Euro per day. The operation period was 6 hours larger than the period considered in this research, meaning that the exploration of extra time can lead to higher revenues. There was no uncertainty in demand, being the “forecasts” equal to real client requests. The staff was considered to be hired per service, and the authors did not consider a limitation of the number of staff working simultaneously. This has the advantage of not having staff idle time, although we would argue that it would be unlikely to find people wanting to work in these conditions. The costs of staff considered by the authors were proportional to the car time used: for relocations, the unitary cost was 0.20 Euro per minute of relocation movement; and for maintenance, the unitary cost was 0.007 Euro per minute of client movement. The revenues for client usage were calculated based on the same price, 0.30 Euro per minute (this research considers 0.29 Euro per minute of usage). The authors did not take into account the cost of fuel related to vehicle usage by the clients. Vehicle depreciation costs were higher than the value used in this research, due to the fact that the fleet was composed by more expensive vehicles acquired with financial credit resource. The different characteristics between this research and the research carried out in Jorge et al. (2014) are enumerated in Table 33.

Table 33: Comparison between this research and Jorge et al. (2014) – main characteristics

	Jorge et al. (2014)	**This research**
Allowed movements	One-way	One-way
Location of vehicles	Station-based (69 stations)	Free-float (46 zones)
Staff number	Unlimited and hired per service	Limited and hired for the operation period
Period of operation	6 a.m. to midnight (total of 18h)	8 a.m. to 20 p.m. (total of 12h)
Demand compared to forecasts	Without uncertainty	With uncertainty
Full demand trips	1777	1648 (8% demand level)
Full demand minutes	23711	19177
Parking cost	Payed by parking space 2€/day per space	Payed by vehicle 1.67€/day per vehicle
Vehicle depreciation cost	17€/vehicle per day (20,000€ vehicle + interests)	8.22€/vehicle per day (15,000€ vehicle without interests)
Relocation and maintenance cost	Payed by vehicle minute	Includes staff wage, public transport title cost, and fuel cost of vehicle movement
Revenues (client usage)	0.30 €/minute	0.29€/ minute
Cost of fuel for client trip	Not considered	0.09€/km (0.028€/minute)

The authors concluded that relocations allow the increase of profit in 2015.6 Euro per day for the best policy considered, which is way different than the obtained for this research (see Table 34). Analyzing the original values presented in Jorge et al, (2014), copied to Table 35, it can be seen that this improvement is reached due to a decrease of the number of vehicles and parking spots (the model developed by the authors determine the optimal number of vehicles and parking spots), made possible by the introduction of relocations that allowed to continue to fulfill all demand requests. Probably the constraint of trying to satisfy all demand leads to a high number of vehicles and consequently a need for more parking spaces, which can be reduced with adding relocations. And this enables a large reduction of the costs, namely due to the high unitary costs of vehicle depreciation.

To see what would happen if instead of stations we had zones (meaning that there would not be a need for parking places), used the same costs, and applied the tools developed in this research, we simulated a scenario with only client movements to be used as a base of comparison, and performed a simulation using the optimization model of the real-time decision support tool, both using the same number of vehicles adopted in Jorge et al. (2014). The main results are included in Table 35.

Table 34: Comparison between this research and Jorge et al. (2014) – Best scenarios in terms of profit

	Best relocation policy (2.A) with 267 vehicles	**Optimization model with 100 vehicles and 5 staff members**
Increase in profit, compared to base model	+2015.6€	-139€ (it decreases)
Staff time (min)		
- movements	2967 (relocations)	2034 (relocation + maintenance)
- maintenance	Not referred	300
- idle	None	1272
Staff cost		
- wage	--	42€ per day per staff
- relocations	0.20€ per minute of relocation	0.09€/km (0.028€/minute) fuel cost
- maintenance	0.007€ per minute of vehicle usage	--
Base model	Different number of vehicles, different number of parking spaces	Same number of vehicles

. We also adapted the original results in Jorge et al. (2014) by applying the same unitary costs referred in 5.5.1.1, with the exception of the costs related to staff activity (due to the fact that staff is hired using a different process). The costs of client movements were introduced to the adapted version using the average cost of 0.028 Euro per minute. Moreover, the adapted results from Jorge et al. (2014) and simulated results using the developed tool do not include maintenance (to be at the same level of comparison).

Clearly, it can be verified that the profit improvement between base and simulated scenario from the research published in Jorge et al. (2014) adapted for comparison and the simulations using the tool developed in the present work are similar (623.1 versus

724.9 Euro) and there are due to the cut in the number of vehicles, which leads to a decrease in depreciation and parking costs that surpass the cost of the introduction of staff services. As expected the 100% demand fulfilled (representing a total of 23711 minutes) by the simulations included in Jorge et al. (2014) results in higher revenues and consequently in higher profit than the 97.3% and 93.3% (18816 and 17886 minutes of a total potential of 19177 minutes) of the models considered in the present research.

Table 35: Comparison between this research and Jorge et al. (2014) – values

	[Jorge et al. 2014] Original		**[Jorge et al. 2014] Adapted for comparison**		**Simulated results With the same number of vehicles**	
	Base	Policy 2.A	Base	Policy 2.A	Base	Optimization
Operation period (h)	18	18	18	18	12	12
% relocation	--	100	--	100	--	(58 movements)
% accepted trips	100	100	100	100	97.3	93.3
Number of vehicles	390	267	390	267	390	267
Number of staff	Paid by service (maintenance)	Paid by service (maintenance + relocations)	0	Paid by service (only relocations)	0	5
Parking	739 spaces	480 spaces	Paid by vehicle	Paid by vehicle	Paid by vehicle	Paid by vehicle
Time driven by clients (min)	23711	23711	23711	23711	18816	17886
Time of relocations (min)	0	2967	0	2967	0	2292
Depreciation cost of vehicles (€)	6630	4539	3205.80	2194.74	3205.80	2194.74
Parking cost (€)	1478	960	651.30	445.89	651.30	445.89
Staff costs (€)	165.98	759.38	--	593.4	--	251.15
Client movement costs (€)	--	--	663.91	663.91	527.60	497.52
Revenues (€)	7113.30	7113.30	6876.19	6876.19	5456.64	5186.14
Profit (€)	-1160.7	854.9	2355.2	2978.3	1071.9	1796.8
Profit improvement (€)	2015.6		623.1		724.9	

All this allows to state that the conclusion of the authors in the referred paper is specifically applied for the situation of having one-way and station-based carsharing systems where:

- the stock of parking spots is paid and important to guarantee quality of service;
- the depreciation cost of vehicles is high;
- and, all demand needs to be served.

The increase in profit verified by the authors is not due to the increase in revenues generated by the relocations per se (considered in this research as negligible), but indirectly by the reduction of costs related to the cut in the number of vehicles and parking spots leveraged by relocations when trying to serve 100% of the demand. Everything indicates that if the authors decided to reduce the served client requests to, for example, 90%, there wouldn't be a need for relocations to reach a similar profit.

6 Conclusions

Carsharing is a form of collaborative consumption that is pointed as a way to mitigate today's urban area problems related to car dependency. It is a short-time period car rental service intended to replace private vehicle ownership, giving access to a vehicle whenever it is required, while providing an incentive to minimize driving.

Operationally, carsharing services evolved from station-based systems and round-trip movements, into free-float locations and one-way movements. The simplest set up in the former has been the operational choice for systems with a small number of vehicles and stations, since it is easier to manage and does not require many staff hours, nonetheless it is not adapted to users' needs. By increasing one step on the level of operational complexity, we have one-way station-based systems. One-way movements give more flexibility to users, being a critical factor to attract new clients to the system. Additionally, it lets a higher utilization of vehicles as they do not need to be idle during the rental period as it happens when clients are forced to a roundtrip. The downside is that it can lead to having a surplus of vehicles in stations with high demand as destination, and a lack of vehicles in stations with high demand as origin, unbalancing the demand and supply quotient.

The most complex operational set up is reached by one-way free-floating systems. This allows individuals to use a vehicle of the system as if it was their own vehicle. However, it does not mean complete freedom, since vehicles need to be delivered inside an operating area. One-way and free-floating carsharing systems, have been the main focus of the scientific work in recent years, namely in solving the vehicle imbalance problem that naturally evolves from letting clients freely move inside an operation area. In an attempt to contribute to a better process of how to make these relocations a real-time detailed decision support tool was developed in this thesis work, allowing to define periodic staff orders adapted to system status and aimed to profit optimization. This was lacking in the literature since either relocations were considered to happen without the need to define staff activities or staff activities have been the focus on the models but without looking at their effect on system profit. Moreover the stochasticity of the demand of such systems has not been considered or when it was considered it was for very small systems.

The structure of the tool is composed by three main elements: a forecasting model, a staff activity assignment model, and a filter. The forecasting model allows to predict the demand for the immediate future, the assignment model designs a reaction plan for the staff activity based on forecasts and the status of the system, and the filter discard the planned activities that cannot be fulfilled due to physical constraints.

Two different assignment models were developed in order to compare its effectiveness: a rule-based model and an optimization model. The rule-based model is composed by rules that initiate reactions to the system parameters, while the optimization model uses Mixed Integer Linear Programming to design the staff activity that maximizes the profit. The optimization model considers the option of staff moving together inside the same vehicle when sharing the exact same origin-destination pair. This was designated by trip joining of staff.

A simulator was developed and coded to test the real-time decision support tool using a virtual environment. To serve as comparison with the two versions of the real-time decision support tool, it was included a base model that only considered client movements.

A test application was performed in a virtual environment with the characteristics of the Lisbon municipality. The demand was estimated, by using a web-based survey designed and applied in order to obtain the inhabitant behaviors and preferences towards transportation choices. The online survey was then corrected with computer assisted personal interviews (CAPI). Using the survey sample, it was established the synthetic population and agenda of trips for each individual. The demand for carsharing was defined by filtering the target potential clients, and then applying the discrete choice model considering optimistic characteristics for the carsharing service.

Since the value of carsharing trips was high when compared to other scientific research publications, the number of carsharing trips was reduced into three different levels 8%, 15% and 25%, for sensitivity analysis purposes.

The different levels of demand were tested for the two distinct models (rule-based and optimization) and a comparison base model that only simulated client trips (not considering staff), using different number of vehicles for the vehicle fleet and different number of elements for the staff personnel, with and without maintenance requests.

It was verified that the use of staff in the carsharing system normally reduces the value of profits, due to the costs associated to staff activity and small improvements in revenues. There were few exceptions where the profit values were similar between scenarios with and without staff.

The results of the rule-based model were close to the results verified for the optimization model, having the optimization model slightly better outcomes. The savings of having trip joining associated to the activity of staff on the optimization model were not significant, ranging from 0.05% to 0.1% of the total revenues.

A thoroughly analysis of the results led to conclude that the number of relocations that can physically be performed by each staff member (considering human constraints and current technology), adding to the fact that not all relocations end up in accepted demand, provide a small increase in the revenues, which is unlikely to overcome the costs associated to staff activity (salaries, public transport title, fuel spent in relocation movements).

Therefore, the best practice from a profit point of view is to keep enough members of staff to respond to maintenance requests, and fill their idle time by having them performing prioritized relocations (for example, vehicles not being used for an extended period of time). Responding to maintenance requests is of the utmost importance in order to guarantee that the vehicle unavailability does not escalate with time.

This research has contributed to clarify the profit impact of hiring staff to perform relocations and solve the imbalance problem of one-way carsharing system. Other hypothesis can be explored using the same simulation environment, for instance:

- Are price incentives a better option to staff relocations? It was concluded that the possible revenues of staff relocation are unlikely to surpass the costs contributing to an increase of profit. The attribution of credit in minutes of usage for performed certain trips can be a way to improve vehicle utilization and profit.
- What would be the impact of using autonomous vehicles? Considering that the introduction of autonomous vehicles in an urban area will lead to the merge of taxi service and carsharing concepts. It would be interesting to understand what would be the impact of the new service when compared to the sum of the parts.

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Appendices

A. Simulation aggregate results for 8% of demand scenarios

(Note: the designation “react” corresponds to the rule-based model)

id1. model	id2. cars	id3. staff	id4. maint.gen.factor	profit	in2. total paid by clients	out1. total costs	out2. wage	out3. car depreciation	out4. staff mov in cars	out5. staff mov in pt	out6. client mov	out7. parking	a1. %accepted trips	a2. avg dist car-client accepted (m)	a3. avg dist car-client rejected (m)	a4. #rejected trips car dist >1 and <2km	a5. #rejected trips car dist >2 and <3km	a6. #rejected trips car dist> 3km	a7. #rejected no car at any dist	a8. #total rejected trips	a9. #total accepted trips	a10. #total trips
base	50	0	0	2247.99	3029.34	781.35	0	411	0	0	286.85	83.5	55.4	541.1	1788.3	496	179	60	0	735	913	1648
base	100	0	0	2797.09	4179.48	1382.39	0	822	0	0	393.39	167	76	462	1586.2	303	78	15	0	396	1252	1648
base	150	0	0	2742.44	4670.16	1927.72	0	1233	0	0	444.22	250.5	84.3	409.8	1417.5	231	25	3	0	259	1389	1648
base	200	0	0	2525.33	4981.62	2456.29	0	1644	0	0	478.29	334	89.3	366	1386	158	17	1	0	176	1472	1648
base	300	0	0	1822.61	5300.04	3477.43	0	2466	0	0	510.43	501	94.8	298	1287	83	2	0	0	85	1563	1648
base	400	0	0	982.46	5467.08	4484.62	0	3288	0	0	528.62	668	97.5	275.3	1258.6	42	0	0	0	42	1606	1648
base	50	0	0.5	2141.16	2911.02	769.86	0	411	0	0	275.36	83.5	53.3	544.2	1875.9	485	201	84	0	770	878	1648
base	100	0	0.5	2784.39	4165.56	1381.17	0	822	0	0	392.17	167	75.7	461.9	1583.4	307	78	15	0	400	1248	1648
base	150	0	0.5	2713.84	4638.84	1925	0	1233	0	0	441.5	250.5	83.8	416.9	1428.1	237	27	3	0	267	1381	1648
base	200	0	0.5	2504.4	4957.26	2452.86	0	1644	0	0	474.86	334	89	368.4	1394.5	162	18	1	0	181	1467	1648
base	300	0	0.5	1816.36	5293.08	3476.72	0	2466	0	0	509.72	501	94.8	298.6	1285	84	2	0	0	86	1562	1648
base	400	0	0.5	982.46	5467.08	4484.62	0	3288	0	0	528.62	668	97.5	277.2	1258.6	42	0	0	0	42	1606	1648
react	50	5	0	2007.65	3017.8	1010.15	210	411	15.1	5.95	284.6	83.5	55.6	542	1865.6	477	180	75	0	732	916	1648
react	100	5	0	2579.65	4201.15	1621.5	210	822	18.78	5.95	397.77	167	76.6	473.7	1577	301	72	12	0	385	1263	1648
react	100	10	0	2426.12	4305.22	1879.1	420	822	50.6	11.9	407.6	167	78.4	476.5	1574.6	273	75	8	0	356	1292	1648
react	150	5	0	2543.37	4718.86	2175.49	210	1233	27.01	5.95	449.03	250.5	85.7	418.2	1429.8	211	20	5	0	236	1412	1648
react	150	10	0	2379.74	4793.13	2413.39	420	1233	41.77	11.9	456.22	250.5	86.8	419.4	1450.8	193	19	5	0	217	1431	1648
react	150	15	0	2176.3	4812.97	2636.67	630	1233	46.78	17.85	458.54	250.5	87.3	420.3	1424.9	189	16	5	0	210	1438	1648
react	200	5	0	2343.13	5046.76	2703.63	210	1644	25.56	5.95	484.12	334	90.8	374.5	1377.4	135	16	0	0	151	1497	1648
react	200	10	0	2135.57	5070.75	2935.18	420	1644	38.54	11.9	486.74	334	91.3	373.7	1326.2	134	10	0	0	144	1504	1648
react	200	15	0	1913.8	5064.61	3150.81	630	1644	38.63	17.85	486.33	334	91.3	370	1329.8	134	10	0	0	144	1504	1648
react	300	5	0	1658.2	5378.78	3720.58	210	2466	17.67	5.95	519.96	501	96	302	1239.7	66	0	0	0	66	1582	1648
react	300	10	0	1435.05	5374.8	3939.75	420	2466	21.11	11.9	519.74	501	95.9	302.4	1246.1	68	0	0	0	68	1580	1648
react	300	15	0	1217.64	5372.62	4154.98	630	2466	20.71	17.85	519.42	501	95.8	303.6	1217.9	69	0	0	0	69	1579	1648
react	300	20	0	997.25	5365.26	4368.01	840	2466	19.79	23.8	517.42	501	95.9	301.5	1240.5	68	0	0	0	68	1580	1648
react	400	5	0	784.44	5504.96	4720.52	210	3288	15.71	5.95	532.86	668	98.1	274.6	1296	32	0	0	0	32	1616	1648
react	400	10	0	567.48	5504.96	4937.48	420	3288	16.72	11.9	532.86	668	98.1	275.2	1296	32	0	0	0	32	1616	1648
react	400	15	0	345.88	5499.7	5153.82	630	3288	17.92	17.85	532.05	668	98	274.6	1299.5	33	0	0	0	33	1615	1648
react	400	20	0	141.46	5508.4	5366.94	840	3288	13.49	23.8	533.65	668	98.1	277.1	1322.4	32	0	0	0	32	1616	1648
react	50	5	0.5	2071.41	3087.14	1015.73	210	411	13.75	5.95	291.53	83.5	56.6	540.2	1869.3	461	176	79	0	716	932	1648
react	100	5	0.5	2584.03	4204.12	1620.09	210	822	16.92	5.95	398.22	167	76.6	470.6	1616.6	290	79	17	0	386	1262	1648
react	100	10	0.5	2410.3	4282.08	1871.78	420	822	44.72	11.9	406.16	167	78	467.7	1515.9	291	69	2	0	362	1286	1648
react	150	5	0.5	2541.6	4716	2174.4	210	1233	25.82	5.95	449.13	250.5	85.6	420.7	1401.6	214	20	3	0	237	1411	1648
react	150	10	0.5	2370.9	4783.07	2412.17	420	1233	41.06	11.9	455.71	250.5	86.7	419	1420.5	197	19	3	0	219	1429	1648
react	150	15	0.5	2152.43	4784.54	2632.11	630	1233	44.56	17.85	456.2	250.5	86.8	418.5	1409.5	197	17	4	0	218	1430	1648
react	200	5	0.5	2328.04	5030.31	2702.27	210	1644	25.89	5.95	482.43	334	90.6	376.1	1385.7	139	16	0	0	155	1493	1648
react	200	10	0.5	2161.57	5097.61	2936.04	420	1644	36.51	11.9	489.63	334	91.6	375.8	1349.5	128	11	0	0	139	1509	1648
react	200	15	0.5	1918.03	5069.78	3151.75	630	1644	38.83	17.85	487.07	334	91.2	368.5	1328.6	136	9	0	0	145	1503	1648
react	300	5	0.5	1663.38	5382.01	3718.63	210	2466	15.99	5.95	519.69	501	96.1	299.8	1271	65	0	0	0	65	1583	1648
react	300	10	0.5	1434.7	5373.32	3938.62	420	2466	20.7	11.9	519.02	501	95.9	301.6	1257.7	67	1	0	0	68	1580	1648
react	300	15	0.5	1204.55	5361.59	4157.04	630	2466	23.97	17.85	518.22	501	95.8	304.8	1231.7	70	0	0	0	70	1578	1648
react	300	20	0.5	999.82	5368	4368.18	840	2466	19.79	23.8	517.59	501	95.9	301	1242.3	67	0	0	0	67	1581	1648
react	400	5	0.5	781.99	5500.34	4718.35	210	3288	13.9	5.95	532.5	668	97.9	278.2	1310.4	34	0	0	0	34	1614	1648
react	400	10	0.5	567.48	5504.96	4937.48	420	3288	16.72	11.9	532.86	668	98.1	275.6	1296	32	0	0	0	32	1616	1648
react	400	15	0.5	345.88	5499.7	5153.82	630	3288	17.92	17.85	532.05	668	98	275.9	1299.5	33	0	0	0	33	1615	1648
react	400	20	0.5	138.26	5506.85	5368.59	840	3288	15.23	23.8	533.56	668	98	277.1	1316.2	33	0	0	0	33	1615	1648
opt	50	5	0	2021.329	3048.48	1027.151	210	411	28.91	5.95	287.793	83.5	56	538.9	1839.7	484	162	79	0	725	923	1648
opt	100	5	0	2624.004	4266.48	1642.476	210	822	33.14	5.95	404.388	167	77.7	473.4	1614.3	283	70	15	0	368	1280	1648
opt	100	10	0	2515.961	4421.34	1905.379	420	822	63.77	11.9	420.705	167	80.3	463.7	1569.8	261	51	13	0	325	1323	1648
opt	150	5	0	2587.346	4785	2197.654	210	1233	38.83	5.95	459.378	250.5	86.2	410.7	1399	210	15	3	0	228	1420	1648
opt	150	10	0	2404.456	4849.38	2444.924	420	1233	63.82	11.9	465.705	250.5	87.6	409.7	1409.9	186	16	3	0	205	1443	1648
opt	150	15	0	2198.187	4873.74	2675.553	630	1233	75.87	17.85	468.333	250.5	88	409.6	1404.5	179	14	4	0	197	1451	1648
opt	200	5	0	2360.833	5079.06	2718.227	210	1644	35.21	5.95	489.069	334	91.6	373.5	1346.1	131	7	1	0	139	1509	1648
opt	200	10	0	2157.297	5117.34	2960.043	420	1644	57.53	11.9	492.615	334	92.4	369.6	1343.2	116	9	1	0	126	1522	1648
opt	200	15	0	1929.731	5129.52	3199.789	630	1644	80.05	17.85	493.893	334	92.6	369	1316.3	116	5	1	0	122	1526	1648
opt	300	5	0	1641.473	5371.38	3729.907	210	2466	27.69	5.95	519.264	501	96.2	302.4	1261.5	62	1	0	0	63	1585	1648
opt	300	10	0	1450.585	5421.84	3971.255	420	2466	46.46	11.9	525.897	501	96.9	302.4	1209.9	51	0	0	0	51	1597	1648
opt	300	15	0	1196.484	5380.08	4183.596	630	2466	48.44	17.85	520.308	501	96.3	299.9	1235.3	61	0	0	0	61	1587	1648
opt	300	20	0	1024.343	5435.76	4411.417	840	2466	53.94	23.8	526.68	501	97.1	306.3	1301.9	46	2	0	0	48	1600	1648
opt	400	5	0	761.715	5486.22	4724.505	210	3288	21.05	5.95	531.504	668	97.8	272.7	1264.1	36	0	0	0	36	1612	1648
opt	400	10	0	553.559	5512.32	4958.761	420	3288	35.89	11.9	534.969	668	98.2	274.2	1238.4	29	0	0	0	29	1619	1648
opt	400	15	0	357.688	5533.2	5175.512	630	3288	33.98	17.85	537.678	668	98.4	275.8	1283.1	26	0	0	0	26	1622	1648
opt	400	20	0	151.413	5548.86	5397.447	840	3288	38.10	23.8	539.55	668	98.7	275.5	1268.3	21	0	0	0	21	1627	1648
opt	50	5	0.5	2036.362	3060.66	1024.298	210	411	29.05	5.95	284.80	83.5	56.5	553.2	1813.6	458	195	64	0	717	931	1648
opt	100	5	0.5	2610.59	4238.45	1627.86	210	822	24.17	5.95	398.74	167	77.1	469.3	1634.2	275	84	19	0	378	1270	1648
opt	100	10	0.5	2409.893	4304.76	1894.867	420	822	64.87	11.9	409.10	167	78.1	464	1555.7	294	54	13	0	361	1287	1648
opt	150	5	0.5	2567.36	4765.86	2198.5	210	1233	42.30	5.95	456.75	250.5	86.2	417	1410.4	208	17	3	0	228	1420	1648
opt	150	10	0.5	2382.964	4828.5	2445.536	420	1233	66.75	11.9	463.38	250.5	87.4	418.8	1399.6	191	13	3	0	207	1441	1648
opt	150	15	0.5	2201.898	4875.48	2673.582	630	1233	74.00	17.85	468.23	250.5	88	409.3	1390	181	13	3	0	197	1451	1648
opt	200	5	0.5	2354.587	5068.62	2714.033	210	1644	32.71	5.95	487.38	334	91.4	379.2	1376.9	131	10	1	0	142	1506	1648
opt	200	10	0.5	2139.666	5101.68	2962.014	420	1644	60.60	11.9	491.52	334	92.2	373.6	1355.6	119	9	1	0	129	1519	1648
opt	200	15	0.5	1954.406	5148.66	3194.254	630	1644	73.67	17.85	494.73	334	92.9	372.2	1287.2	114	2	1	0	117	1531	1648
opt	300	5	0.5	1648.16	5381.82	3733.66	210	2466	30.67	5.95	520.04	501	96.4	302.4	1229.5	60	0	0	0	60	1588	1648
opt	300	10	0.5	1454.17	5423.58	3969.41	420	2466	45.08	11.9	525.43	501	96.9	306.4	1227.2	50	1	0	0	51	1597	1648
opt	300	15	0.5	1214.118	5397.48	4183.362	630	2466	46.19	17.85	522.32	501	96.5	300.7	1249.8	58	0	0	0	58	1590	1648
opt	300	20	0.5	1016.528	5428.8	4412.272	840	2466	55.05	23.8	526.42	501	97	301.3	1290.7	47	2	0	0	49	1599	1648
opt	400	5	0.5	760.284	5486.22	4725.936	210	3288	22.48	5.95	531.50	668	97.8	275.5	1272.4	36	0	0	0	36	1612	1648
opt	400	10	0.5	567.812	5526.24	4958.428	420	3288	34.37	11.9	536.16	668	98.4	271.7	1249.3	26	0	0	0	26	1622	1648
opt	400	15	0.5	357.265	5538.42	5181.155	630	3288	39.15	17.85	538.16	668	98.5	276.5	1277.4	24	0	0	0	24	1624	1648
opt	400	20	0.5	129.783	5526.24	5396.457	840	3288	39.30	23.8	537.35	668	98.2	270.8	1305.6	29	0	0	0	29	1619	1648
base	390	0	0	1071.83	5456.53	4384.7	0.00	3205.80	0.00	0.00	527.60	651.30	97.3	275.9	1255	45	0	0	0	45	1603	1648
opt	267	5	0	1796.84	5186.14	3389.3	210	2194.74	35.20	5.95	497.52	445.89	93.3	315.5	1307.1	106	5	0	0	111	1537	1648

id1. model	id2. cars	id3. staff	id4. maint.gen.factor	b1. total car distance	b2. #trips with staff in car	b3. car distance with staff (km.veh)	b4. car distance with clients (km.veh)	b5. car time used by clients (h.veh)	b6. car time staff moves (k.veh)	b7. car time idle available (h.veh)	b8. cat time idle need. maint (h.veh)	b9. car time idle being maint. (h.veh)	b10. #cars not used during simulation	c1. staff distance by car (km.ind)	c2. staff distance by pt (km.ind)	c3. staff time idle (h.ind)	c4. staff time in car (h.ind)	c5. staff time in pt (h.ind)	c6. staff time in maintenance (h.ind)	c7. %fulfilled maint	c8. #fullfilled maint requests	c9. #total maint req	c10. #staff moves by vehicle	c11. #staff moves by pt	d1. car distance saved - trip joining (km)	d2. car time saved - trip joining (h)
base	50	0	0	3187.2	0	0	3187.2	174.1	0	425.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	100	0	0	4371	0	0	4371	240.2	0	959.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	150	0	0	4935.8	0	0	4935.8	268.4	0	1531.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	200	0	0	5314.3	0	0	5314.3	286.3	0	2113.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	300	0	0	5671.4	0	0	5671.4	304.6	0	3295.4	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0
base	400	0	0	5873.6	0	0	5873.6	314.2	0	4485.8	0	0	65	0	0	0	0	0	0	0	0	0	0	0	0	0
base	50	0	0.5	3059.6	0	0	3059.6	167.3	0	403.7	29	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0
base	100	0	0.5	4357.4	0	0	4357.4	239.4	0	944.5	16.1	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0
base	150	0	0.5	4905.6	0	0	4905.6	266.6	0	1495.2	38.2	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0
base	200	0	0.5	5276.2	0	0	5276.2	284.9	0	2063.4	51.7	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0
base	300	0	0.5	5663.6	0	0	5663.6	304.2	0	3285.7	10.1	0	15	0	0	0	0	0	0	0	0	3	0	0	0	0
base	400	0	0.5	5873.6	0	0	5873.6	314.2	0	4439.1	46.7	0	62	0	0	0	0	0	0	0	0	9	0	0	0	0
react	50	5	0	3330	51	167.8	3162.2	173.4	8.5	418.1	0	0	0	167.8	295.1	27.5	8.5	24	0	0	0	0	51	71	0	0
react	100	5	0	4628.3	66	208.7	4419.6	241.4	11	947.6	0	0	0	208.7	208	29.7	11	19.3	0	0	0	0	66	58	0	0
react	100	10	0	5091.1	108	562.2	4528.9	247.4	19.5	933.1	0	0	0	562.2	306.5	68.5	19.5	32	0	0	0	0	108	96	0	0
react	150	5	0	5289.2	52	300.1	4989.2	271.2	10.2	1518.6	0	0	0	300.1	118.6	35.8	10.2	14	0	0	0	0	52	42	0	0
react	150	10	0	5533.2	83	464.1	5069.1	275.5	15.5	1509	0	0	0	464.1	185.6	83.2	15.5	21.3	0	0	0	0	83	64	0	0
react	150	15	0	5614.7	85	519.8	5094.9	276.6	16.5	1506.9	0	0	0	519.8	209.8	140.5	16.5	23	0	0	0	0	85	69	0	0
react	200	5	0	5663.1	50	284	5379.1	290	9.7	2100.3	0	0	0	284	157.2	35	9.7	15.3	0	0	0	0	50	45	0	0
react	200	10	0	5836.5	63	428.2	5408.2	291.4	12.7	2095.9	0	0	0	428.2	130.8	91.7	12.7	15.7	0	0	0	0	63	47	0	0
react	200	15	0	5832.9	71	429.2	5403.6	291.1	13.8	2095.1	0	0	0	429.2	143.4	148.8	13.8	17.3	0	0	0	0	71	52	0	0
react	300	5	0	5973.6	29	196.3	5777.3	309.1	5.8	3285	0	0	15	196.3	78.5	46.2	5.8	8	0	0	0	0	29	24	0	0
react	300	10	0	6009.4	34	234.5	5774.9	308.9	7.2	3283.9	0	0	14	234.5	67.7	105.2	7.2	7.7	0	0	0	0	34	23	0	0
react	300	15	0	6001.4	32	230.1	5771.4	308.8	6.7	3284.6	0	0	15	230.1	68.3	165.7	6.7	7.7	0	0	0	0	32	23	0	0
react	300	20	0	5969	32	219.9	5749.1	308.3	6.3	3285.3	0	0	16	219.9	64.1	226.7	6.3	7	0	0	0	0	32	21	0	0
react	400	5	0	6095.2	22	174.6	5920.7	316.4	5	4478.6	0	0	65	174.6	33.1	50.7	5	4.3	0	0	0	0	22	13	0	0
react	400	10	0	6106.4	23	185.8	5920.7	316.4	5.3	4478.3	0	0	64	185.8	33.1	110.3	5.3	4.3	0	0	0	0	23	13	0	0
react	400	15	0	6110.8	24	199.1	5911.7	316.1	5.5	4478.4	0	0	65	199.1	34.4	170.2	5.5	4.3	0	0	0	0	24	13	0	0
react	400	20	0	6079.4	26	149.9	5929.5	316.6	5	4478.4	0	0	63	149.9	46.8	229	5	6	0	0	0	0	26	18	0	0
react	50	5	0.5	3392	46	152.8	3239.2	177.4	7.7	409.1	3.3	2.5	0	152.8	309.9	27	7.7	22.8	2.5	100	5	5	46	64	0	0
react	100	5	0.5	4612.7	55	188.1	4424.6	241.6	9.2	943	3.3	3	0	188.1	269.7	27.2	9.2	20.7	3	100	6	6	55	59	0	0
react	100	10	0.5	5009.8	102	496.9	4512.9	246.1	18.2	930	3.2	2.5	0	496.9	345.8	65.5	18.2	33.8	2.5	83.3	5	6	102	101	0	0
react	150	5	0.5	5277.2	49	286.9	4990.3	271	9.7	1511.4	4.9	3	0	286.9	170.2	32	9.7	15.3	3	100	6	6	49	42	0	0
react	150	10	0.5	5519.7	79	456.2	5063.5	274.9	14.8	1503.6	3.5	3.2	0	456.2	216.5	80	14.8	22	3.2	87.5	7	8	79	66	0	0
react	150	15	0.5	5564	84	495.1	5068.9	275	16	1502.5	3.5	3	0	495.1	238.9	136.3	16	24.7	3	100	6	6	84	73	0	0
react	200	5	0.5	5647.9	47	287.6	5360.3	289.1	9.2	2094.4	4.7	2.7	0	287.6	171.1	32.8	9.2	15.3	2.7	100	6	6	47	45	0	0
react	200	10	0.5	5846	63	405.7	5440.3	293	12.7	2087.4	3.9	3	0	405.7	166.3	86.7	12.7	17.7	3	100	6	6	63	53	0	0
react	200	15	0.5	5843.4	69	431.5	5411.9	291.4	13.5	2089.2	3.4	2.5	0	431.5	168.7	145.7	13.5	18.3	2.5	100	5	5	69	55	0	0
react	300	5	0.5	5952	28	177.7	5774.3	309.3	5.3	3271.4	9.3	4.7	14	177.7	181.3	37.8	5.3	12.2	4.7	83.3	10	12	28	32	0	0
react	300	10	0.5	5996.9	35	230	5766.9	308.8	7.3	3276.5	4.3	3	15	230	87.3	100	7.3	9.7	3	85.7	6	7	35	28	0	0
react	300	15	0.5	6024.4	36	266.4	5758	308.1	8	3272.7	6.6	4.5	17	266.4	144.7	155.7	8	11.8	4.5	81.8	9	11	36	34	0	0
react	300	20	0.5	5970.9	32	219.9	5751	308.5	6.3	3275.6	5.9	3.7	15	219.9	122.4	219.7	6.3	10.3	3.7	100	8	8	32	30	0	0
react	400	5	0.5	6071.2	23	154.5	5916.7	316.1	4.8	4471.3	4.3	3.5	63	154.5	88.3	44.7	4.8	7	3.5	100	7	7	23	21	0	0
react	400	10	0.5	6106.4	23	185.8	5920.7	316.4	5.3	4472.2	3.1	3	64	185.8	57.3	106	5.3	5.7	3	85.7	6	7	23	17	0	0
react	400	15	0.5	6110.8	24	199.1	5911.7	316.1	5.5	4472.3	4.2	2	66	199.1	85.7	164.8	5.5	7.7	2	100	4	4	24	19	0	0
react	400	20	0.5	6097.7	25	169.2	5928.5	316.5	5.3	4468.1	5.1	5	64	169.2	70	222.3	5.3	7.3	5	100	10	10	25	22	0	0
opt	50	5	0	3518.9	45	321.2	3197.7	175.2	7.5	417.3	0	0	0	428.6	557.7	21.2	9.8	29	0	0	0	0	59	78	107.4	2.3
opt	100	5	0	4861.5	57	368.2	4493.2	245.2	9.5	945.3	0	0	0	462.5	535.7	21.5	11.8	26.7	0	0	0	0	71	80	94.3	2.3
opt	100	10	0	5383.2	109	708.6	4674.5	254.1	18.2	927.7	0	0	0	941	926.6	48	23.7	48.3	0	0	0	0	142	145	232.3	5.5
opt	150	5	0	5535.6	60	431.4	5104.2	275	10.2	1514.8	0	0	0	499.4	459.4	26.7	11.7	21.7	0	0	0	0	69	65	68	1.5
opt	150	10	0	5883.6	103	709.1	5174.5	278.7	17.2	1504.1	0	0	0	869.6	736.8	63.5	21.2	35.3	0	0	0	0	127	106	160.5	4
opt	150	15	0	6046.7	129	843	5203.7	280.1	21.5	1498.4	0	0	0	1153.2	794.9	112.7	28.7	38.7	0	0	0	0	172	116	310.2	7.2
opt	200	5	0	5825.4	54	391.2	5434.1	291.9	9.2	2099	0	0	0	448.4	421.7	30.5	10.5	19	0	0	0	0	62	57	57.1	1.3
opt	200	10	0	6112.7	87	639.2	5473.5	294.1	14.7	2091.2	0	0	0	847	528.2	74.2	18.8	27	0	0	0	0	112	79	207.8	4.2
opt	200	15	0	6377.1	123	889.4	5487.7	294.8	21	2084.2	0	0	0	1272.4	553.4	124.7	30.3	25	0	0	0	0	179	75	383	9.3
opt	300	5	0	6077.3	40	307.7	5769.6	308.7	7.2	3284.2	0	0	11	374.7	240.8	40.3	8.3	11.3	0	0	0	0	47	34	67.1	1.2
opt	300	10	0	6359.5	70	516.2	5843.3	311.6	12.2	3276.2	0	0	7	670.5	344	88.8	15.5	15.7	0	0	0	0	90	47	154.4	3.3
opt	300	15	0	6319.4	69	538.2	5781.2	309.2	12	3278.8	0	0	12	743.3	254	152.2	16.2	11.7	0	0	0	0	94	35	205.1	4.2
opt	300	20	0	6451.2	80	599.3	5852	312.4	13.5	3274.1	0	0	10	869.9	235.7	209.5	19.8	10.7	0	0	0	0	118	32	270.6	6.3
opt	400	5	0	6139.5	30	233.9	5905.6	315.3	5.3	4479.4	0	0	63	292.9	178.3	45.2	6.5	8.3	0	0	0	0	37	25	59	1.2
opt	400	10	0	6342.9	47	398.8	5944.1	316.8	8.2	4475	0	0	60	523.1	183.5	101.8	10.8	7.3	0	0	0	0	63	22	124.4	2.7
opt	400	15	0	6351.8	47	377.6	5974.2	318	8.2	4473.9	0	0	59	545.3	148.1	161.3	12	6.7	0	0	0	0	70	20	167.6	3.8
opt	400	20	0	6418.3	55	423.3	5995	318.9	9.8	4471.3	0	0	54	617	143	219.7	14	6.3	0	0	0	0	80	19	193.7	4.2
opt	50	5	0.5	3493.9	46	322.8	3164.4	175.9	7.8	401.5	12.6	2	0	392.8	519.7	21.5	9.5	27	2	80	4	5	55	79	70	1.7
opt	100	5	0.5	4699	39	268.6	4430.4	243.6	6.7	934.7	10	5	0	327.4	495.6	21.2	8.2	25.7	5	90.9	10	11	48	72	58.8	1.5
opt	100	10	0.5	5266.4	102	720.8	4545.5	247.4	17	929.7	3.9	2	0	944.1	885.3	51.7	22	44.3	2	100	4	4	132	133	223.2	5
opt	150	5	0.5	5545	69	470	5075	273.9	11.7	1484.7	24.5	5.2	0	539.7	594.4	15.5	13.3	26	5.2	78.6	11	14	79	78	69.7	1.7
opt	150	10	0.5	5890.4	108	741.7	5148.7	277.5	18	1489.1	10.9	4.5	0	958.9	768.8	55.5	23.3	36.7	4.5	90	9	10	140	110	217.2	5.3
opt	150	15	0.5	6024.8	119	822.2	5202.6	280.2	19.8	1496.3	2.1	1.5	0	1143.7	781.4	111.3	27.8	39.3	1.5	100	3	3	167	118	321.5	8
opt	200	5	0.5	5778.8	54	363.4	5415.3	291.3	9.2	2083.1	12.4	4	0	442.2	417.4	23.2	10.8	22	4	80	8	10	64	66	78.7	1.7
opt	200	10	0.5	6134.6	96	673.3	5461.3	293.2	16	2074.5	11.3	5	0	803.9	540.9	68.3	18.7	28	5	90.9	10	11	112	84	130.6	2.7
opt	200	15	0.5	6315.6	116	818.6	5497	295.9	19.7	2072.9	7.1	4.5	0	1197	606.3	116	28.5	31	4.5	100	9	9	169	89	378.4	8.8
opt	300	5	0.5	6119.1	43	340.8	5778.2	309.3	7.7	3269.9	10.1	3	6	391.7	284.4	36.8	8.5	11.7	3	85.7	6	7	48	35	50.8	0.8
opt	300	10	0.5	6338.9	67	500.9	5838.1	311.7	11.3	3269.6	4.9	2.5	6	670.8	387.4	86	14.8	16.7	2.5	100	5	5	88	50	169.9	3.5
opt	300	15	0.5	6316.8	72	513.2	5803.6	310.2	12.7	3269.4	4.9	2.8	13	672.2	284.9	147.3	16.2	13.7	2.8	85.7	6	7	93	41	159.1	3.5
opt	300	20	0.5	6460.8	83	611.7	5849.1	312	14	3263.9	6.5	3.5	8	844.2	294.4	202.7	19.5	14.3	3.5	87.5	7	8	116	43	232.4	5.5
opt	400	5	0.5	6155.4	31	249.8	5905.6	315.3	5.5	4475	3.2	1	63	314.8	181.9	43.8	6.8	8.3	1	66.7	2	3	39	25	65.1	1.3
opt	400	10	0.5	6339.2	47	381.9	5957.3	317.6	8.3	4467.6	4	2.5	58	516.3	175.3	99	11.2	7.3	2.5	100	5	5	64	22	134.4	2.8
opt	400	15	0.5	6414.4	57	435	5979.5	318.3	10	4461.2	7	3.5	60	540.5	167.7	156	12.5	8	3.5	87.5	7	8	72	24	105.6	2.5
opt	400	20	0.5	6407.3	57	436.7	5970.6	317.6	10	4462.9	5.6	4	64	633.6	126	215.8	14.5	5.7	4	100	8	8	84	17	196.9	4.5
base	390	0	0	5862.2	0	0	5862.2	313.6	0	4366.4	0	0	59	0	0	0	0	0	0	0	0	0	0	0	0	0
opt	267	5	0	5919.1	58	391.1	5528	298.1	9.8	2896.1	0	0	0	485.1	487.3	21.8	12.5	25.7	0	0	0	0	73	76	84	2.7

B. Simulation aggregate results for 15% of demand scenarios

(Note: the designation “react” corresponds to the rule-based model)

id1. model	id2. cars	id3. staff	id4. maint.gen.factor	profit	in2. total paid by clients	out1. total costs	out2. wage	out3. car depreciation	out4. staff mov in cars	out5. staff mov in pt	out6. client mov	out7. parking	a1. %accepted trips	a2. avg dist car-client accepted (m)	a3. avg dist car-client rejected (m)	a4. #rejected trips car dist >1 and <2km	a5. #rejected trips car dist >2 and <3km	a6. #rejected trips car dist> 3km	a7. #rejected no car at any dist	a8. #total rejected trips	a9. #total accepted trips	a10. #total trips
base	100	0	0	4940.03	6559.99	1619.96	0	822	0	0	630.96	167	63.9	494.1	1758.5	741	266	87	0	1094	1939	3034
base	150	0	0	5441.32	7661.19	2219.87	0	1233	0	0	736.37	250.5	74.4	430.2	1734.3	549	164	63	0	776	2257	3034
base	200	0	0	5625.81	8411.54	2785.73	0	1644	0	0	807.73	334	81.4	388.3	1657.5	428	90	46	0	564	2469	3034
base	300	0	0	5509.49	9383.67	3874.18	0	2466	0	0	907.18	501	89.8	330.5	1517.6	254	43	12	0	309	2724	3034
base	400	0	0	4890.83	9799.09	4908.26	0	3288	0	0	952.26	668	93.4	280.7	1475.7	169	25	7	0	201	2832	3034
base	500	0	0	4122.7	10050.47	5927.77	0	4110	0	0	982.77	835	95.5	249.1	1465.4	116	20	1	0	137	2896	3034
base	100	0	0.5	4857.14	6465.87	1608.73	0	822	0	0	619.73	167	63.1	501.2	1807	751	252	116	0	1119	1914	3034
base	150	0	0.5	5391.3	7606.79	2215.49	0	1233	0	0	731.99	250.5	73.8	435.1	1735.7	564	165	66	0	795	2238	3034
base	200	0	0.5	5489.25	8260.99	2771.74	0	1644	0	0	793.74	334	79.9	389.2	1641.6	464	98	47	0	609	2424	3034
base	300	0	0.5	5457.08	9326.12	3869.04	0	2466	0	0	902.04	501	89.3	337.2	1488.3	272	42	11	0	325	2708	3034
base	400	0	0.5	4868.76	9774.94	4906.18	0	3288	0	0	950.18	668	93.1	286.8	1476.5	178	25	7	0	210	2823	3034
base	500	0	0.5	4113.81	10040.61	5926.8	0	4110	0	0	981.8	835	95.4	251.4	1460.9	119	20	1	0	140	2893	3034
react	100	5	0	4864.68	6736.5	1871.82	210	822	19.83	5.95	647.04	167	65.8	487.5	1823.3	705	211	121	0	1037	1997	3034
react	100	10	0	4707.75	6826.41	2118.66	420	822	43.68	11.9	654.08	167	66.9	484.2	1952.2	687	187	131	0	1005	2029	3034
react	150	5	0	5241.86	7702.49	2460.63	210	1233	20.99	5.95	740.19	250.5	74.8	428.6	1753.1	541	158	65	0	764	2270	3034
react	150	10	0	5058.93	7765.13	2706.2	420	1233	45.99	11.9	744.81	250.5	75.6	428.3	1694.2	528	162	50	0	740	2294	3034
react	150	15	0	4914	7871.68	2957.68	630	1233	69.83	17.85	756.5	250.5	76.7	426.5	1791	481	155	71	0	707	2327	3034
react	200	5	0	5405.41	8436.19	3030.78	210	1644	25.52	5.95	811.31	334	81.8	391.4	1610.5	410	118	25	0	553	2481	3034
react	200	10	0	5244.69	8522.2	3277.51	420	1644	45.86	11.9	821.75	334	82.4	385.7	1689.3	398	88	47	0	533	2501	3034
react	200	15	0	5070.69	8586.24	3515.55	630	1644	60.84	17.85	828.86	334	83	387.6	1662.9	370	113	32	0	515	2519	3034
react	300	5	0	5276.07	9397.46	4121.39	210	2466	26.51	5.95	911.93	501	90	331.3	1525.8	251	34	19	0	304	2730	3034
react	300	10	0	5061.11	9416.02	4354.91	420	2466	42.85	11.9	913.16	501	90.1	330.3	1499.9	249	38	12	0	299	2735	3034
react	300	15	0	4868.08	9444.41	4576.33	630	2466	45.43	17.85	916.05	501	90.3	330.3	1511.6	242	39	12	0	293	2741	3034
react	300	20	0	4641.4	9431.08	4789.68	840	2466	44.05	23.8	914.83	501	90.2	328.4	1492.8	246	39	12	0	297	2737	3034
react	400	5	0	4743.68	9904.87	5161.19	210	3288	24.14	5.95	965.1	668	94.3	279.7	1465.1	148	19	7	0	174	2860	3034
react	400	10	0	4528.57	9908.17	5379.6	420	3288	26.44	11.9	965.26	668	94.4	280.2	1468.8	143	19	7	0	169	2865	3034
react	400	15	0	4307.51	9902.04	5594.53	630	3288	26.25	17.85	964.43	668	94.3	281	1476.8	146	20	7	0	173	2861	3034
react	400	20	0	4091.52	9902.04	5810.52	840	3288	26.29	23.8	964.43	668	94.3	281.1	1476.8	146	20	7	0	173	2861	3034
react	500	5	0	3934.95	10098.28	6163.33	210	4110	13.76	5.95	988.62	835	95.9	249.7	1441.9	110	12	1	0	123	2911	3034
react	500	10	0	3719	10098.28	6379.28	420	4110	13.76	11.9	988.62	835	95.9	249.7	1441.9	110	12	1	0	123	2911	3034
react	500	15	0	3501.5	10100.24	6598.74	630	4110	16.95	17.85	988.94	835	95.9	249.8	1445.6	110	12	1	0	123	2911	3034
react	500	20	0	3288.86	10103.7	6814.84	840	4110	16.83	23.8	989.21	835	96	250.2	1435.3	109	12	1	0	122	2912	3034
react	100	5	0.5	4718.42	6569.62	1851.2	210	822	14.79	5.95	631.46	167	64.3	495.6	1740.1	757	243	83	0	1083	1951	3034
react	100	10	0.5	4719.06	6830.85	2111.79	420	822	37.77	11.9	653.12	167	67.2	482.5	1794.1	683	217	96	0	996	2038	3034
react	150	5	0.5	5241.42	7700.09	2458.67	210	1233	17.46	5.95	741.76	250.5	74.7	434	1676.1	548	176	44	0	768	2266	3034
react	150	10	0.5	5072.08	7783.77	2711.69	420	1233	46.78	11.9	749.51	250.5	75.5	432	1764.2	518	157	69	0	744	2290	3034
react	150	15	0.5	4920.21	7874.53	2954.32	630	1233	65.83	17.85	757.14	250.5	76.4	428.4	1778.4	493	149	73	0	715	2319	3034
react	200	5	0.5	5402.24	8429.93	3027.69	210	1644	20.98	5.95	812.76	334	81.6	392.7	1598.5	420	113	26	0	559	2475	3034
react	200	10	0.5	5249.99	8526.26	3276.27	420	1644	45.48	11.9	820.89	334	82.5	381.8	1695.8	388	98	44	0	530	2504	3034
react	200	15	0.5	5011.99	8523.62	3511.63	630	1644	62.55	17.85	823.23	334	82.5	391.8	1609.3	404	97	30	0	531	2503	3034
react	300	5	0.5	5261.34	9376.23	4114.89	210	2466	22.7	5.95	909.24	501	89.7	332.6	1486.9	265	36	12	0	313	2721	3034
react	300	10	0.5	5066.23	9418.18	4351.95	420	2466	38.63	11.9	914.42	501	90	334.6	1532.9	247	42	14	0	303	2731	3034
react	300	15	0.5	4821.57	9394.44	4572.87	630	2466	47.32	17.85	910.7	501	90	333.1	1586.7	242	35	25	0	302	2732	3034
react	300	20	0.5	4638.19	9431.32	4793.13	840	2466	45.22	23.8	917.11	501	90	330.5	1507.8	254	35	14	0	303	2731	3034
react	400	5	0.5	4739.08	9899.47	5160.39	210	3288	23.73	5.95	964.71	668	94.2	282.2	1474.9	149	20	7	0	176	2858	3034
react	400	10	0.5	4528.57	9908.17	5379.6	420	3288	26.44	11.9	965.26	668	94.4	280.4	1468.8	143	19	7	0	169	2865	3034
react	400	15	0.5	4296.56	9891.05	5594.49	630	3288	26.81	17.85	963.83	668	94.1	282.8	1454	152	19	7	0	178	2856	3034
react	400	20	0.5	4067.12	9875.43	5808.31	840	3288	26.38	23.8	962.13	668	94	284.7	1462.5	156	19	7	0	182	2852	3034
react	500	5	0.5	3937.03	10098.77	6161.74	210	4110	11.84	5.95	988.95	835	95.9	251.1	1424.6	111	12	1	0	124	2910	3034
react	500	10	0.5	3709.73	10088.76	6379.03	420	4110	14.8	11.9	987.33	835	95.8	251.6	1461.5	108	17	1	0	126	2908	3034
react	500	15	0.5	3496.88	10091.41	6594.53	630	4110	13.97	17.85	987.71	835	95.9	249	1469.9	107	17	1	0	125	2909	3034
react	500	20	0.5	3287.2	10099.2	6812	840	4110	14.47	23.8	988.73	835	95.9	250.8	1432.7	110	12	1	0	123	2911	3034
opt	100	5	0	4920.65	6812.81	1892.16	210	822	35.78	5.95	651.43	167	66.5	492.1	1762.2	694	231	91	0	1016	2018	3034
opt	100	10	0	4699.38	6838.27	2138.89	420	822	64.38	11.9	653.61	167	67.1	484.5	1827.5	670	217	112	0	999	2035	3034
opt	150	5	0	5342.12	7837.39	2495.27	210	1233	45.5	5.95	750.32	250.5	76.5	422.1	1809.5	490	151	73	0	714	2320	3034
opt	150	10	0	5166.73	7900.96	2734.23	420	1233	61.77	11.9	757.06	250.5	77	413.3	1898.2	484	134	79	0	697	2337	3034
opt	150	15	0	4933.79	7900.78	2966.99	630	1233	77.62	17.85	758.02	250.5	77	418.8	1729.2	478	161	58	0	697	2337	3034
opt	200	5	0	5440.36	8494.39	3054.03	210	1644	42.85	5.95	817.23	334	82.3	384	1617.9	401	109	27	0	537	2497	3034
opt	200	10	0	5245.25	8554.63	3309.38	420	1644	76.26	11.9	823.22	334	83	375.9	1597.9	386	106	25	0	517	2517	3034
opt	200	15	0	5034.7	8577.06	3542.36	630	1644	93.49	17.85	823.02	334	83.4	378.6	1633.6	375	97	31	0	503	2531	3034
opt	300	5	0	5271.35	9402.23	4130.88	210	2466	37.73	5.95	910.2	501	90.1	326.1	1489	249	38	12	0	299	2735	3034
opt	300	10	0	5089.47	9469.83	4380.36	420	2466	63.65	11.9	917.81	501	90.7	324.6	1514.9	230	39	12	0	281	2753	3034
opt	300	15	0	4860.49	9455.66	4595.17	630	2466	64.29	17.85	916.03	501	90.5	327.8	1504.2	239	36	12	0	287	2747	3034
opt	300	20	0	4613.09	9441.13	4828.04	840	2466	81.69	23.8	915.55	501	90.5	324.8	1502.4	236	39	12	0	287	2747	3034
opt	400	5	0	4690.54	9849.88	5159.34	210	3288	29.12	5.95	958.27	668	93.8	279	1488.7	157	24	7	0	188	2846	3034
opt	400	10	0	4478.93	9875.92	5396.99	420	3288	46.34	11.9	962.75	668	93.9	282.9	1466.5	158	19	7	0	184	2850	3034
opt	400	15	0	4295.18	9916.16	5620.98	630	3288	49.91	17.85	967.22	668	94.3	280.4	1445.9	151	14	7	0	172	2862	3034
opt	400	20	0	4105.3	9954.66	5849.36	840	3288	58.86	23.8	970.7	668	94.8	285.8	1502.5	132	20	7	0	159	2875	3034
opt	500	5	0	3928.02	10108.31	6180.29	210	4110	29.62	5.95	989.72	835	95.9	253.7	1470.4	106	16	1	0	123	2911	3034
opt	500	10	0	3701.18	10098.97	6397.79	420	4110	32	11.9	988.89	835	95.9	250.3	1464	106	17	1	0	124	2910	3034
opt	500	15	0	3495.87	10125.37	6629.5	630	4110	45.51	17.85	991.14	835	96.1	253.2	1436.2	102	14	1	0	117	2917	3034
opt	500	20	0	3290.2	10142.44	6852.24	840	4110	49.88	23.8	993.56	835	96.3	251.1	1444.8	97	14	1	0	112	2922	3034
opt	100	5	0.5	4830.73	6712.41	1881.68	210	822	31.06	5.95	645.67	167	65.4	497.3	1898.2	695	230	125	0	1050	1984	3034
opt	100	10	0.5	4678.88	6808.56	2129.68	420	822	61.91	11.9	646.87	167	66.8	476.1	1898.4	647	240	121	0	1008	2026	3034
opt	150	5	0.5	5290.79	7775.49	2484.7	210	1233	38.21	5.95	747.04	250.5	75.7	419.4	1722.8	528	145	63	0	736	2298	3034
opt	150	10	0.5	5147.75	7886.83	2739.08	420	1233	65.66	11.9	758.02	250.5	76.7	424.7	1762.5	477	165	66	0	708	2326	3034
opt	150	15	0.5	4915.19	7871.88	2956.69	630	1233	73.22	17.85	752.12	250.5	76.9	419.8	1732.5	486	154	60	0	700	2334	3034
opt	200	5	0.5	5412.58	8461.32	3048.74	210	1644	42.06	5.95	812.73	334	81.9	376.8	1706.3	403	94	51	0	548	2486	3034
opt	200	10	0.5	5258	8553.56	3295.56	420	1644	64.4	11.9	821.26	334	82.9	376.9	1635.8	385	102	31	0	518	2516	3034
opt	200	15	0.5	5057.53	8586.54	3529.01	630	1644	76.86	17.85	826.3	334	83.2	379	1570.6	399	92	18	0	509	2525	3034
opt	300	5	0.5	5269	9408.6	4139.6	210	2466	44.78	5.95	911.87	501	90.1	328.5	1483.2	251	38	11	0	300	2734	3034
opt	300	10	0.5	5035.98	9403.82	4367.84	420	2466	58.37	11.9	910.57	501	90.1	328.7	1500.8	249	41	11	0	301	2733	3034
opt	300	15	0.5	4830.45	9433.72	4603.27	630	2466	75.45	17.85	912.97	501	90.4	326.2	1480.6	241	38	11	0	290	2744	3034
opt	300	20	0.5	4617.44	9448.89	4831.45	840	2466	84.66	23.8	915.99	501	90.6	326.5	1514.4	235	35	14	0	284	2750	3034
opt	400	5	0.5	4706.77	9873.71	5166.94	210	3288	33.2	5.95	961.79	668	94	282.7	1486.6	151	24	7	0	182	2852	3034
opt	400	10	0.5	4480.66	9879.38	5398.72	420	3288	48.68	11.9	962.14	668	94.1	284.1	1508.8	147	24	7	0	178	2856	3034
opt	400	15	0.5	4274.59	9901.63	5627.04	630	3288	58.14	17.85	965.05	668	94.2	286.5	1479.1	147	21	7	0	175	2859	3034
opt	400	20	0.5	4081.02	9940.69	5859.67	840	3288	70.11	23.8	969.76	668	94.6	291.1	1482.9	139	18	7	0	164	2870	3034
opt	500	5	0.5	3924.06	10106.33	6182.27	210	4110	31.65	5.95	989.67	835	95.9	248.9	1432.2	108	15	1	0	124	2910	3034
opt	500	10	0.5	3710.7	10118.94	6408.24	420	4110	39.57	11.9	991.77	835	96	250.9	1449.6	105	15	1	0	121	2913	3034
opt	500	15	0.5	3465.08	10087.31	6622.23	630	4110	42.46	17.85	986.92	835	95.8	254.5	1432.2	111	15	1	0	127	2907	3034
opt	500	20	0.5	3285.67	10142.06	6856.39	840	4110	54.65	23.8	992.94	835	96.3	248.6	1451.6	97	14	1	0	112	2922	3034

id1. model	id2. cars	id3. staff	id4. maint.gen.factor	b1. total car distance	b2. #trips with staff in car	b3. car distance with staff (km.veh)	b4. car distance with clients (km.veh)	b5. car time used by clients (h.veh)	b6. car time staff moves (k.veh)	b7. car time idle available (h.veh)	b8. cat time idle need. maint (h.veh)	b9. car time idle being maint. (h.veh)	b10. #cars not used during simulation	c1. staff distance by car (km.ind)	c2. staff distance by pt (km.ind)	c3. staff time idle (h.ind)	c4. staff time in car (h.ind)	c5. staff time in pt (h.ind)	c6. staff time in maintenance (h.ind)	c7. %fulfilled maint	c8. #fulfilled maint requests	c9. #total maint req	c10. #staff moves by vehicle	c11. #staff moves by pt	d1. car distance saved - trip joining (km)	d2. car time saved - trip joining (h)
base	100	0	0	7010.7	0	0	7010.7	377	0	823	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	150	0	0	8181.9	0	0	8181.9	440.3	0	1359.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	200	0	0	8974.8	0	0	8974.8	483.4	0	1916.6	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
base	300	0	0	10079.7	0	0	10079.7	539.3	0	3060.7	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
base	400	0	0	10580.7	0	0	10580.7	563.2	0	4236.8	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0
base	500	0	0	10919.6	0	0	10919.6	577.6	0	5422.4	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0
base	100	0	0.5	6885.9	0	0	6885.9	371.6	0	775.7	52.7	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0
base	150	0	0.5	8133.2	0	0	8133.2	437.2	0	1301	61.8	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0
base	200	0	0.5	8819.3	0	0	8819.3	474.8	0	1832.1	93.1	0	1	0	0	0	0	0	0	0	0	14	0	0	0	0
base	300	0	0.5	10022.7	0	0	10022.7	536	0	2992.8	71.3	0	1	0	0	0	0	0	0	0	0	12	0	0	0	0
base	400	0	0.5	10557.6	0	0	10557.6	561.8	0	4142.7	95.5	0	10	0	0	0	0	0	0	0	0	14	0	0	0	0
base	500	0	0.5	10908.9	0	0	10908.9	577	0	5374.7	48.3	0	47	0	0	0	0	0	0	0	0	12	0	0	0	0
react	100	5	0	7409.6	63	220.3	7189.3	387.2	10.5	802.3	0	0	0	220.3	230.9	29.5	10.5	20	0	0	0	0	63	59	0	0
react	100	10	0	7752.9	123	485.3	7267.6	392.3	20.5	787.2	0	0	0	485.3	540.9	59.2	20.5	40.3	0	0	0	0	123	118	0	0
react	150	5	0	8457.6	68	233.3	8224.4	442.7	11.5	1345.8	0	0	0	233.3	162.5	30.2	11.5	18.3	0	0	0	0	68	55	0	0
react	150	10	0	8786.8	126	511	8275.7	446.3	21.7	1332.1	0	0	0	511	374.5	60	21.7	38.3	0	0	0	0	126	113	0	0
react	150	15	0	9181.4	175	775.9	8405.5	452.4	30.7	1316.9	0	0	0	775.9	531.5	93	30.7	56.3	0	0	0	0	175	168	0	0
react	200	5	0	9298.2	62	283.6	9014.5	484.8	11	1904.2	0	0	0	283.6	152.2	29.7	11	19.3	0	0	0	0	62	58	0	0
react	200	10	0	9640.1	118	509.5	9130.6	489.8	20.7	1889.6	0	0	0	509.5	286.6	66.3	20.7	33	0	0	0	0	118	99	0	0
react	200	15	0	9885.5	149	676	9209.5	493.5	26.2	1880.4	0	0	0	676	361.5	111.5	26.2	42.3	0	0	0	0	149	127	0	0
react	300	5	0	10427.2	56	294.6	10132.6	540.1	10.8	3049.1	0	0	1	294.6	134.7	33.5	10.8	15.7	0	0	0	0	56	47	0	0
react	300	10	0	10622.4	80	476.2	10146.3	541.2	15.7	3043.2	0	0	0	476.2	148.4	86.7	15.7	17.7	0	0	0	0	80	53	0	0
react	300	15	0	10683.1	84	504.8	10178.3	542.8	15.7	3041.6	0	0	0	504.8	134.7	148.3	15.7	16	0	0	0	0	84	48	0	0
react	300	20	0	10654.2	90	489.4	10164.8	542	16.7	3041.3	0	0	1	489.4	167.4	202.3	16.7	21	0	0	0	0	90	63	0	0
react	400	5	0	10991.6	38	268.3	10723.4	569.2	8	4222.8	0	0	9	268.3	78	43.7	8	8.3	0	0	0	0	38	25	0	0
react	400	10	0	11018.9	44	293.8	10725.1	569.4	8.8	4221.7	0	0	5	293.8	78.8	101.8	8.8	9.3	0	0	0	0	44	28	0	0
react	400	15	0	11007.5	44	291.6	10715.9	569.1	8.7	4222.3	0	0	9	291.6	91.1	161.3	8.7	10	0	0	0	0	44	30	0	0
react	400	20	0	11008	45	292.1	10715.9	569.1	9	4221.9	0	0	9	292.1	93.6	220.7	9	10.3	0	0	0	0	45	31	0	0
react	500	5	0	11137.6	23	152.9	10984.7	580.4	4.7	5415	0	0	40	152.9	32.7	51.3	4.7	4	0	0	0	0	23	12	0	0
react	500	10	0	11137.6	23	152.9	10984.7	580.4	4.7	5415	0	0	40	152.9	32.7	111.3	4.7	4	0	0	0	0	23	12	0	0
react	500	15	0	11176.6	26	188.3	10988.2	580.5	5.2	5414.4	0	0	40	188.3	41.3	169.5	5.2	5.3	0	0	0	0	26	16	0	0
react	500	20	0	11178.3	28	187	10991.3	580.7	5.5	5413.8	0	0	39	187	55.4	228.5	5.5	6	0	0	0	0	28	17	0	0
react	100	5	0.5	7180.6	53	164.4	7016.3	377.6	8.8	802.2	6.9	4.5	0	164.4	241.1	26.3	8.8	20.3	4.5	100	9	9	53	57	0	0
react	100	10	0.5	7676.5	107	419.6	7256.9	392.6	17.8	776.5	7.6	5.5	0	419.6	547.8	55.5	17.8	41.2	5.5	100	11	11	107	117	0	0
react	150	5	0.5	8435.9	53	194.1	8241.8	442.5	8.8	1331.3	10.7	6.7	0	194.1	226.8	26.8	8.8	17.7	6.7	100	14	14	53	52	0	0
react	150	10	0.5	8847.7	124	519.8	8327.9	447.3	21.5	1322.6	4.9	3.7	0	519.8	387.2	57.8	21.5	37	3.7	100	8	8	124	109	0	0
react	150	15	0.5	9144.2	170	731.5	8412.7	452.6	29.3	1305.1	7.5	5.5	0	731.5	617.8	87.5	29.3	57.7	5.5	100	11	11	170	169	0	0
react	200	5	0.5	9263.8	50	233.2	9030.7	484.5	8.8	1891.8	9.9	5	0	233.2	183.5	28.8	8.8	17.3	5	100	10	10	50	50	0	0
react	200	10	0.5	9626.3	105	505.3	9121	490	19	1873.5	10.5	7	0	505.3	346.8	59.7	19	34.3	7	100	14	14	105	98	0	0
react	200	15	0.5	9842	147	695	9147	489.9	26.5	1875.7	4.4	3.5	0	695	389.5	106.3	26.5	43.7	3.5	87.5	7	8	147	130	0	0
react	300	5	0.5	10354.8	48	252.2	10102.6	538.9	8.7	3036.3	9.7	6.5	1	252.2	192.2	29	8.7	15.8	6.5	92.9	13	14	48	46	0	0
react	300	10	0.5	10589.5	75	429.3	10160.2	541.3	14.3	3021.8	13	9.5	1	429.3	271.4	72.8	14.3	23.3	9.5	95	19	20	75	68	0	0
react	300	15	0.5	10644.7	88	525.8	10118.9	539.9	16.7	3026.4	8.8	8.2	0	525.8	225.9	131.8	16.7	23.3	8.2	100	17	17	88	67	0	0
react	300	20	0.5	10692.6	88	502.5	10190.1	542	16.7	3027.9	7.9	5.5	0	502.5	213.9	195.5	16.7	22.3	5.5	91.7	11	12	88	65	0	0
react	400	5	0.5	10982.6	37	263.6	10719	568.9	7.5	4213.5	5.6	4.5	10	263.6	110.1	38	7.5	10	4.5	100	9	9	37	30	0	0
react	400	10	0.5	11018.9	44	293.8	10725.1	569.4	8.8	4214.2	3.9	3.7	5	293.8	130.9	95.8	8.8	11.7	3.7	100	8	8	44	35	0	0
react	400	15	0.5	11007.1	46	297.9	10709.2	568.5	9.5	4203.1	10.5	8.5	10	297.9	143.9	147	9.5	15	8.5	94.4	17	18	46	45	0	0
react	400	20	0.5	10983.5	47	293.1	10690.3	567.6	9.5	4204.9	9.4	8.7	8	293.1	145.5	207.2	9.5	14.7	8.7	100	18	18	47	41	0	0
react	500	5	0.5	11119.9	19	131.5	10988.4	580.4	3.8	5395.5	13.8	6.5	40	131.5	184.3	39.3	3.8	10.3	6.5	86.7	13	15	19	25	0	0
react	500	10	0.5	11134.8	23	164.4	10970.4	579.8	4.7	5393	11.9	10.7	43	164.4	148.4	94.3	4.7	10.3	10.7	95.7	22	23	23	28	0	0
react	500	15	0.5	11129.7	26	155.2	10974.6	580	5	5403.4	6.7	5	40	155.2	100.4	161.7	5	8.3	5	90.9	10	11	26	24	0	0
react	500	20	0.5	11146.7	24	160.8	10985.9	580.4	4.8	5402.1	6.6	6	40	160.8	129.6	219.8	4.8	9.3	6	100	12	12	24	25	0	0
opt	100	5	0	7635.7	54	397.5	7238.1	391.5	9	799.5	0	0	0	463.6	525.3	20.5	10.5	29	0	0	0	0	63	86	66	1.5
opt	100	10	0	7977.6	104	715.3	7262.3	393	17.5	789.5	0	0	0	1080.5	810.2	51.2	26.2	42.7	0	0	0	0	156	129	365.2	8.7
opt	150	5	0	8842.5	68	505.6	8336.9	450.4	11.3	1338.2	0	0	0	590	617.1	17.7	13	29.3	0	0	0	0	78	88	84.4	1.7
opt	150	10	0	9098.2	101	686.4	8411.8	454.1	16.8	1329.1	0	0	0	951.6	914.5	53	23.3	43.7	0	0	0	0	140	131	265.2	6.5
opt	150	15	0	9284.9	131	862.5	8422.4	454.1	22.2	1323.8	0	0	0	1418.1	1127.4	81.3	36	62.7	0	0	0	0	213	163	555.6	13.8
opt	200	5	0	9556.5	66	476.1	9080.4	488.2	11.3	1900.5	0	0	0	554.1	501.3	20.8	13.5	25.7	0	0	0	0	79	76	78	2.2
opt	200	10	0	9994.3	119	847.4	9146.9	491.6	20.7	1887.7	0	0	0	1199	819.1	45.2	29.8	45	0	0	0	0	174	129	351.6	9.2
opt	200	15	0	10183.4	160	1038.7	9144.7	492.9	26.7	1880.4	0	0	0	1435.7	1027.4	90.2	37.2	52.7	0	0	0	0	223	154	397	10.5
opt	300	5	0	10532.6	60	419.3	10113.3	540.4	10.2	3049.5	0	0	0	510.3	570.3	20.5	12.5	27	0	0	0	0	74	80	91.1	2.3
opt	300	10	0	10905.2	109	707.3	10197.9	544.2	18.2	3037.6	0	0	0	1094.8	685.8	56.2	27.8	36	0	0	0	0	167	106	387.5	9.7
opt	300	15	0	10892.5	113	714.3	10178.2	543.4	18.8	3037.7	0	0	0	979.8	649.1	118.8	25.8	35.3	0	0	0	0	155	100	265.5	7
opt	300	20	0	11080.4	132	907.7	10172.7	542.6	22.2	3035.2	0	0	0	1350.3	819.3	161	34.3	44.7	0	0	0	0	205	131	442.6	12.2
opt	400	5	0	10971.1	46	323.6	10647.5	566.1	7.8	4226.1	0	0	7	489	375.5	30.2	11.2	18.7	0	0	0	0	66	56	165.4	3.3
opt	400	10	0	11212.1	69	514.9	10697.3	567.6	11.7	4220.8	0	0	7	703.4	480.6	80.7	15.3	24	0	0	0	0	91	70	188.5	3.7
opt	400	15	0	11301.5	80	554.6	10746.9	569.9	13.5	4216.6	0	0	7	909.9	442.1	138	20.7	21.3	0	0	0	0	123	64	355.3	7.2
opt	400	20	0	11439.5	95	654	10785.5	572.1	15.8	4212.1	0	0	7	1052.2	527.9	188.7	25	26.3	0	0	0	0	150	79	398.2	9.2
opt	500	5	0	11325.9	44	329.1	10996.9	580.9	8	5411.1	0	0	43	384.3	311.9	36.8	9.2	14	0	0	0	0	51	42	55.3	1.2
opt	500	10	0	11343.3	47	355.6	10987.7	580.4	8	5411.6	0	0	43	543.7	333.8	93.8	11.8	14.3	0	0	0	0	70	43	188.2	3.8
opt	500	15	0	11518.3	66	505.6	11012.6	581.9	11	5407.1	0	0	38	860.5	425.2	141.2	18.8	20	0	0	0	0	113	60	354.8	7.8
opt	500	20	0	11593.8	74	554.2	11039.6	582.9	12.5	5404.6	0	0	37	924.1	383.5	202.7	20.3	17	0	0	0	0	121	51	369.9	7.8
opt	100	5	0.5	7519.2	52	345.1	7174.1	385.8	8.7	784.4	17.7	3.5	0	427	531.7	16.7	10.8	29	3.5	87.5	7	8	65	85	81.9	2.2
opt	100	10	0.5	7875.3	109	687.9	7187.4	391.3	18.2	774.3	13.5	2.8	0	972.1	917.2	43	25.7	48.5	2.8	85.7	6	7	154	145	284.3	7.5
opt	150	5	0.5	8725	57	424.5	8300.4	446.9	9.5	1313.8	25.6	4.2	0	494	581.1	16.7	10.8	28.3	4.2	64.3	9	14	65	84	69.4	1.3
opt	150	10	0.5	9152	108	729.5	8422.4	453.3	18.2	1300.4	21.8	6.3	0	993.4	897.3	41.8	24.3	47.5	6.3	86.7	13	15	145	143	263.9	6.2
opt	150	15	0.5	9170.5	120	813.6	8356.9	452.4	20.2	1301.3	19.5	6.7	0	1210.9	1067	85.7	30.7	57	6.7	100	14	14	183	159	397.3	10.5
opt	200	5	0.5	9497.7	67	467.4	9030.3	486.3	11.2	1856.2	37.9	8.5	0	549.6	518.5	9.7	12.8	29	8.5	81	17	21	77	87	82.3	1.7
opt	200	10	0.5	9840.7	112	715.6	9125.1	491.6	19	1865	17.4	7	0	1033.9	773.4	43.7	27.5	41.8	7	100	14	14	163	126	318.4	8.5
opt	200	15	0.5	10035.1	131	849.9	9181.1	493.5	21.8	1862	16	6.5	0	1372.6	956.7	85.7	34.5	53.3	6.5	100	13	13	206	156	522.6	12.7
opt	300	5	0.5	10629.4	72	497.5	10131.9	540.7	12.3	3030.8	13.1	3	0	547	527.5	19	13.7	24.3	3	66.7	6	9	80	74	49.4	1.3
opt	300	10	0.5	10766	99	648.5	10117.5	540.4	16.5	3021.3	15.7	6	0	897.3	717.9	53.3	23	37.7	6	100	12	12	138	111	248.8	6.5
opt	300	15	0.5	10982.5	122	838.3	10144.1	542.2	20.8	3025.5	6	5.5	0	1362.5	832.6	93.2	34	47.3	5.5	100	11	11	201	141	524.1	13.2
opt	300	20	0.5	11118.3	143	940.6	10177.7	543	24.2	3024.2	4.6	4	0	1333.5	790.1	158.8	35.8	41.3	4	100	8	8	213	121	392.8	11.7
opt	400	5	0.5	11055.5	51	368.9	10686.6	567.5	8.8	4193	25.4	5.3	9	459.9	355	25	10.7	19	5.3	92.3	12	13	62	57	91	1.8
opt	400	10	0.5	11231.4	76	540.9	10690.4	567.8	13	4198.9	13.3	7	7	753.9	535	69.7	17.7	25.7	7	100	14	14	104	77	213	4.7
opt	400	15	0.5	11368.8	95	646	10722.8	569.1	16	4199.3	9.7	6	9	1031.5	556.3	120.5	25.2	28.3	6	92.3	12	13	150	85	385.5	9.2
opt	400	20	0.5	11554.1	110	769.2	10775.1	571.3	18.3	4186	14.7	9.5	4	1188.3	597	173.2	27.7	29.7	9.5	100	19	19	164	89	419.1	9.3
opt	500	5	0.5	11348	46	351.6	10996.4	580.8	8.2	5386.6	17.4	7	41	411.1	250.4	29.8	9.2	14	7	87.5	14	16	52	42	59.5	1
opt	500	10	0.5	11459.3	60	439.6	11019.6	581.5	10.2	5389.4	12	6.8	41	562.2	304.8	87	12.5	13.7	6.8	87.5	14	16	74	41	122.6	2.3
opt	500	15	0.5	11437.6	64	471.8	10965.8	579.7	10.7	5390.1	12	7.5	43	722.8	395.9	136.5	15.7	20.3	7.5	93.8	15	16	94	53	251.1	5
opt	500	20	0.5	11639.9	84	607.3	11032.6	582.9	14.2	5390	7.5	5.5	40	981.2	405.2	195.3	22.2	17	5.5	100	11	11	132	51	373.9	8

C. Simulation aggregate results for 25% of demand scenarios

(Note: the designation “react” corresponds to the rule-based model)

id1. model	id2. cars	id3. staff	id4. maint.gen.factor	profit	in2. total paid by clients	out1. total costs	out2. wage	out3. car depreciation	out4. staff mov in cars	out5. staff mov in pt	out6. client mov	out7. parking	a1. %accepted trips	a2. avg dist car-client accepted (m)	a3. avg dist car-client rejected (m)	a4. #rejected trips car dist >1 and <2km	a5. #rejected trips car dist >2 and <3km	a6. #rejected trips car dist> 3km	a7. #rejected no car at any dist	a8. #total rejected trips	a9. #total accepted trips	a10. #total trips
base	150	0	0	8539.33	11063.38	2524.05	0	1233	0	0	1040.55	250.5	69.6	444.6	1870.9	948	385	160	0	1493	3418	4911
base	200	0	0	9142.01	12285.28	3143.27	0	1644	0	0	1165.27	334	76.2	396.9	1814.9	776	277	116	0	1169	3742	4911
base	300	0	0	9455.79	13728.09	4272.3	0	2466	0	0	1305.3	501	84.3	338.7	1675.4	554	177	38	0	769	4142	4911
base	400	0	0	9234.46	14583.96	5349.5	0	3288	0	0	1393.5	668	89	300.3	1552.4	428	110	4	0	542	4369	4911
base	500	0	0	8780.71	15186.8	6406.09	0	4110	0	0	1461.09	835	92	269.9	1488.8	332	58	1	0	391	4520	4911
base	600	0	0	8170.37	15613.48	7443.11	0	4932	0	0	1509.11	1002	94.3	248.3	1437.8	253	27	1	0	281	4630	4911
base	150	0	0.5	8362.47	10868.58	2506.11	0	1233	0	0	1022.61	250.5	68.3	455.7	1895.6	972	406	178	0	1556	3355	4911
base	200	0	0.5	8929.62	12047.21	3117.59	0	1644	0	0	1139.59	334	74.9	401.2	1872.2	790	302	139	0	1231	3680	4911
base	300	0	0.5	9272.52	13526.77	4254.25	0	2466	0	0	1287.25	501	83.2	343.8	1659.3	600	190	35	0	825	4086	4911
base	400	0	0.5	9182.33	14527.26	5344.93	0	3288	0	0	1388.93	668	88.6	303.5	1562.1	441	115	6	0	562	4349	4911
base	500	0	0.5	8699.49	15093.37	6393.88	0	4110	0	0	1448.88	835	91.6	275.7	1497.1	344	66	2	0	412	4499	4911
base	600	0	0.5	8151.54	15592.2	7440.66	0	4932	0	0	1506.66	1002	94.1	252.4	1447	257	30	1	0	288	4623	4911
react	150	5	0	8394.77	11168.18	2773.41	210	1233	17.83	5.95	1056.13	250.5	69.9	446.1	1882.6	945	380	153	0	1478	3434	4912
react	150	10	0	8146.16	11156.26	3010.1	420	1233	38.64	11.9	1056.06	250.5	69.7	448.1	1934.1	910	376	203	0	1489	3423	4912
react	150	15	0	8149.33	11430.07	3280.74	630	1233	66.13	17.85	1083.26	250.5	71.4	448.9	1964	865	344	196	0	1405	3507	4912
react	200	5	0	8976.38	12369.02	3392.64	210	1644	21.66	5.95	1177.03	334	76.6	392.3	1815.9	765	278	108	0	1151	3761	4912
react	200	10	0	8770.57	12409.98	3639.41	420	1644	46.84	11.9	1182.67	334	76.8	399.5	1840.4	755	254	133	0	1142	3770	4912
react	200	15	0	8646.34	12537.63	3891.29	630	1644	70.9	17.85	1194.54	334	77.7	396.9	1869.2	721	240	133	0	1094	3818	4912
react	300	5	0	9306.69	13834.94	4528.25	210	2466	24.82	5.95	1320.48	501	84.9	337.7	1672	539	167	38	0	744	4168	4912
react	300	10	0	9198.09	13980.2	4782.11	420	2466	49.16	11.9	1334.05	501	85.7	335.6	1671.4	510	152	39	0	701	4211	4912
react	300	15	0	9042.67	14072.04	5029.37	630	2466	70.06	17.85	1344.46	501	86.3	333.7	1674.2	483	155	34	0	672	4240	4912
react	300	20	0	8795.77	14056.29	5260.52	840	2466	87	23.8	1342.72	501	86.3	334.6	1664.6	499	135	39	0	673	4239	4912
react	400	5	0	9086.38	14695.03	5608.65	210	3288	30.23	5.95	1406.47	668	89.6	294	1555.8	406	101	6	0	513	4399	4912
react	400	10	0	8877.85	14731.36	5853.51	420	3288	53.92	11.9	1411.69	668	89.9	295.1	1534.2	403	90	4	0	497	4415	4912
react	400	15	0	8660.26	14734.31	6074.05	630	3288	59.26	17.85	1410.94	668	90	292.1	1553.2	392	95	4	0	491	4421	4912
react	400	20	0	8487.26	14783.75	6296.49	840	3288	60.2	23.8	1416.49	668	90.2	292.6	1568.8	380	94	7	0	481	4431	4912
react	500	5	0	8615.9	15275.27	6659.37	210	4110	27.88	5.95	1470.54	835	92.6	270.5	1493.8	307	53	4	0	364	4548	4912
react	500	10	0	8440.76	15336.9	6896.14	420	4110	40.87	11.9	1478.37	835	93	269.9	1487	290	54	2	0	346	4566	4912
react	500	15	0	8231.02	15345.74	7114.72	630	4110	43.52	17.85	1478.35	835	93.1	268.4	1439.6	297	43	1	0	341	4571	4912
react	500	20	0	8003.84	15337.14	7333.3	840	4110	46.83	23.8	1477.67	835	93	266.9	1504.2	286	56	2	0	344	4568	4912
react	600	5	0	8023.27	15718.82	7695.55	210	4932	23.45	5.95	1522.15	1002	94.8	247.1	1380.3	240	16	1	0	257	4655	4912
react	600	10	0	7835.56	15760.12	7924.56	420	4932	32.12	11.9	1526.54	1002	95	246.1	1400.3	227	17	1	0	245	4667	4912
react	600	15	0	7626.22	15770.97	8144.75	630	4932	35.55	17.85	1527.35	1002	95.1	245.6	1385.8	225	16	1	0	242	4670	4912
react	600	20	0	7413.37	15777.28	8363.91	840	4932	37.63	23.8	1528.48	1002	95.1	245.4	1385.9	223	17	1	0	241	4671	4912
react	150	5	0.5	8262.95	11012.18	2749.23	210	1233	12.23	5.95	1037.55	250.5	69.1	449.3	1929.5	917	406	195	0	1518	3394	4912
react	150	10	0.5	8094.68	11095.75	3001.07	420	1233	34.91	11.9	1050.76	250.5	69.3	447.5	1882.4	928	422	159	0	1509	3403	4912
react	150	15	0.5	8055.5	11319.28	3263.78	630	1233	59.52	17.85	1072.91	250.5	70.7	452.2	1980.7	869	351	221	0	1441	3471	4912
react	200	5	0.5	8934.39	12314.88	3380.49	210	1644	17.24	5.95	1169.3	334	76.4	394.8	1802.6	791	262	108	0	1161	3751	4912
react	200	10	0.5	8821.87	12458.58	3636.71	420	1644	40.3	11.9	1186.51	334	77.1	399.3	1814.9	746	266	112	0	1124	3788	4912
react	200	15	0.5	8592.05	12467.38	3875.33	630	1644	59.39	17.85	1190.09	334	77.1	400.5	1833.2	736	275	113	0	1124	3788	4912
react	300	5	0.5	9293.51	13812.87	4519.36	210	2466	18.29	5.95	1318.12	501	84.5	338.3	1684.8	549	165	45	0	759	4153	4912
react	300	10	0.5	9103.44	13869.98	4766.54	420	2466	44.41	11.9	1323.23	501	85.1	336.6	1672.7	532	155	43	0	730	4182	4912
react	300	15	0.5	9011.75	14033.89	5022.14	630	2466	66.93	17.85	1340.36	501	86.1	334	1677.3	486	164	31	0	681	4231	4912
react	300	20	0.5	8755.59	14004.83	5249.24	840	2466	80.94	23.8	1337.5	501	86	332.5	1684	488	162	36	0	686	4226	4912
react	400	5	0.5	9037.08	14623.61	5586.53	210	3288	15.41	5.95	1399.17	668	89.1	296.3	1541.9	427	100	6	0	533	4379	4912
react	400	10	0.5	8905.04	14748.86	5843.82	420	3288	44.04	11.9	1411.88	668	90	295.6	1579.5	383	103	6	0	492	4420	4912
react	400	15	0.5	8674.38	14754.22	6079.84	630	3288	61.57	17.85	1414.42	668	90.1	294.1	1567.9	378	103	6	0	487	4425	4912
react	400	20	0.5	8460.04	14757.51	6297.47	840	3288	63.22	23.8	1414.45	668	90.1	291	1560.4	390	89	8	0	487	4425	4912
react	500	5	0.5	8596.24	15240.46	6644.22	210	4110	15.54	5.95	1467.73	835	92.3	269.9	1465.3	322	55	2	0	379	4533	4912
react	500	10	0.5	8421.94	15315.63	6893.69	420	4110	42.33	11.9	1474.46	835	92.9	267.2	1492.2	294	50	4	0	348	4564	4912
react	500	15	0.5	8230.11	15347.22	7117.11	630	4110	45.74	17.85	1478.52	835	93	270.2	1467.5	295	49	0	0	344	4568	4912
react	500	20	0.5	8011.12	15340.88	7329.76	840	4110	42.14	23.8	1478.82	835	93	269.9	1465.2	295	46	1	0	342	4570	4912
react	600	5	0.5	7995.69	15680.17	7684.48	210	4932	17.72	5.95	1516.81	1002	94.6	247.9	1386.6	246	18	0	0	264	4648	4912
react	600	10	0.5	7826	15752.65	7926.65	420	4932	35.05	11.9	1525.7	1002	95	247.8	1404.1	226	20	1	0	247	4665	4912
react	600	15	0.5	7611.76	15755.68	8143.92	630	4932	35.67	17.85	1526.4	1002	95	247.2	1396.3	227	18	1	0	246	4666	4912
react	600	20	0.5	7396.55	15755.42	8358.87	840	4932	34.91	23.8	1526.16	1002	95	248.6	1419.4	224	20	1	0	245	4667	4912
opt	150	5	0	8402.06	11187.84	2785.78	210	1233	31.47	5.95	1054.86	250.5	70.1	446.5	1949.1	919	347	201	0	1467	3445	4912
opt	150	10	0	8313.69	11348.26	3034.57	420	1233	48.52	11.9	1070.65	250.5	71	447.2	1967.1	865	347	212	0	1424	3488	4912
opt	150	15	0	8141.79	11408.99	3267.2	630	1233	60.22	17.85	1075.63	250.5	71.4	442.7	1944.6	880	333	193	0	1406	3506	4912
opt	200	5	0	8940.37	12334.44	3394.07	210	1644	31.46	5.95	1168.66	334	76.6	392.4	1791	764	284	99	0	1147	3765	4912
opt	200	10	0	8881.51	12541.23	3659.72	420	1644	58.56	11.9	1191.26	334	77.6	394.3	1885.6	702	266	130	0	1098	3814	4912
opt	200	15	0	8788.29	12711.59	3923.3	630	1644	87.45	17.85	1210	334	78.7	395.4	1838	680	258	107	0	1045	3867	4912
opt	300	5	0	9330.36	13872.74	4542.38	210	2466	35.68	5.95	1323.75	501	85.1	335	1670.4	532	166	33	0	731	4181	4912
opt	300	10	0	9123.34	13907.82	4784.48	420	2466	58.84	11.9	1326.74	501	85.3	330.2	1644	542	149	32	0	723	4189	4912
opt	300	15	0	8913.36	13952.05	5038.69	630	2466	91.93	17.85	1331.91	501	85.7	330.7	1657.9	517	155	31	0	703	4209	4912
opt	300	20	0	8744.02	14015.42	5271.4	840	2466	96.61	23.8	1343.99	501	85.8	330.7	1603.3	530	144	25	0	699	4213	4912
opt	400	5	0	9133.64	14766.53	5632.89	210	3288	46.68	5.95	1414.26	668	90	294.3	1537.2	393	93	3	0	489	4423	4912
opt	400	10	0	8991.7	14876.68	5884.98	420	3288	71.45	11.9	1425.63	668	90.7	295.7	1530.1	372	80	5	0	457	4455	4912
opt	400	15	0	8723.25	14831.65	6108.4	630	3288	82.13	17.85	1422.42	668	90.4	294.6	1530.3	386	81	5	0	472	4440	4912
opt	400	20	0	8533.24	14875.61	6342.37	840	3288	97.07	23.8	1425.5	668	90.8	288.5	1511.9	371	81	1	0	453	4459	4912
opt	500	5	0	8626.98	15294.27	6667.29	210	4110	33.89	5.95	1472.45	835	92.7	264.5	1475.2	302	54	2	0	358	4554	4912
opt	500	10	0	8466.71	15399.6	6932.89	420	4110	72.34	11.9	1483.65	835	93.3	266.3	1469	279	49	0	0	328	4584	4912
opt	500	15	0	8193.13	15341.06	7147.93	630	4110	77.72	17.85	1477.36	835	93	265.4	1420.9	300	43	0	0	343	4569	4912
opt	500	20	0	7958.79	15340.23	7381.44	840	4110	96.72	23.8	1475.92	835	93.1	263.7	1489.6	282	53	2	0	337	4575	4912
opt	600	5	0	8015.03	15721.87	7706.84	210	4932	36.71	5.95	1520.18	1002	94.8	246.6	1429.2	228	25	1	0	254	4658	4912
opt	600	10	0	7817.95	15780.15	7962.2	420	4932	68.87	11.9	1527.43	1002	95.2	242.5	1378.9	217	18	0	0	235	4677	4912
opt	600	15	0	7609.77	15798.84	8189.07	630	4932	77.73	17.85	1529.49	1002	95.3	243.8	1372.2	216	16	0	0	232	4680	4912
opt	600	20	0	7344.3	15771.97	8427.67	840	4932	104.07	23.8	1525.8	1002	95.2	244.4	1419.9	202	34	0	0	236	4676	4912
opt	150	5	0.5	8293.85	11066.27	2772.42	210	1233	29.39	5.95	1043.58	250.5	69.4	447.7	1959.7	920	378	206	0	1504	3408	4912
opt	150	10	0.5	8163.92	11192.78	3028.86	420	1233	55.31	11.9	1058.15	250.5	70	450.6	1936.8	898	381	194	0	1473	3439	4912
opt	150	15	0.5	8067.99	11331.66	3263.67	630	1233	61.4	17.85	1070.92	250.5	70.7	449	1964.4	874	366	200	0	1440	3472	4912
opt	200	5	0.5	8948.52	12342.44	3393.92	210	1644	28.65	5.95	1171.32	334	76.5	398.6	1902.3	740	271	144	0	1155	3757	4912
opt	200	10	0.5	8864.66	12532.29	3667.63	420	1644	65.36	11.9	1192.37	334	77.6	396.9	1902.4	712	253	136	0	1101	3811	4912
opt	200	15	0.5	8541.72	12412.25	3870.53	630	1644	65.12	17.85	1179.56	334	76.9	404.6	1870.9	735	270	129	0	1134	3778	4912
opt	300	5	0.5	9304.14	13836.87	4532.73	210	2466	29.2	5.95	1320.58	501	84.9	338.6	1675.8	537	169	37	0	743	4169	4912
opt	300	10	0.5	9136.8	13933.86	4797.06	420	2466	66.94	11.9	1331.22	501	85.5	333.8	1642.9	527	155	32	0	714	4198	4912
opt	300	15	0.5	8950.63	13986.84	5036.21	630	2466	87.27	17.85	1334.09	501	86	333.3	1646.4	514	148	28	0	690	4222	4912
opt	300	20	0.5	8641.2	13882.61	5241.41	840	2466	83.63	23.8	1326.98	501	85.1	334.3	1624.6	551	155	28	0	734	4178	4912
opt	400	5	0.5	9104.42	14722.35	5617.93	210	3288	35.45	5.95	1410.53	668	89.8	299.7	1539	406	93	3	0	502	4410	4912
opt	400	10	0.5	8932.62	14823.54	5890.92	420	3288	79.1	11.9	1423.92	668	90.2	296.3	1532.2	393	84	4	0	481	4431	4912
opt	400	15	0.5	8715.67	14845.12	6129.45	630	3288	100.71	17.85	1424.89	668	90.4	294.1	1529.4	380	88	3	0	471	4441	4912
opt	400	20	0.5	8513.06	14841.45	6328.39	840	3288	85.85	23.8	1422.74	668	90.6	296.5	1527.9	371	88	4	0	463	4449	4912
opt	500	5	0.5	8643.47	15318.51	6675.04	210	4110	39.27	5.95	1474.82	835	92.9	269.7	1436.9	305	44	0	0	349	4563	4912
opt	500	10	0.5	8453.33	15380.57	6927.24	420	4110	69.6	11.9	1480.74	835	93.3	265.1	1438.1	290	40	0	0	330	4582	4912
opt	500	15	0.5	8202.83	15352.1	7149.27	630	4110	77.29	17.85	1479.13	835	93.1	266.6	1424.4	298	41	0	0	339	4573	4912
opt	500	20	0.5	7991.33	15380.54	7389.21	840	4110	98.22	23.8	1482.19	835	93.3	264.4	1480.7	274	56	0	0	330	4582	4912
opt	600	5	0.5	7990.29	15703.28	7712.99	210	4932	45.37	5.95	1517.67	1002	94.9	247	1370.3	231	20	0	0	251	4661	4912
opt	600	10	0.5	7806.25	15761.21	7954.96	420	4932	65.41	11.9	1523.65	1002	95.2	242.6	1360.7	219	15	0	0	234	4678	4912
opt	600	15	0.5	7596.36	15769.06	8172.7	630	4932	63.86	17.85	1526.99	1002	95.1	246.3	1401.6	217	23	0	0	240	4672	4912
opt	600	20	0.5	7374.19	15800.62	8426.43	840	4932	98.03	23.8	1530.6	1002	95.4	245.8	1371.4	211	17	0	0	228	4684	4912

id1. model	id2. cars	id3. staff	id4. maint.gen.factor	b1. total car distance	b2. #trips with staff in car	b3. car distance with staff (km.veh)	b4. car distance with clients (km.veh)	b5. car time used by clients (h.veh)	b6. car time staff moves (k.veh)	b7. car time idle available (h.veh)	b8. cat time idle need. maint (h.veh)	b9. car time idle being maint. (h.veh)	b10. #cars not used during simulation	c1. staff distance by car (km.ind)	c2. staff distance by pt (km.ind)	c3. staff time idle (h.ind)	c4. staff time in car (h.ind)	c5. staff time in pt (h.ind)	c6. staff time in maintenance (h.ind)	c7. %fulfilled maint	c8. #fullfilled maint requests	c9. #total maint req	c10. #staff moves by vehicle	c11. #staff moves by pt	d1. car distance saved - trip joining (km)	d2. car time saved - trip joining (h)
base	150	0	0	11561.7	0	0	11561.7	635.8	0	1164.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	200	0	0	12947.4	0	0	12947.4	706	0	1694	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	300	0	0	14503.3	0	0	14503.3	789	0	2811	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	400	0	0	15483.4	0	0	15483.4	838.2	0	3961.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
base	500	0	0	16234.3	0	0	16234.3	872.8	0	5127.2	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0
base	600	0	0	16767.9	0	0	16767.9	897.3	0	6302.7	0	0	32	0	0	0	0	0	0	0	0	0	0	0	0	0
base	150	0	0.5	11362.4	0	0	11362.4	624.6	0	1084.6	90.8	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0
base	200	0	0.5	12662.1	0	0	12662.1	692.4	0	1602.2	105.5	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0
base	300	0	0.5	14302.8	0	0	14302.8	777.4	0	2683.5	139.1	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0
base	400	0	0.5	15432.5	0	0	15432.5	834.9	0	3845.7	119.4	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0
base	500	0	0.5	16098.7	0	0	16098.7	867.4	0	4897.2	235.4	0	5	0	0	0	0	0	0	0	0	31	0	0	0	0
base	600	0	0.5	16740.6	0	0	16740.6	896.1	0	6139.4	164.5	0	25	0	0	0	0	0	0	0	0	25	0	0	0	0
react	150	5	0	11932.9	64	198.1	11734.8	641.8	10.7	1147.5	0	0	0	198.1	181.8	30.3	10.7	19	0	0	0	0	64	57	0	0
react	150	10	0	12163.3	124	429.3	11734	641.2	21	1137.8	0	0	0	429.3	447.8	59.2	21	39.8	0	0	0	0	124	118	0	0
react	150	15	0	12771	184	734.8	12036.2	656.9	31.7	1111.4	0	0	0	734.8	764.2	86.7	31.7	61.7	0	0	0	0	184	178	0	0
react	200	5	0	13318.8	64	240.7	13078.1	710.9	10.8	1678.3	0	0	0	240.7	173.6	30.5	10.8	18.7	0	0	0	0	64	56	0	0
react	200	10	0	13661.2	126	520.4	13140.8	713.2	22.2	1664.6	0	0	0	520.4	388.4	59.5	22.2	38.3	0	0	0	0	126	115	0	0
react	200	15	0	14060.4	185	787.8	13272.6	720.6	32.2	1647.3	0	0	0	787.8	554.8	94.8	32.2	53	0	0	0	0	185	159	0	0
react	300	5	0	14947.7	61	275.7	14672	795.1	10.8	2794.1	0	0	0	275.7	153.4	32.2	10.8	17	0	0	0	0	61	51	0	0
react	300	10	0	15368.9	117	546.2	14822.7	803.5	20.7	2775.9	0	0	0	546.2	302.8	66	20.7	33.3	0	0	0	0	117	100	0	0
react	300	15	0	15716.9	153	778.4	14938.5	808.7	27.5	2763.8	0	0	0	778.4	388.9	110.5	27.5	42	0	0	0	0	153	126	0	0
react	300	20	0	15885.9	174	966.7	14919.2	807.8	31.5	2760.7	0	0	0	966.7	435.3	163.8	31.5	44.7	0	0	0	0	174	134	0	0
react	400	5	0	15963.3	65	335.9	15627.4	844.5	12	3943.5	0	0	0	335.9	137.3	31.7	12	16.3	0	0	0	0	65	49	0	0
react	400	10	0	16284.6	108	599.1	15685.4	846.6	20	3933.4	0	0	0	599.1	219.3	74.7	20	25.3	0	0	0	0	108	76	0	0
react	400	15	0	16335.5	114	658.4	15677.1	846.8	21.3	3931.9	0	0	0	658.4	216	134.3	21.3	24.3	0	0	0	0	114	73	0	0
react	400	20	0	16407.7	125	668.9	15738.7	849.6	23.2	3927.2	0	0	0	668.9	245.7	188.7	23.2	28.2	0	0	0	0	125	85	0	0
react	500	5	0	16649.1	60	309.8	16339.4	877.9	10.7	5111.4	0	0	5	309.8	117.3	35.7	10.7	13.7	0	0	0	0	60	41	0	0
react	500	10	0	16880.4	88	454.1	16426.3	881.4	16	5102.6	0	0	4	454.1	172.7	84.3	16	19.7	0	0	0	0	88	59	0	0
react	500	15	0	16909.7	85	483.6	16426.1	881.9	15.8	5102.2	0	0	5	483.6	159.4	147.5	15.8	16.7	0	0	0	0	85	50	0	0
react	500	20	0	16938.9	84	520.3	16418.6	881.4	16.2	5102.4	0	0	5	520.3	170.2	205.2	16.2	18.7	0	0	0	0	84	56	0	0
react	600	5	0	17173.3	54	260.6	16912.8	903.4	9.7	6287	0	0	30	260.6	103.6	37.3	9.7	13	0	0	0	0	54	39	0	0
react	600	10	0	17318.5	63	356.9	16961.6	905.8	11.8	6282.4	0	0	29	356.9	110	95.2	11.8	13	0	0	0	0	63	39	0	0
react	600	15	0	17365.6	64	395	16970.6	906.4	12.5	6281.1	0	0	25	395	112.2	154.2	12.5	13.3	0	0	0	0	64	40	0	0
react	600	20	0	17401.3	69	418.1	16983.2	906.7	13.5	6279.8	0	0	26	418.1	117.3	211.8	13.5	14.7	0	0	0	0	69	44	0	0
react	150	5	0.5	11664.2	46	135.9	11528.3	632.9	7.7	1137.3	13.1	9	0	135.9	246.6	23.7	7.7	19.7	9	100	18	18	46	58	0	0
react	150	10	0.5	12063	108	387.9	11675.1	637.7	18.2	1125.9	10.2	8	0	387.9	490.7	54.2	18.2	39.7	8	100	16	16	108	115	0	0
react	150	15	0.5	12582.6	165	661.4	11921.2	650.5	28.2	1100.8	13	7.5	0	661.4	818.5	82.8	28.2	61.5	7.5	93.8	15	16	165	176	0	0
react	200	5	0.5	13183.9	48	191.6	12992.3	707.8	8	1663.5	12.6	8.2	0	191.6	264.8	25.2	8	18.7	8.2	94.4	17	18	48	52	0	0
react	200	10	0.5	13631.2	109	447.8	13183.4	716	19.3	1645.3	10.9	8.5	0	447.8	448.2	55.2	19.3	37	8.5	100	17	17	109	108	0	0
react	200	15	0.5	13883.1	155	659.9	13223.2	716.5	27	1628.3	17	11.2	0	659.9	666.8	87.2	27	54.7	11.2	95.8	23	24	155	155	0	0
react	300	5	0.5	14849.1	42	203.2	14645.8	793.8	7.5	2771.7	16.2	10.8	0	203.2	227.8	23.7	7.5	18	10.8	100	23	23	42	53	0	0
react	300	10	0.5	15196	104	493.5	14702.6	797.1	18.5	2767.6	10.1	6.7	0	493.5	351.6	62.2	18.5	32.7	6.7	93.3	14	15	104	95	0	0
react	300	15	0.5	15636.5	142	743.7	14892.9	806.5	25.5	2744.1	13.7	10.2	0	743.7	456.5	101	25.5	43.3	10.2	91.3	21	23	142	126	0	0
react	300	20	0.5	15760.4	168	899.3	14861.1	804.9	31.2	2738.9	14.6	10.5	0	899.3	555.3	149	31.2	49.3	10.5	100	21	21	168	142	0	0
react	400	5	0.5	15717.7	38	171.3	15546.4	840.4	7	3922.8	17.2	12.5	0	171.3	209.9	24.2	7	16.3	12.5	96.4	27	28	38	48	0	0
react	400	10	0.5	16176.9	94	489.3	15687.5	847.6	17.2	3915.1	11.1	9	0	489.3	293.7	65.8	17.2	28	9	94.7	18	19	94	82	0	0
react	400	15	0.5	16399.9	116	684.1	15715.8	847.9	21.5	3898.4	18	14.2	0	684.1	380.7	109	21.5	35.3	14.2	96.7	29	30	116	100	0	0
react	400	20	0.5	16418.6	118	702.5	15716.1	848.1	22.3	3907.6	13.4	8.5	0	702.5	358.5	175.5	22.3	33.7	8.5	90.5	19	21	118	99	0	0
react	500	5	0.5	16480.8	32	172.7	16308.1	875.9	5.7	5090.4	17.3	10.7	3	172.7	240.1	25.5	5.7	18.2	10.7	95.7	22	23	32	46	0	0
react	500	10	0.5	16853.3	79	470.4	16382.9	880.2	14.5	5084.4	11.7	9.2	2	470.4	308.8	72.3	14.5	24	9.2	95	19	20	79	69	0	0
react	500	15	0.5	16936.3	87	508.3	16428	882	16.5	5082.3	10.7	8.5	4	508.3	281.3	129.3	16.5	25.7	8.5	100	17	17	87	72	0	0
react	500	20	0.5	16899.5	82	468.2	16431.3	881.7	15.5	5075.2	14.6	13	6	468.2	265.6	186.8	15.5	24.7	13	100	26	26	82	73	0	0
react	600	5	0.5	17050.3	33	196.8	16853.4	901.2	6.3	6262.6	20.2	9.7	29	196.8	229.9	26.7	6.3	17.3	9.7	95.2	20	21	33	42	0	0
react	600	10	0.5	17341.7	62	389.5	16952.2	905.3	11.7	6252.9	16.6	13.5	31	389.5	248.9	73.5	11.7	21.3	13.5	100	27	27	62	60	0	0
react	600	15	0.5	17356.3	69	396.3	16960	905.5	13.2	6260.8	11.4	9.2	25	396.3	270	134.7	13.2	23	9.2	95	19	20	69	65	0	0
react	600	20	0.5	17345.1	66	387.8	16957.3	905.5	12.8	6246.2	19.9	15.7	26	387.8	297.7	185.8	12.8	25.7	15.7	100	32	32	66	73	0	0
opt	150	5	0	12070.4	50	349.7	11720.7	643	8.5	1148.5	0	0	0	500.9	565.6	20.3	12.3	27.3	0	0	0	0	73	79	151.2	3.8
opt	150	10	0	12435.2	81	539.1	11896.1	652.2	13.7	1134.1	0	0	0	935.7	834.5	52.5	23.2	44.3	0	0	0	0	137	132	396.5	9.5
opt	150	15	0	12620.6	97	669.1	11951.4	655.7	16.2	1128.1	0	0	0	1083.8	1101	98	26.7	55.3	0	0	0	0	160	166	414.6	10.5
opt	200	5	0	13334.6	48	349.5	12985.1	708.9	8.3	1682.8	0	0	0	495.3	500.3	23.7	11.3	25	0	0	0	0	65	75	145.7	3
opt	200	10	0	13886.9	93	650.7	13236.2	720.8	15.8	1663.4	0	0	0	895.3	950.6	50.2	21.5	48.3	0	0	0	0	127	141	244.6	5.7
opt	200	15	0	14416	151	971.7	13444.4	730.6	25.2	1644.3	0	0	0	1645	1417.2	66.8	42.8	70.3	0	0	0	0	257	202	673.3	17.7
opt	300	5	0	15104.8	58	396.4	14708.3	797.3	9.7	2793	0	0	0	506.7	537.2	20.8	12.2	27	0	0	0	0	73	81	110.2	2.5
opt	300	10	0	15395.3	100	653.8	14741.5	799.3	16.7	2784	0	0	0	976.4	884.1	49.2	25.2	45.7	0	0	0	0	151	137	322.6	8.5
opt	300	15	0	15820.4	144	1021.4	14799	801.8	24	2774.2	0	0	0	1500.2	1196.8	81.5	35.8	62.7	0	0	0	0	215	186	478.8	11.8
opt	300	20	0	16006.8	161	1073.5	14933.3	805.5	26.8	2767.7	0	0	0	1437.7	1282.2	131.3	36.7	72	0	0	0	0	220	182	364.2	9.8
opt	400	5	0	16232.7	75	518.7	15714	848.7	12.5	3938.8	0	0	0	617.1	611.3	15.5	14.8	29.7	0	0	0	0	89	89	98.4	2.3
opt	400	10	0	16634.2	115	793.9	15840.3	855	19.5	3925.5	0	0	0	1124.7	916.3	46.7	27.7	45.7	0	0	0	0	164	137	330.8	8.2
opt	400	15	0	16717.3	134	912.6	15804.7	852.4	22.5	3925.1	0	0	0	1272	1027.9	95	31.7	53.3	0	0	0	0	189	156	359.4	9.2
opt	400	20	0	16917.4	163	1078.5	15838.9	854.9	27.2	3917.9	0	0	0	1760.2	1205.6	134.2	44.5	61.3	0	0	0	0	267	183	681.7	17.3
opt	500	5	0	16737.1	53	376.6	16360.5	879	9	5112	0	0	7	480.5	464.7	24.7	11.3	24	0	0	0	0	67	72	103.9	2.3
opt	500	10	0	17288.8	117	803.8	16485	885	19.8	5095.1	0	0	7	1241	828.6	47.3	29.7	43	0	0	0	0	176	129	437.1	9.8
opt	500	15	0	17278.7	123	863.6	16415.1	881.7	20.5	5097.8	0	0	9	1171.4	964	104.3	28	47.7	0	0	0	0	168	142	307.8	7.5
opt	500	20	0	17473.8	159	1074.7	16399.1	881.6	26.7	5091.7	0	0	9	1839.5	1295.4	132.8	44.8	62.3	0	0	0	0	268	187	764.8	18.2
opt	600	5	0	17298.7	57	407.9	16890.9	903.6	9.5	6286.9	0	0	30	507.4	444.8	24.3	12	23.7	0	0	0	0	72	71	99.5	2.5
opt	600	10	0	17736.6	111	765.2	16971.4	906.9	18.8	6274.3	0	0	21	960.3	722.4	61.5	23.8	34.7	0	0	0	0	141	104	195.1	5
opt	600	15	0	17858	126	863.7	16994.4	908	21	6271	0	0	26	1328.8	798.7	110.2	31.5	38.3	0	0	0	0	189	115	465.1	10.5
opt	600	20	0	18109.7	166	1156.3	16953.4	906.4	27.8	6265.7	0	0	25	1967	774.4	155.2	46.8	38	0	0	0	0	280	114	810.7	19
opt	150	5	0.5	11921.9	45	326.6	11595.3	636	7.7	1131.8	18.8	5.7	0	443.1	465.3	19.5	10.2	24.7	5.7	80	12	15	60	71	116.5	2.5
opt	150	10	0.5	12371.8	86	614.6	11757.2	643.3	14.3	1123	12.4	7	0	811.2	942.6	46.2	19.2	47.7	7	87.5	14	16	115	142	196.7	4.8
opt	150	15	0.5	12581.4	98	682.2	11899.1	651.2	16.3	1110.3	16.1	6	0	1099.6	1039	92.2	26.5	55.3	6	75	12	16	159	164	417.4	10.2
opt	200	5	0.5	13333	47	318.3	13014.7	709.3	8	1617.3	52.8	12.5	0	334.5	508.3	15.2	8.3	24	12.5	80.6	25	31	49	72	16.2	0.3
opt	200	10	0.5	13974.7	100	726.2	13248.5	720.2	17.2	1632.9	23.6	6.2	0	1056.3	906.6	40.8	25	48	6.2	68.4	13	19	147	144	330.1	7.8
opt	200	15	0.5	13829.7	104	723.5	13106.2	713.3	17.3	1603.4	52.3	13.7	0	1096.5	1149.4	74.2	26.5	65.7	13.7	93.3	28	30	159	173	373	9.2
opt	300	5	0.5	14997.6	49	324.4	14673.1	795.2	8.2	2755.8	33.7	7.2	0	408.1	537.8	15.5	10	27.3	7.2	71.4	15	21	60	81	83.7	1.8
opt	300	10	0.5	15535.1	110	743.8	14791.3	800.8	18.3	2745.1	29.5	6.3	0	1055	891.8	40.8	26	46.8	6.3	77.8	14	18	156	141	311.2	7.7
opt	300	15	0.5	15792.9	142	959.1	14823.3	803.8	23.7	2744.5	20.8	7	0	1429.7	1166.5	78	35.3	59.7	7	100	15	15	210	176	470.6	11.7
opt	300	20	0.5	15673.5	138	929.2	14744.2	797.9	23	2701	68.1	10	0	1281.1	1262.3	129.5	32.2	68.3	10	52.6	20	38	193	172	351.9	9.2
opt	400	5	0.5	16066.5	58	393.9	15672.6	846.1	9.8	3874.9	61.6	7.5	0	477	509.3	16.3	11.8	24.3	7.5	69.6	16	23	70	73	83.1	2
opt	400	10	0.5	16700.1	134	878.8	15821.3	851.9	22.3	3891.3	27	7.5	0	1149.6	1003.5	32.2	29.3	51	7.5	89.5	17	19	176	153	270.7	7
opt	400	15	0.5	16951.1	170	1119	15832.1	853.2	28.5	3884.1	23.9	10.3	0	1701.9	1131.2	69.8	42.5	57.3	10.3	84	21	25	254	164	582.9	14
opt	400	20	0.5	16762.1	143	953.8	15808.2	853	23.8	3895.4	19.3	8.5	0	1451.1	1175.9	131	36.8	63.7	8.5	100	17	17	221	169	497.2	13
opt	500	5	0.5	16823.2	63	436.3	16386.9	880.4	10.5	5052	50.8	6.3	8	494.8	536.6	14.2	11.5	28	6.3	48.1	13	27	69	84	58.5	1
opt	500	10	0.5	17226	118	773.3	16452.7	883.9	19.8	5061.8	23.4	11	3	937	869.7	41.8	24.2	43	11	91.7	22	24	144	129	163.7	4.3
opt	500	15	0.5	17293.5	119	852.9	16434.8	882.3	20	5057.5	30.2	9.8	5	1191	920.2	95.2	28.7	46.3	9.8	95.5	21	22	169	131	338	8.7
opt	500	20	0.5	17560.2	172	1091.4	16468.8	883.9	28.7	5062.1	15.2	10	8	1711.4	1140.4	128	44.7	57.3	10	90.9	20	22	268	172	620	16
opt	600	5	0.5	17367.1	70	504.1	16863	902.5	11.8	6232.8	46.7	6.2	26	619.6	561.2	12.8	14.3	26.7	6.2	77.8	14	18	85	80	115.5	2.5
opt	600	10	0.5	17656.2	106	726.8	16929.5	905.8	18	6239.3	26.5	10.3	25	961.3	773.1	49.3	23.3	37	10.3	95.7	22	23	138	110	234.5	5.3
opt	600	15	0.5	17676.1	104	709.6	16966.5	906.3	17.3	6250.2	16.7	9.5	26	1014.2	770.5	106.7	24.8	39	9.5	86.4	19	22	149	109	304.7	7.5
opt	600	20	0.5	18095.9	153	1089.2	17006.7	908.1	25.5	6227.6	24.8	14	23	1728	889.4	145	40	41	14	93.3	28	30	240	122	638.8	14.5