FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Hybrid Strategies for Open Smart Parking with Agent Process Modelling Simulation

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Mestrado Integrado em Engenharia Informática e Computação

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Abstract

Parking in cities is becoming a scarce resource and, besides new regulation policies that limit parking spots, cost and time, drivers can have difficulty finding a vacant space near their destination. Therefore, drivers waste time looking for somewhere to park, which causes frustration, increases pollution and congestion in crowded locations. Drivers compete between them due to the scarcity of parking resources, creating a demand-supply problem that leads to providers competition, ultimately a market-based problem. Moreover, the introduction of autonomous vehicles adds complexity to this scenario by requiring an automatic and efficient system for parking.

The scientific community regards the use of Intelligent Transportation Systems as a viable solution. Hence, a Smart Parking System is an intelligent system that aids drivers in selecting and reserving parking spaces which match their preferences among competing alternatives. Also, by using negotiation for this purpose, the utility to a parking manager can be maximized, reducing traffic congestion and improving parking resources or availability. However, studies on the impact of intelligent solutions to manage public parking spots are few and represent a relevant gap that needs bridging when following the path towards Smart Cities.

Furthermore, Smart Parking dynamics depend on the synergy of the behaviours of drivers, parking lot managers and, occasionally, a city manager. As such, a multi-agent system is a straightforward solution for modelling this system to find parking allocation dynamics that maximize the satisfaction of all agents, while aspiring to distribute the traffic load better.

The solution proposed comprises a distributed agent-based simulation that allows the evaluation of the impact of new market dynamics such as tariffs, reservation or time available in the individual and overall satisfaction metrics. As such, drivers are sensible to new tariffs and Parking managers can try to distribute their users in a more profitable way, such as balancing the availability of nearby parking lots. Finally, being a naturally distributed problem, the use of distributed agent capabilities implemented as micro-services is also introduced. Agent behaviours are modelled following an Agent Process Model methodology, using process models to orchestrate the micro-services interaction. The use of micro-services in this context allows greater flexibility and scalability to support numerous agents and diverse scenario configurations.

As a result, during the development of this dissertation, we discovered that dynamic prices have a role in solving the parking problem, both to drivers and managers. However, traffic flow within the city did not improve as expected. Nevertheless, the solution designed can accommodate more complex agent behaviours and market processes to enhance parking efficiency further.

Keywords: Smart Parking, Negotiation, Agents, Micro-Services

Resumo

O estacionamento em cidade é um recurso escasso e, com as políticas de regulação que limitam as vagas, o custo e o tempo máximo de parqueamento, torna-se difícil estacionar próximo do destino pretendido. Este problema causa frustração aos condutores e aumenta os níveis de poluição e o congestionamento em locais mais concorridos. Adicionalmente, a escassez de estacionamento aumenta a concorrência entre condutores, o que origina um problema de oferta-procura e gera competição entre os fornecedores, ou seja, cria um problema de mercados. Por sua vez, o aparecimento de veículos autónomos torna este cenário ainda mais complexo, exigindo um sistema automático e eficiente para gestão do estacionamento.

É reconhecido que o uso de sistemas de *Smart Parking* terá um grande impacto na resolução deste problema. O uso de negociação permite maximizar a utilidade para um gestor de estacionamento, reduzindo o tráfego e melhorando os seus recursos, ou a sua disponibilidade. Existem poucos estudos sobre o impacto de soluções inteligentes na gestão de parqueamento público, o que constitui uma relevante lacuna a colmatar quando se pretendem criar *Smart Cities*. Sendo as dinâmicas de *Smart Parking* dependentes da sinergia dos comportamentos dos condutores, gestores de estacionamento e, por vezes, de um gestor municipal, os sistemas multiagente são a forma natural de modelar este sistema para encontrar uma alocação de estacionamento que maximize a satisfação de todos os agentes, enquanto se otimiza a distribuição do tráfego.

A solução proposta consiste numa simulação distribuída baseada em agentes que permite avaliar o impacto de novas dinâmicas de mercado (tarifas, tempo disponível ou reservas) em métricas de satisfação individuais e globais. Os condutores são sensíveis a novas tarifas e os gestores de estacionamento tentam distribuir os clientes de um modo mais lucrativo. Por fim, sendo este um problema naturalmente distribuído, também foi proposto o uso de capacidades distribuídas para os agentes, definidas como micro-serviços. Os comportamentos dos agentes são modelados seguindo a metodologia *Agent Process Model*, que usa modelos de processos para coordenar a interação entre micro-serviços. Esta arquitetura é flexível e escalável, suportando um maior número de agentes e configurações de cenários.

Este trabalho permitiu identificar os preços dinâmicos como um fator crítico para a resolução do problema proposto, quer do ponto de vista dos condutores como dos gestores de estacionamento. No entanto, o fluxo de tráfego na cidade não diminuiu como esperado. Porém, a solução desenhada é capaz de simular comportamentos de agentes e processos de mercado mais complexos que permitem continuar a melhorar a eficiência do estacionamento.

Keywords: Smart Parking, Negociação, Agentes, Micro-Serviços

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"The significant problems we have cannot be solved at the same level of thinking with which we created them"

Albert Einstein

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Abbreviations

API	Application Programming Interface
APM	Agent Process Modelling
BDI	Belief, Desire and Intention
BPMN	Business Process Model and Notation
FIPA	Foundation for Intelligent Physical Agents
ICT	Information and Communication Technologies
IoT	Internet of Things
JADE	Java Agent Development Framework
MAS	Multi-agent Systems
PGI	Parking Guidance and Information
PRS	Parking Reservation Systems
REST	Representational State Transfer
SPS	Smart Parking Systems
STEM	Science, Technology, Engineering, and Mathematics

Chapter 1

Introduction

Most people still prefer to travel in personal vehicles rather than public transport due to its comfort and convenience [Boudali and Ouada, 2017]. However, finding a place to park a car is getting more difficult every day due to the increasing traffic flow and car owners around the world [Kotb et al., 2017]. The most common method to find a parking location is still to manually drive the car looking for a place, which requires both luck and experience [Pham et al., 2015]. Moreover, in densely populated areas such as cities, there are likely more vehicles than parking spots. As such, cruising for parking takes a considerable amount of fuel and time, estimating to be between 30% to 50% of traffic according to recent studies [Fleyeh et al., 2018, Kotb et al., 2017]. The parking problem is not only frustrating and time-consuming but also affects the environment (by causing significant carbon gas emissions) and increases travel cost and traffic congestion [Polycarpou et al., 2013]. The creation of more parking locations is not always a viable solution to this issue. So, implementing more *"intelligent"* parking solutions is seen as a significant challenge to face [Di Napoli et al., 2014]. In this context, new policies are being deployed to restrict the number of parking spots, increase their cost and decrease maximum parking time [Balac et al., 2017]. Consequently, drivers have an increasing need to have more information about parking opportunities.

With the rise of autonomous (driverless) vehicles, new traffic dynamics arise. Firstly, cars might not need to stay parked in the same spot the whole time while waiting for their owners. Secondly, they do not require proximity parking, unlike regular ones, as such, they can park in farther less expensive locations at no cost to their users [Balac et al., 2017]. This scenario shows a need for new regulation policies other than the ones currently implemented: restricting prices and times, for example, might produce harmful traffic dynamics, increasing traffic flow. On the other hand, economics is also affected by these autonomous vehicles dynamics. Since commonly drivers are charged for having their cars in a parking spot, vehicle decisions to change parking autonomously could bring many market-related problems, such as peak demand prices in some hot-spot areas, speculation or even sub-contracting. These unwanted economic situations can be harmful to the system by increasing traffic density, prices and market exploitation, for example. In this scenario, most of the entities (i.e. car drivers and parking managers) are considered to be selfish, meaning they only care about their own goals and preferences, not carrying about the impact of their actions for the overall system. It is essential to understand and create new policies that reduce that impact. Therefore, the existence of an intelligent, efficient and reliable autonomous decision-making system is critical to help every vehicle find a suitable parking spot while maintaining the parking and city managers goals in mind, to reduce the impact of the parking problem [Smolnicki and Sołtys, 2016].

When talking about the economic impact of the parking problem, the number of parking slots in the cities is found to be scarce compared to the vehicles seeking to occupy them. Public parking can be classified into closed and open. Closed public parking relates to places with gate control mechanisms, whereas open ones have unchecked car entry and departure. Traditionally, closed and metered open parking operates like a tariff-based market, where parking managers rent their resources to drivers for a limited amount of time. These parking solutions are usually subject to regulations such as minimum prices and maximum parking period by the respective authorities.

In contrast, other open parking locations are usually free and therefore, are used like collectively owned resource by drivers. Nevertheless, free on-street parking locations, unlike some off-street ones, do not yet possess sensors to collect and disseminate information about their availability, which hinders efforts to implement more flexible parking tariffs[Fleyeh et al., 2018]. However, to help to manage traffic and parking, sharing economy in transportation has been encouraged [Stephany, 2015]. In one hand, some municipalities choose to try to decrease demand by creating bike or car-sharing initiatives [Balac et al., 2017, Patel et al., 2018, Shaheen and Cohen, 2012]. On the other hand, some others try to grow the offer by motivating private owners to rent their vacant parking space [Zhang et al., 2018]. However, shared economy businesses regularly clash with traditional ones, mainly in the matter of the application of existing regulation that the former feel does not apply to their business model, particularly so in the case of peer-to-peer services [Demary, 2015]. More extreme solutions also include traffic restriction programs in cities that only allows vehicles whose license numbers end with particular digits to drive on particular weekdays [C-Y Cynthia Lin et al., 2011].

There have been some efforts in recent years to implement solutions for Smart Parking and provide vehicle-to-vehicle and vehicle-to-infrastructure interaction to improve the parking allocation [Barile et al., 2015]. In the literature, two main mechanisms to reduce the parking problem can be found: Parking Guidance and Information (PGI) systems and Parking Reservation Systems (PRS). PGI systems inform drivers of the location of available parking spots in real-time and provide directions to them, while PRS also include the opportunity to reserve a parking slot ahead of time.

Smart Parking Systems (SPS) are systems that help drivers find vacant parking spots more efficiently [Barile et al., 2015]. In general terms, this means that these systems combine features from both PGI and PRS by guiding drivers to an agreed location. As such, the different actors and their agendas are crucial to achieving coordination. Most of the works in this area consider two main types of participating entities: parking managers, who own and manage parking resources, and drivers, who are looking for an adequate parking spot for their vehicle. Different drivers can have their personal preferences regarding parking, like, for example, the maximum distance from their destination or the maximum price they are willing to pay for the parking location. Likewise, parking managers can have their own goals and restrictions in terms of price, availability and rules for parking. For instance, closed parking lots aim for added profit while open parking, particularly in touristic and shopping locations, strives for shorter parking and increased turnover. In truth, Table 1.1 summarises the properties of the main four parking lot models. In this sense, SPS seems to be the *de facto* solution for the future of parking systems, allowing new economic possibilities with negotiation and reservation support, also providing a positive impact on reducing traffic congestion considering demand-supply rules in traffic flow.

Table 1.1: Properties of different parking models

	Open	**Closed**
Public	• No access control • Free or metered • Goal to increase turnover • Example: regular on-street parking	• Gate control with the possibility of reservation • Free aiming to draw cars outside of the street and provide access to nearby businesses • Paid to obtain maximum profit • Example: parking lot buildings near commercial city areas
Private	• Norms limit access to certain group of people • Usually free • Aims to ensure that drivers allowed to park there, have an available spot • Example: on-street parking spots for residents or users of a specific shop	• Only some people can open the gate • Can be free, for example, home or work garages • Or can be paid periodically, like a subscription for being able to access the parking lot

Nonetheless, being actor-centric systems, Smart Parking might also introduce new dynamics in parking management and new regulation policies should be created to reduce chaotic situations. A notable research gap in SPS is to consider city-level parking (governmental policies) management and traffic preferences as such regulator entity or a city manager. Improved models shall be created to study parking management at each level and consider entity behaviours in multiple situations, such as selfish and harmful actions.

From an economic perspective, traffic management involves pricing some parking locations higher to discourage drivers from parking at predictable popular areas. Hence, drivers can be considered consumers and the city or other parking managers as the providers or retailers of a parking market. Therefore, aligning agents' strategies to seek their own goals with improved negotiation mechanisms, such as being regulation aware or tariff-responsive, could produce results in better distributing the traffic better. Because increases in demand would imply price hikes, these mechanisms could dissuade drivers from parking in overcrowded locations. Simulation allows to test and explore different "what-if" scenarios in a reduced amount of time while maintaining the level of detail necessary. In this scenario, a natural approach is to adopt agent-based systems for representing the entities. In other words, it signifies considering each of the entities as an autonomous agent and the overall system as a multi-agent system. Multi-agent systems allow heterogeneous software agents to execute some action autonomously by using their own set of knowledge and communicating. Therefore, the agents can negotiate with one another [Di Napoli et al., 2014]. In general, these agents are autonomous as well as heterogeneous and will, consequently, reflect the complexity and diversity of the city in a very flexible way. Accordingly, using a multi-agent system to represent their interests and handle the negotiation to achieve each one's goals seems to a logical solution. In this domain, simulation allows checking the possible consequences of new and different market models and policies for the city before their real-world implementation. Hence, this simulation is indispensable for city policy-makers to assert if these new policies are beneficial and can achieve better parking and traffic conditions.

Differently from the traditional software agent system approach in which the software contains all the agent capabilities, externalising the agent capabilities as services is becoming a trend [Kravari and Bassiliades, 2018, Krivic et al., 2018] because each unique agent can be designed using the most appropriate technologies as long as it can communicate with others. Therefore micro-service-based agents can support better horizontal scaling than traditional multi-agent systems, leading to more lightweight, distributed and reusable systems. As such, it is possible to model and simulate agents with distinct decision processes which could lead to a higher number of scenarios.

Due to the traffic and market dynamics, city-level parking management, as well as traffic management, is understood not to have a proper or straightforward solution, but the overall research goal in this field should be the development of tools and models that enable explaining and predicting the behaviour of the system and its entities when these dynamics change. It is imperative to evaluate complex decision models for each actor mixing current behaviours and proposing new strategies, in both market or traffic fields, that can lead to a more sustainable city which is called Smart City. A Smart City can be seen as a six-dimensional system involving people, living, governance, mobility, economy, and environment, which uses information and communication technologies (ICT) to improve the efficiency and welfare of the municipality [Di Napoli et al., 2014, Patel et al., 2018]. Hence, all entities' decisions can influence the overall system.

As such, changes in parking market characteristics have an impact on traffic, as the benefits of implementing new dynamics with different pricing and parking capacity policies and their coexistence can reveal correlation and be distinct from the sum of the benefits gained by applying them individually [Olus Inan et al., 2019].

1.1 Motivation

The need for new studies in Smart Cities and the necessity of gathering plausible solutions for traffic problems motivate this work. Current issues in the fields discussed in the previous section highlight its relevance. Firstly, increments in traffic flow and the introduction of autonomous decision systems could lead to unwanted situations. Secondly, Smart Parking simulations in large populations are still missing proper analysis, meaning the existing solutions not considering recent technological advances that enable the simulation of a large number of drivers as well as, parking spots and the coordination between them, either cooperatively or competitively. Moreover, agent-based modelling for this purpose still needs more in-depth analysis due to the infinitude of scenarios found in traffic situations. In this context, micro-services, due to their reduced computational costs and easy replication, seem to add a viable technical approach to this problem. Also, distinct services can represent different decision behaviours. This feature enables the simulation and later analysis of not only different agent behaviours but also the impact of novel market approaches when coexisting with traditional markets.

In this context, using process modelling to design agent behaviours, could leverage the orchestration of the decisions by thinking about behaviours as if they were processes. This methodology, called Agent Process Modelling (APM), proves to be advantageous. Firstly, the use of a standard process representation for the agent behaviour makes it more readable even for people who do not understand its technological implementation [Küster et al., 2014]. Secondly, agent implementation is understandable for designers and, thus, more easily improved. Thirdly, agent capabilities can be designed and implemented as independent web-services. This architectural choice helps decouple agent logic from implementation and abstract task's execution details

[Endert et al., 2007]. Finally, the APM framework also focuses on cloud-native agent-processes that do not require *"living threads"*, which makes them notably scalable and easily integrated with other services [Markus et al., 2008].

Dynamic price simulation in market-based environments such as parking management is also relevant for city planners and city managers that want to determine whether these practices can help improve traffic flow in the city. Regulation policies appear in this context as a way to shape behaviours to keep the system running in the desired way. In some scenarios, this might be the only way to improve the system's state or to move it out of chaotic situations. Depending on the scenario and the system characteristics, market self-regulation could be sufficient to ensure that.

In this work, the evidence of needing regulation policies will also be subject of analysis. A fascinating outcome of this project is the assessment of the necessity to regulate a system, verifying that it will not go the proper state just by itself. Furthermore, with the increase of peer-to-peer markets, it seems natural to study the application of market-based approaches in parking management scenarios and the consequences of it on the overall system. As such, future development in traffic models has a great need for studying the dynamics of these new market models and their impact on the current ones.

1.2 Goals

This thesis aims to evaluate the impact of dynamic prices in the context of market-based smart parking by modelling and simulating Smart Parking Systems where multiple autonomous software agents seek to achieve their own goals by making decisions in different levels of abstraction. On the one hand, drivers must choose a specific parking spot or deliberate the city path they should follow to get to the parking point. On the other hand, managers need to evaluate current tariff prices as well as assess their overall profit and impact in the occupancy while following some city regulation. Agents are considered selfish, which means an agent's decisions can impact other agent's performance. In other words, one's actions could lead to the dynamics of the system being in an unstable or unwanted state. Specific goals of this work comprise the evaluation of this impact by designing and running realistic simulation scenarios where a parking allocation mechanism could no only decrease overall traffic congestion, time and fuel spent searching for parking but also increase market profit. Thus, the specific goals of this dissertation include:

Goal 1. Analyse the relevant entities (drivers and managers) related to Smart Parking and their characteristics, such as private and public parking lots, open or closed parking spots, among others and their relationship with the overall traffic congestion in a city-wide perspective;

Goal 2. Study the impact of market-related mechanisms between the agents. In other words, evaluate whether some agent's market actions from one agent could impact the overall performance of another agent and the traffic itself;

Goal 3. Develop a distributed simulation system where agent behaviours are modelled as processes and capabilities as web-services to decouple strategies and allow more accessible validation and improvement, regardless of the implementation;

Goal 4. Design and run simulation experiments varying system characteristics, such as different map configuration and traffic situations, or market dynamics, as fixed versus dynamic prices to evaluate the performance of each actor accordingly to the metrics introduced in Section 5.1.

Overall, this work comprises a study of different parking management scenarios and the evaluation of the solutions using both cooperation and competition mechanisms through negotiation. In the end, more particular contributions might include simulation results for cooperative parking lots (one manager) versus multiple competing managers, evaluation of dynamic markets creation as a way to reduce traffic flow, as well as to improve each entity satisfaction of its own goals, and the design of new market-based processes for the related participants.

1.3 Hypotheses

From a technological perspective, the existence of multiple autonomous participants with distinct interests assumes a distributed approach. As such, an agent-based approach is deemed to be a suitable way to perform the simulation. Besides, the use of business processes and micro-services helps to ensure a more decoupled architecture. Additionally, this architecture simplifies the process of replacing the micro-services with improved, more complex and realistic logic beyond the scope of this dissertation. Therefore, the same agent processes can use real-life services for purposes other than simulation.

Our research question is then related to "what would happen to the overall traffic and individual satisfaction when the market characteristics are dynamic?". As such, the hypotheses formulated derive from this question. In this context, since selfish entities bind this work, each of the participants is believed to follow only their interests. Moreover, changes in the environment (agents' world) could imply a measurable impact on their satisfaction. From a systemic perspective, changing market prices of open or closed parking could affect the overall traffic and if the characteristics are optimal, even decline traffic levels while achieving adequate levels of satisfaction for the stakeholders.

In this optimal scenario, the market environment should consider a mixed amount of open and closed parking with different intentions and pricing schemes. In this setting, the term open refers to municipally operated facilities with no access control and the expression closed applies to buildings with access control which are managed by private entities. Thus, the following hypotheses are formulated, driving this work towards understanding how it is possible to achieve the optimal balance between prices in open and closed parking:

Hypothesis 1. *Parking managers' satisfaction can be represented as a function of their occupancy, and to fulfil their goals to get occupancy between some minimum and maximum thresholds, they should update their tariffs frequently*

Hypothesis 2. *Drivers are sensible to parking prices: if parking managers change their prices, drivers should decide to change parking spots and therefore imply traffic variations that are visible in a city management perspective*

Hypothesis 3. *Dynamic pricing in open parking could be implemented as an effort to improve the parking slots availability, thus relieving traffic problems when closed parking lots only cannot guarantee the supply.*

Hypothesis 4. *Even in the case where dynamic market prices effectively work, there shall exist some cases where explicit regulation policies are indeed necessary, and the system's metrics should evidence this need.*

On a more technological perspective, this dissertation finally aims to prove that, given the simulation scenario's requirements for a distributed approach, modelling a solution using distributed agents is preferred. Furthermore, the simultaneous use of micro-services and business processes is thought to aid in better decoupling the solutions architecture and provide better results.

1.4 Contributions

Our hypotheses, presented in Section 1.3, evidence the impact of markets in traffic scenarios, namely the smart parking in a city-level. The study of parking agent models and how their decisions could affect the system is hugely relevant, and much needed to propose new strategies that could help to leverage traffic systems in the future.

Therefore, this dissertation aims to assess the impact of parking agent decision processes and pricing regulation on a city-level scale. The discussion about the findings in the relationship between open and closed parking spots shows a valuable contribution to determine how these innovative market characteristics can affect and improve traffic in the city.

Summarising, the general contributions of this work comprise:

- A first attempt to tackle the impact of the open parking to traffic flow;

- The development of a simulation tool for evaluating market and traffic dynamics considering both open and closed parking lots;
- The design of the related entities' behaviours following a process model approach:
- Insights about using Agent Process Modelling methodology to create cloud-native agents for simulation in the traffic domain;
- The definition of a set of metrics that could help to evidence the need for regulation in a Smart Parking environment

1.5 Structure

This dissertation is composed of six chapters. The present chapter introduced the motivation, goals, hypotheses and contribution expected for this project. In Chapter 2, the background information needed to comprehend this document better can be found. These topics include Smart Parking, the market structures already in place and current technological state for the existing parking solutions. A State of The Art analysis of the related literature can be found in Chapter 3. The analysis covers Smart Parking in more detail and reviews research found on the use of agents, micro-services and business processes in this context. A gap analysis is also presented. Chapter 4 starts by explaining the methodology used to design this project. Besides, the reasoning behind the solution design is presented, followed by implementation details on every component. Through Chapter 5, the simulation experiments are presented and evaluated. Here, details on the metrics used and run configuration are described. This chapter ends with a discussion on the experimental results. Finally, Chapter 6 discusses the implementation decisions and experimental findings. This document is concluded by suggesting some possible future work.

Chapter 2

Smart Parking Management and Related Problems

2.1 Smart Parking

In the context of this work, a Smart Parking is defined as a system that aims to assist drivers in finding a vacant parking spot for their vehicle by collecting and disseminating information about parking condition such as, availability and prices [Lin et al., 2017]. Its main goals include reducing traffic congestion, parking search time, as well as parking contention by making slot allocation more efficient [Wang, 2011]. For this purpose, this definition encompasses various degrees of automation and functionalities. Some Smart Parking systems solely report real-time parking availability and use these to dynamically change parking rates and influence drivers to choose specific locations. As an improvement, there solutions attempting to accurately predict future parking availability based on past data, to better balance reducing drivers' parking search time and increasing providers' revenue for maximum communal satisfaction.

Others take it a step further and also allow reservations to ensure the availability of an empty parking spot upon arrival to the destination. However, this may cause inefficient utilisation of reserved slots keeping them idle when there is a demand. Furthermore, reservations raise issues of cost of cancellation because there is the possibility of parking requests being refused despite the reservation not happening. As a result, drivers are unable to park, and parking managers lose revenue, which causes frustration for both.

Approaches with a higher degree of computerisation, with little to no need for human interaction, include algorithms for automatic parking allocation. Nonetheless, these systems assume that all parking requests are known ahead of time and that there is a sole entity responsible for managing all available car parks. However, this is not the case in most cities.

2.2 Parking Market

Despite its common usage, the classification of parking lots as public and private is used in different contexts to mean different things. One criterion for this distinction based on access to the lot, which is used in Chapter 1, more specifically in Table 1.1. According to this criteria, a public parking lot is one where everyone has access, even if by paying, and a private one implies that only a restricted group of drivers has a right to park there. The other criterion is the one relevant for this section, the management entity. From this perspective, a public parking lot is managed by a municipal organization, which aims to provide better welfare to the city. On the other hand, private lots are managed by a private entity that is competing against other providers for maximum profit.

2.2.1 Importance of pricing policies

A considerable amount of literature has been published on the importance of parking policies and pricing for traffic. Overall, there seems to be some evidence to indicate that parking availability and prices affect driver search patterns and, in so doing, influence traffic [Andrew Kelly and Peter Clinch, 2006]. Consequently, most cities already have policies to price car parks according to predicted demand by pricing popular locations higher, either all the time or in special events, to attempt to balance overall availability and decrease traffic congestion.

Assuming $D_{popular}$ to be a known set of popular destinations and $price_A$ to be the price of parking in A, parking managers can set a maximum price for popular locations and, then calculate the price for their remaining resources using a function that takes into account several components, including this price and the distance to it. Equation 2.1 illustrates an example of such calculation where the city is divided into sectors.

$$price_A = price_{max} - 2^{\frac{distance_{A,N}}{r} - 1} * discount \tag{2.1}$$

where:

$price_{max}$ = price for popular destinations ($price_{max} = price_d, D \in D_{popular}$)
$distance_{A,B}$ = distance between locations A and B
r = distance to divide the the city in sectors
N = closest popular destination ($N \in D_{popular}$)
$discount$ = price factor to be reduced

However, this function is not dynamic and can lead to congested areas, not disappearing but relocating. A possible solution is to routinely alter the current price based on an ideal occupancy range goal. This approach is sometimes also called performance pricing, because instead of choosing a price, the manager chooses a performance standard and lets the market adjust the price, within predefined limits, to reach it [Manville et al., 2018]. Because users usually prefer to pay less if they can still park near their destination, this dynamic helps balance the availability of parking lots. A simple example of this is to add a dynamic component dependent on the occupancy rate of the lot, like the one shown in Equation 2.2.

$$price = price_{base} * (1 + occ) \tag{2.2}$$

where:

$price_{base}$ = fixed minimum price for tariff
occ = the percentage of occupied slots in the lot

2.2.2 Current market policies

Municipal parking has often fixed prices based on distance from highly-demanded locations. However, these are commonly under-priced or free. Additionally, price updates are done manually using a convoluted formula to increase an equally undefined measure of system welfare.

Despite also having fixed prices, privately managed lots are usually over-priced and therefore mostly vacant compared to public ones. However, privately managed parking lots prices are aimed for personal gain. As such, their prices are highly dependent on nearby competition and demand for the location. Besides, some lots associated with commercial activity also apply different rates depending on the use, having some discounts for customers, for instance. When present, performance pricing is mostly found connected to private closed parking where there is more collection of trustworthy information about availability. However, this pricing policy faces issues from administrative entities regarding price boundaries and maximum update regularity.

2.3 Current technological state

The concepts of IoT and Smart Parking are highly connected. In this context, drivers can broadcast their interest in a particular location which provides demand data. From the provider side, low-cost sensors placed at parking spots (both legal and illegal ones) collect and transmit availability data in real-time to devices representing every interested party [Gupta et al., 2017]. Access to this data allows drivers to find a suitable parking spot with higher likelihood and reduce search time. Furthermore, it enables cities to manage their parking supply carefully and control illegal parking. Thus, Smart Parking uses Machine-To-Machine technologies aimed at safety as well as the convenience of the users.

Chapter 3

Literature Review

This section introduces with greater detail the context of this project and presents a survey of preceding literature. Section 3.1 explains some of the work done in Smart Parking. Then, multi-agent systems and their benefits to Smart Parking are presented in Section 3.2.1. In Section 3.3, the micro-service architecture and its connection to multi-agent systems are introduced. Lastly, Section 3.4 exhibits business processes and markets related to parking.

3.1 Smart parking

Cities with more dense traffic and on-street parking have a greater need for smart parking solution to decrease the volume of drivers cruising for free parking. These solutions also bring economic benefits. Firstly, distributing parking availability information can shorten the time drivers spend searching for parking, reduce air pollution, fuel consumption and traffic congestion. Secondly, these solutions can also increase park revenue by reducing the idle time for the parking spots, and the same sensors can also detect unapproved parking. Thirdly, by making the traffic more fluent, urban mobility increases, which, in turn, can boost the city's events and business opportunities [Lin et al., 2017].

In this context, Smart Cities use Intelligent Transportation Systems (ITS) to improve transportation. ITS are technological applications for transport and infrastructure that provide communication between different frameworks to increase productivity, safety and environmental performance. Associated with Smart Parking, there are two ITS central systems involved: the Parking Guidance and Information and the Parking Reservation systems [Kotb et al., 2017]. As a whole, Smart Parking can be summed by the administrative and operational services shown in Figure 3.1.

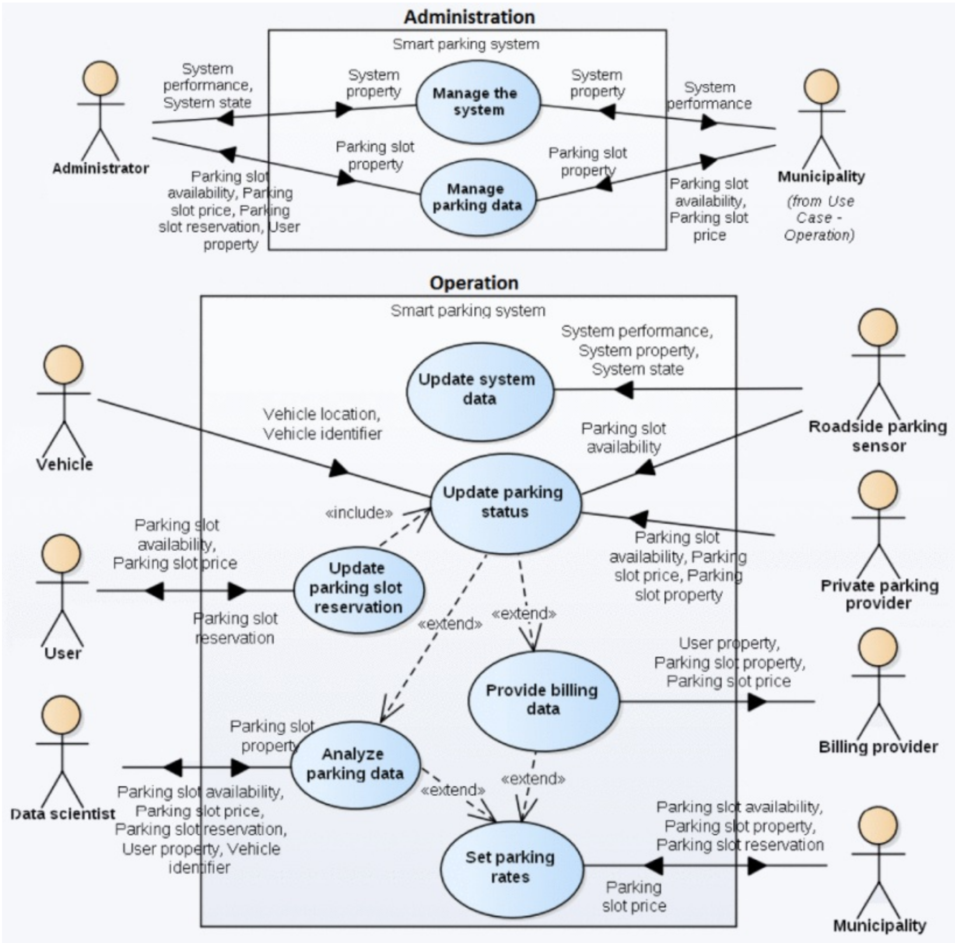


Figure 3.1: Example of Smart Parking Use Cases [Lin et al., 2017]

3.1.1 Parking Guidance and Information Systems

Parking Guidance and Information (PGI) systems provide information about the availability of parking spaces in monitored areas to interested drivers. They reduce overall traffic congestion by helping drivers find free parking spaces easily. A PGI system has four main components [Kotb et al., 2017]: parking monitoring mechanism, parking space information dissemination, telecommunications network and control centre. The parking monitoring mechanism employs a variety of different IoT sensors used to perceive if a parking space is available [Gupta et al., 2017]. These sensors all have different characteristics in both reliability and cost to the park and must be chosen according to them [Kotb et al., 2017, Polycarpou et al., 2013].

This type of systems has existed since the 1970s through the use of variable message signs located nearby parking lots. Since then, PGI has evolved and, with the use of different sensors and technologies, can now offer more detailed information within the parking lot and be used in on-street parking. Besides, these systems now incorporate web and mobile applications to provide real-time access to data on parking availability from several locations as well as guiding drivers to free slots [Polycarpou et al., 2013].

However, while the use of PGI increases the probability of finding free parking spaces, these systems also modify the driver's behaviour from searching to competing for parking [Kotb et al., 2017]. The reason for this competition is that numerous drivers receive the same information. As such, they tend to flock to the same available parking location, which is likely not to be free by the time they arrive [Geng and Cassandras, 2013]. In an attempt to mitigate this problem, some authors choose to add parking prediction techniques to the information shown to each user and guide them to a location with a higher probability of being free by the expected time of arrival [Liu et al., 2018, Qiu et al., 2018, Rajabioun and Ioannou, 2015].

3.1.2 Parking Reservation Systems

Parking Reservation (PRS) systems allow drivers to book a parking space and avoid conflicts at arrival. These systems can, not only, reduce traffic congestion like PGI but also, maximize parking resources utilization and revenue and minimise drivers' cost [Kotb et al., 2017]. PRS can be sub-divided in three categories: Web/Mobile, Deterministic and Pricing-based.

Web/Mobile PRS systems at their base are PGI systems with the added functionality of a driver being able to reserve a parking location of his choosing ahead of time. Gupta *et al.* [Gupta et al., 2017] and Mangwani [Mangwani, 2018] proposed two such systems with the use of IoT. However, in these systems, the user must choose manually which parking location to reserve. Techniques from the other two sub-categories can be applied to obtain a better overall allocation. Deterministic PRS systems assume the driver's arrival time to the parking lot has to be known *a priori* and that there are sufficient resources to serve all the vehicles in a time frame. Then, the system either minimises some cost function for the driver or maximizes the parking lot revenue. IParker [Kotb et al., 2016] is an example of such a system which combines intelligent resource allocation, real-time reservations, and dynamic pricing policies by using mixed-integer linear programming. However, the cost function minimised for drivers carries the same weight for monetary cost, walking distance and search time, which may not be accurate for everyone.

Pricing-based PRS systems allow the price of a parking space to dynamically change to efficiently manage the parking resource utilization and steer general traffic flow. These pricing policies are usually archived by using agents representing drivers and a kind of parking manager. In this context, both agents can communicate to find a suiting price either by negotiation [Barile et al., 2015, Di Napoli et al., 2014] or auctions [Kong et al., 2018]. However, auctions raise fairness issues by making better parking spots available only to the wealthiest. Another method would be to make the price depend on some aspect beneficial to the manager. For instance, prices could rise linearly to demand or decrease in under-used areas [Barile et al., 2015, Nocera et al., 2014].

3.1.3 Evaluation metrics

In this context, it is relevant to mention the metrics customarily employed to measure the success of the Smart Parking System. These include traffic flow, lot availability and utility for every agent involved.

Cruising for parking can have tremendous repercussions on street traffic, particularly in areas where short-term parking is the norm, like shopping or school areas. As such, SPS is considered to have a beneficial impact on the city when this metric is reduced.

However, this system still needs to ensure that most drivers find a place to park their vehicle. As such, one of the most recognised tools for assessing Smart Parking is gauging whether the rate of successful parking increases[Houissa et al., 2017]. Another metric that can be used is parking lot availability ratios[Di Napoli et al., 2014, Harper et al., 2018, Kotb et al., 2016]. If parking lots obtain similar occupancy rates across the city, there are more possibilities that every driver can find a suitable parking spot for his activities.

$$SW = \frac{\sum_{i \in PR}(U_D(i) * U_{PM}(i) * U_{CM}(i))}{|PR|} \tag{3.1}$$

where:

PR = set of parking requests
U_D = utility for the driver
U_{PM} = utility for the parking manager
U_{CM} = utility for the city manager

Furthermore, agents individual utility is a well-established approach in evaluating the performance of Smart Parking[Di Napoli et al., 2014, Kong et al., 2018, Kotb et al., 2016] because it can illustrate how the parking allocation works differently for every stakeholder in the system. To observe a combination of all the utilities, system welfare, calculated by Equation 3.1, is used [Barile et al., 2017, Barile et al., 2015]. Therefore, the ultimate goal is to increase system welfare.

3.2 Agent-based Models

As Ferber defined in [Ferber, 1997],

"An agent is a real or virtual autonomous entity, operating in an environment, able to perceive and act on it, which can communicate with other agents, which exhibits an independent behavior, which can be seen as the consequence of his knowledge, its interactions with other agents and goals it need to achieved".

These models are suitable for assessing the consequences that emerge from the collective behaviour of individual entities. The reason for this is that agents provide a bottom-up approach to representing the scenario to be simulated.

Used in the scope of most STEM (Science, Technology, Engineering and Mathematics) disciplines, these computational models are suitable approaches for simulation scenarios where real-world testing would be too expensive, dangerous, environmentally damaging, or even physically impossible [Leitão and Rückemann, 2013]. Therefore, making it possible to study how new dynamics could impact population-level complex phenomena. However, modelling and simulating systems with increasing scale and detail/precision, also increases computational requirements, to the point of parallel solutions can become a necessity [Rousset et al., 2016].

3.2.1 Multi-agent Systems

The concept of Multi-agent Systems (MAS), derived from the field of distributed artificial intelligence, is defined by the use of decentralized parallel execution of autonomous agents[Leitão and Rückemann, 2013]. These systems aim to find solutions for problems too complex for a single agent or monolithic system.

As mentioned in Section 3.1.2, the actors in transportation systems, in particular, Smart Parking, (drivers and parking managers) have characteristics that match the definition of autonomous agents well. This fact plus the high level of complexity of the system allows for modelling Smart Parking Systems in terms of agents who interact in such a way to reach their goals, both selfishly and cooperatively [Vasirani and Ossowski, 2012].

In truth, Shin and Jun [Shin and Jun, 2014] propose a system with five actors: parking lot, parking management systems, a central server, personal navigation device and driver. In this system, the central server is responsible for the parking allocation by answering the drivers' requests with the best available parking location for reservation or if none is available with the most probable to be available by the time the driver arrives. A year later, Barile *et al.* [Barile et al., 2015] describe two types of agents, drivers and parking manager, as a refinement of previous work [Di Napoli et al., 2014, Nocera et al., 2014]. The parking managers act on behalf of the city and can respond to drivers requests with an offer of the park that better matches it.

The driver can only accept or reject the offer based on their own parameterized utility function. Consequently, this system can now simulate drivers with different preferences. In the same topic, Boudali *et al.* [Boudali and Ouada, 2017] propose a similar multi-agent system with a more distributed approach, as drivers can only negotiate with nearby parking facilities, and using a multi-criteria ranking method to try to mitigate reservation conflicts and reduce the time the reserved parking spot is idle.

However, the solutions described above do not include private parking. Kong *et al.* [Kong et al., 2018] suggest a system where private parking owners can exchange their parking spots during the workday. If the exchange is impossible, they are encouraged to rent the parking spaces to a central platform who then auctions parking time-slots in all available parking spaces (private and public) to drivers.

Another use for agents in Smart Parking is guidance to the most probable location with available parking. By assuming on-street parking to be free, Houissa *et al.* [Houissa et al., 2017] use a system with two agents, drivers and street segments, where the former tries to learn which is the next segment in the itinerary to maximize a driver's chances of finding a parking spot faster. The downfall of this system is that the learning process must be restarted for each driver due to the objective function, the driver's final destination, changing.

3.2.2 Agent Frameworks

It should be emphasized that there is a clear distinction between agent-based models and multi-agent systems. The former is to be used in a simulation context, whereas the latter have real-life applications. Therefore, on the one hand, Agent-based Models frameworks have simulation infrastructure, like scheduling and synchronization between agents, but are not capable of agent-based solutions. On the other hand, MAS frameworks are built for developing these solutions by following specifications that enable successful interaction with other agent systems. However, by nature, these platforms lack functionalities specific for simulation purposes[Leitão and Rückemann, 2013]. Notwithstanding, both frameworks can be used for simulation purposes depending on the context and model requirements.

There numerous agent-based modelling and simulation tools available, each with a somewhat distinctive reason for its existence, all concerning different levels of generality, usability, mutability, scalability and performance of the system. For example, most Agent Development Frameworks require proficiency in programming languages such as Java, C/C++, Python or Basic. However, there are a few tools that enable non-technical users to build higher-level simulation models by using Application Programming Interfaces (APIs), graphical add-ons and libraries, but these lack flexibility in a simulation application. As such, an ideal framework should require a minimal learning curve, while being able to create simulations adaptable to any domain and execute them robustly regardless of computing machine [Abar et al., 2017].

The majority of multi-agent platforms do not provide native support to run multi-agent simulations in parallel. In other words, they are not prepared for horizontal scaling. These properties can be achieved by developing dedicated models or implementing wrappers from the very start. However, this approach is technically complicated, and non-specialist programmers model most agents. Therefore, Parallel and Distributed Multi-agent systems are a better solution as they enable the simulation to run on several distinct nodes with agents distributed evenly amongst them, as well as, the communication and synchronization between the said processing nodes [Rousset et al., 2016]. However, these solutions are still far from perfect. The remainder of Section 3.2.2 presents some known Agent Frameworks as well as their strengths and limitations in terms of designing and executing multi-agent simulations.

3.2.2.1 JADE and Jadex

JADE (Java Agent Development Framework) is a platform to implement multi-agent systems which comply with FIPA specifications for interoperability [Bellifemine et al., 2005]. According to Bellfemine *et al.*, “The Foundation for Intelligent Physical Agents (FIPA) is an international nonprofit association of companies and organisations sharing the effort to produce specifications for generic agent technologies” [Bellifemine et al., 2001]. As such, this organisation identified some key features that are vital for managing an agent-based system, like the existence of an Agent Management System, Agent Communication Channel and Directory Facilitator, as well as, describing agent content language and ontology [Bellifemine et al., 2001].

JADE aims to simplify the development of distributed agent-based solutions by providing features to deploy, manage and debug them while maintaining easy integration with other tools [Leitão and Rückemann, 2013, Lamersdorf et al., 2011]. However, due to targeting agent-based applications, it does not provide any time discretisation or synchronisation support for simulation. Also, JADE’s agents are written in Java and use multiple transport protocols like Java-RMI, HTTP or IIOP to implement FIPA compliant communication [Bellifemine et al., 2001]. These messaging protocols allow for agents to be distributed across several nodes but, reveal to be unfit for parallel computing as they are inefficient in high-performance networks by making use of synchronous calls [Rousset et al., 2016].

In this context, Jadex (JADE extension) appears as a layer on top of JADE to design and implement intelligent agents using belief, desire and intention (BDI) model. This modelling paradigm is based on the notion of agent mental states and plans, consequently allowing for higher-level development of rational agents. In this platform, the agents are specified in XML with plan details written in Java [Leon et al., 2015]. By using the JADE platform as a base, the development of agents in Jadex can still utilise all the tools available in JADE [Lamersdorf et al., 2011], but also shares all the shortcomings stated.

3.2.2.2 Repast

The Repast Suite is a collection of agent-based modelling and simulation platforms for the creation of both reactive and BDI object-oriented agents. These platforms are known for their high modelling strength and a vast range of applicable simulation domains, at the cost of, requiring high model development effort and proficiency of programming languages.

Repast Symphony and Repast J are modelling systems designed to serve users with medium to large-scale simulation needs. Both include user-friendly graphical interfaces. Symphony is Java and ReLogo-based having visual, intuitive model development and management tools with flow-charts. Repast J uses common or Logo-like C++ programming languages and also provides built-in simulation results logging and charting tools.

Repast for High-Performance Computing (RepastHPC) is a C++-based modelling system specially designed for high-performance environments and, therefore, is adapted to parallel environments. RepastHPC's synchronization method is event-driven but, supports defining a periodic scheduled event, so that time-driven simulations can be achieved. Although highly scalable, agent communication is carried out not by messages but method calls, this translates to no communication that yields agent modification being permitted between remote agents. As such, RepastHPC will only high efficiency and scalability on read-only models [Rousset et al., 2016].

3.2.2.3 NetLogo

NetLogo is an Agent-Based Modeling Toolkit for simulating natural and social phenomena. It uses a platform-specific simple programming language (NetLogo) and user-friendly graphical interfaces which provides an accessible introduction to agent-based modelling. It also provides access to an extensive collection of sample models that are easily modified and extended to match the simulation requirements. These properties make this a viable tool for teaching and research purposes for medium to large-scale models [Abar et al., 2017].

One of the downsides of this tool is restricted application domains provided. Due to the lack of versatility of the framework, complex models, for example, ones that use non-grid environments, are outside the capacity of NetLogo [Robertson, 2005]. Additionally, being a tool built for simulation, this framework is unable to create multi-agent systems for real-life application purposes.

3.2.2.4 Agent Process Modelling

Agent Process Modelling (APM) is a multi-agent system framework that models and orchestrates agent behaviours as processes [Rúbio et al., 2019]. By using Business Process Model Notation (BPMN) standards to define intra-agent behaviours, APM both decouples agent logic from implementation and is comprehensive for a broader audience. Therefore, non-technical users can also understand and improve agent behaviour. The Business Process Model (BPM) engine then used to run the agents is a finite-state-machine, unlike the other platforms where each agent was a computer thread. Therefore, this framework is more lightweight and allows for efficient, distributed simulation operating in a virtually infinite environment [Markus et al., 2008].

In this agent technology, Agent capabilities are developed as micro-services or web-services. As such, agent implementation is more transparent and can be partially reused for similar scenarios. Furthermore, this allows for seamless integrating with a much more comprehensive range of applications and domains [Rúbio et al., 2017].

3.3 Micro-services

Micro-service architecture is developing an application as a suite of small domain-driven services, each running independently and communicating in a light-weight manner with one another. In this way, each service can be modified, added or removed without impacting the system as a whole. In this way, the micro-service architecture is very similar to multi-agent architecture [Krivic et al., 2018]. Table 3.1 shows that micro-services can emulate the same properties as a multi-agent system.

Table 3.1: Agent properties present in micro-services [Krivic et al., 2018]

Agent Property	**Present in micro-services?**
Autonomy	✓
Adaptation	×
Interaction	✓
Mobility	✓
Learning	×
Collaboration	✓
Coordination	✓
Reactivity	✓

Kravari and Bassiliades [Kravari and Bassiliades, 2018] combine intelligent agents and the micro-service architecture to propose a rule-based eCommerce methodology “IoT’s Things” can safely trade on the network. This study shows that Multi-agent systems in a micro-service architecture provide added interoperability, reusability and overall efficiency to the distributed system, as agents who represent things all use different technology and can still negotiate with one another.

3.4 Business Process Modelling

As mentioned in Section 3.2.1, multi-agent systems are suited for complex distributed scenarios. However, there is a disconnection between business and multi-agent oriented software development, which is the reason for the slow adoption of agents in the industry [Endert et al., 2007]. Despite being possible to introduce mentalistic notions to agents, business users map their issues to business processes and entities [Endert et al., 2007]. A business process is a repeatable set of steps or activities that need to be executed to produce value. Modelling these processes is vital to understand who are the actors and steps involved, as well as, try to improve their efficiency [Tjoa et al., 2008]. As such, a mapping between business processes and entities to agents, their actions and decisions, is necessary to bridge this gap.

Markets are economic structures in which at least two parties exchange resources, either goods or services. In markets, processes represent the logical flow aiming to coordinate agent activities and allocate the resources by using negotiation [Rúbio et al., 2017]. In the case of Smart Parking, agents transact a particular parking infrastructure in the required time frame. As such, the parking market can be studied as an exchange of a resource.

Regular commuters tend to have long-term contracts with parking lots, whereas other drivers, such as shoppers, tourists or driver with short-term parking needs, need to search for publicly available opportunities near their destination [Anderson and de Palma, 2004]. The latter can then choose between different parking arrangements. The parking spot may be in a free parking location, on-street or off-street, as such, these work like communally owned parking. Another scenario would be metered on-street parking, where the driver needs to contract that location for a maximum amount of time before legally having to free it. The third scenario would be a paid parking arrangement where the driver needs to pay the time used right before leaving. The last two scenarios can be seen as tariff-based retail markets where there is a parking manager (private or municipal) who acts as a provider and drivers are the customers.

However, the use of technology has allowed for more control on resource management and foster the emergence of a sharing economy, a volatile market where consumers can occasionally take the role of providers [Rúbio et al., 2017, Stephany, 2015]. In truth, Melo *et al.* [Melo et al., 2019] conducted a case study in Porto where parking spots reserved exclusively for city logistics operations were used for short term (10 to 20 minutes) parking. This study concluded that shared parking could effectively reduce delay and travel times, queue lengths, and fuel consumption and, also, show an increase in vehicles average speed. Likewise, there are some efforts to incentive "selfish sharers" rent their own parking space during unused hours to maximise already existing resources [Stephany, 2015, Zhang et al., 2018], therefore introducing peer-to-peer markets to this scenario.

3.5 Gap Analysis

All of the studies reviewed in the theme of Smart Parking support the hypothesis that this is a viable solution for the parking problem. Table A.1, in Appendix A, shows a summary of the characteristics of these systems studied in the literature and their goals.

Much of the available literature on this subject deals with the question of implementing more efficient reservation policies. Others have highlighted the relevance of providing better guidance for drivers in increasing their parking success.

Furthermore, almost every paper written on the topic of Smart Parking considers that every entity involved in the parking problem is selfish. Nonetheless, some studies also include a central entity to represent the system as a whole or the city's interests [Boudali and Ouada, 2017, Rizvi et al., 2018]. This entity is usually responsible for allocating every driver to a parking slot and, as a result, obtain better global social welfare. However, this approach does not account for the existence of privately managed parking lots for which the city has no means to change parking conditions directly.

There is a relatively small body of literature that is concerned with understanding market policies that could also help alleviate the parking problem. These generally model individual managers for each parking location with the power to dynamically modify parking rates [Balac et al., 2017, Kotb et al., 2016] or employ city-wide methods for calculating prices based on a performance metric [Nocera et al., 2014, Barile et al., 2017]. As such, the studies reviewed either consider only on-street parking or closed off-street car parks.

Overall, much of the current literature on Smart Parking pays particular attention to the impact these systems have for both drivers and an entity responsible for parking resources. There are little studies on the role these systems have in improving system-wide satisfaction or welfare.

Chapter 4

An Agent-Process Model Approach for Smart Parking

This project proposes to use a micro-service based multi-agent system simulation to represent all stakeholders of the parking problem. As seen in Section 3.2.1, Multi-agent systems can represent the parking context, and all the entities involved very naturally and intuitively. Therefore, using MAS provides a model much more convenient to calibrate and to yield accurate results. The use of micro-services to model the agents' capacities also provides scalability and flexibility to accommodate a great variety of scenarios.

4.1 Methodology

This project considers a city with several open and closed parking locations, which are monitored and whose characteristics, like, for example, availability and price, are known to every agent of the system. In this context, it is assumed the existence of IoT sensors and devices that collect these parking slots availability and help better allocate parking in a city.

In an attempt to produce more reliable results, the simulation scenarios are based on real-world map information collected from the OpenStreetMap API. As such, given the limit GPS coordinates, the position of all the parking locations, both on and off-street, and the paths that unite them are determined. However, this source does not provide sufficient data, particularly regarding parking lot properties. Therefore, there is a need for additional data that allows further parameterization of the simulated environment, like the addition or removal of streets or parking capacity.

4.1.1 Open versus Closed Parking Overview

Previous studies [Balac et al., 2017, Kong et al., 2018] mostly defined private parking spaces as those who are exclusively owned by someone and, as such, are accessible only for a limited group of drivers, like residential garages or parking spots reserved for a particular shop's customers. By contrast, the term "public parking" is generally understood to mean the locations which are available for everyone, such as regular on-street spots. The scope of this thesis only contemplates public parking and considers all on-street parking is considered to be open and off-street lots to be closed.

There are some City Councils [Cork City Council and QPark, 2018] which provide reports of their public parking facilities and respective prices and availability. These can be used to model parking locations and base prices for this simulation. At the moment, there are four scenarios designed for this simulation, each with different pricing strategies for both open and closed lots.

4.1.2 Entity Overview

The academic literature in Smart Parking [Barile et al., 2015, Di Napoli et al., 2014, Harper et al., 2018, Nocera et al., 2014] has identified two entities involved: drivers and parking managers. In this works, the set of parking managers have total control over every parking facility in the scenario. So, they can have selfish, greedy motivations or, also, model the global efforts of the city. However, there is a body of literature that describes city managers who have more macroscopic goals for parking. Consequently, in this project, there are three types of agents to model these entities.

Drivers represent the people or autonomous vehicles who need to find a parking spot that meets their requirements. These requirements can be a maximum distance from the final destination, the minimum time required and budget. However, these agents also have preferences to model different driver profiles. This preferences can be modelled as weights in the utility function, as such, drivers can prefer distance from destination or prices to be minimum. Hence, drivers objective is to minimize total daily costs, including the parking fee, total driving distance and round-trip from parking to the final destination by negotiating where to park. For this purpose, these agents can search for parking.

Parking Managers reflect car parks owners, both public and private, who want to maximize their profit or obtain improved spot turnover. Similarly to drivers, each parking manager has variable weights associated with the profit and lot availability. Thus various profiles can be modelled. This agent can manage the parking slots under its supervision and change the price asked for them.

Lastly, the City Manager represents the public interests in the parking arrangement. Therefore, this entity is mostly responsible for enforcing parking regulations and distributing drivers across different parking locations better. Consequently, its actions aim to decrease traffic flow and increase parking turnover near central city locations, such as near touristic, commercial and school areas. As such, the utility for this agent is dependent on the car park availability and distance from these troublesome locations.

4.2 Overall Architecture

From an architectural perspective, this project has three main components further detailed in Sections 4.3 to 4.5: the simulation service, the (APM) agent service, and decision logic. Figure 4.1 shows a components diagram of this architecture

The simulation service is responsible for designing and running the simulation experiments. This service provides a graphical interface for visualizing the simulation scenario and the agents' behaviour. The actors specified in the simulation service then use the decision processes specified in the APM service to navigate the simulation.

The agent service is the base for designing, running and monitoring intelligent agents that represent the entities defined in Section 4.1.2. As such, it specifies and implements the decision process of every stakeholder of the parking problem. HTTP requests are used to obtain information from the other two services. However, agents need to communicate between themselves and wait for events triggered by the simulation service. For these situations, the use of Kafka messages was deemed more suitable.

The decision logic service provides the agent capabilities and simulation context. Notwithstanding, real-world micro-services that provide agents with the knowledge needed for decision-making can easily replace this last service.

The workflow of this solution starts providing the simulation configuration parameters to the simulation service, which include a map of parking lots, the number of drivers and which processes each entity in the system uses. After the configuration is complete, this service is tasked with the creation of the corresponding agents in the APM service and with uploading parking lot information to the decision logic service.

When after the instruction to start simulation is given, the simulation sends a message to the APM service every time the driver actors reach specific points where they must make decisions, like intersections and parking locations. Upon receiving decisions requests, the driver agent uses the decision logic service to obtain information about the environment and, while negotiating with other agents, like parking managers, utilize their capabilities to modify this environment. The actions include the occupation and liberation of parking slots by drivers and price modifications by managers. After this decision process has concluded, the agent service reports the decision back to the simulation and awaits further events, such as messages or timers.

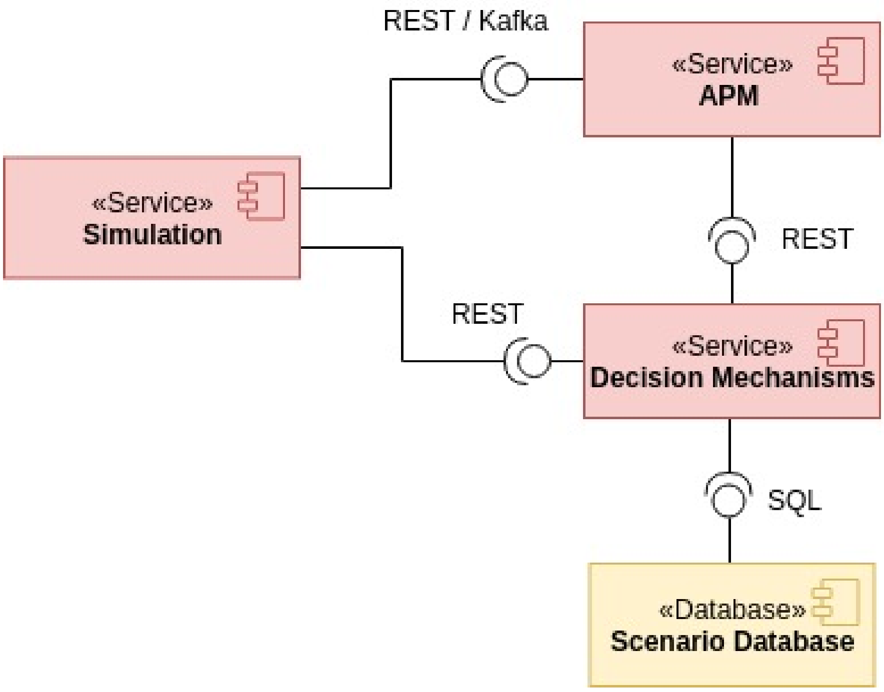


Figure 4.1: Component Diagram of the overall structure

4.3 Simulation Service

The simulation service is implemented in JavaScript using a server written in Node.js, and client-side served in P5.js for a graphical interface. The use of web-sockets enables synchronization between the server and various clients that are observing the same simulation. As mentioned in Section 4.2, this service also connects with a Kafka broker to send messages to the agent service.

Figure 4.2 shows the interface for configuring the simulation. As can be seen in this Figure, there is a map illustrating the city located on the right side of the screen. In this map, the lines represent roads. The small squares that are connected by the roads denote decision points. These represent any location where drivers can make a decision, such as intersections or closed parking lots. For coherence, both roads and decision points use the same colour scheme, so any brown shape represents that parking is not allowed while green signifies that it. In other words, green roads and decision points show on-street and off-street parking, respectively. Lastly, the thinner green shapes, shown solely for map readability purposes, represent the contour of closed parking facilities. On the left side, there is a column containing all the forms provided for setting up the simulation parameters and editing the map. On the top, the first three menus allow downloading map information from OpenStreetMap, loading previous configurations and saving the current one, respectively.

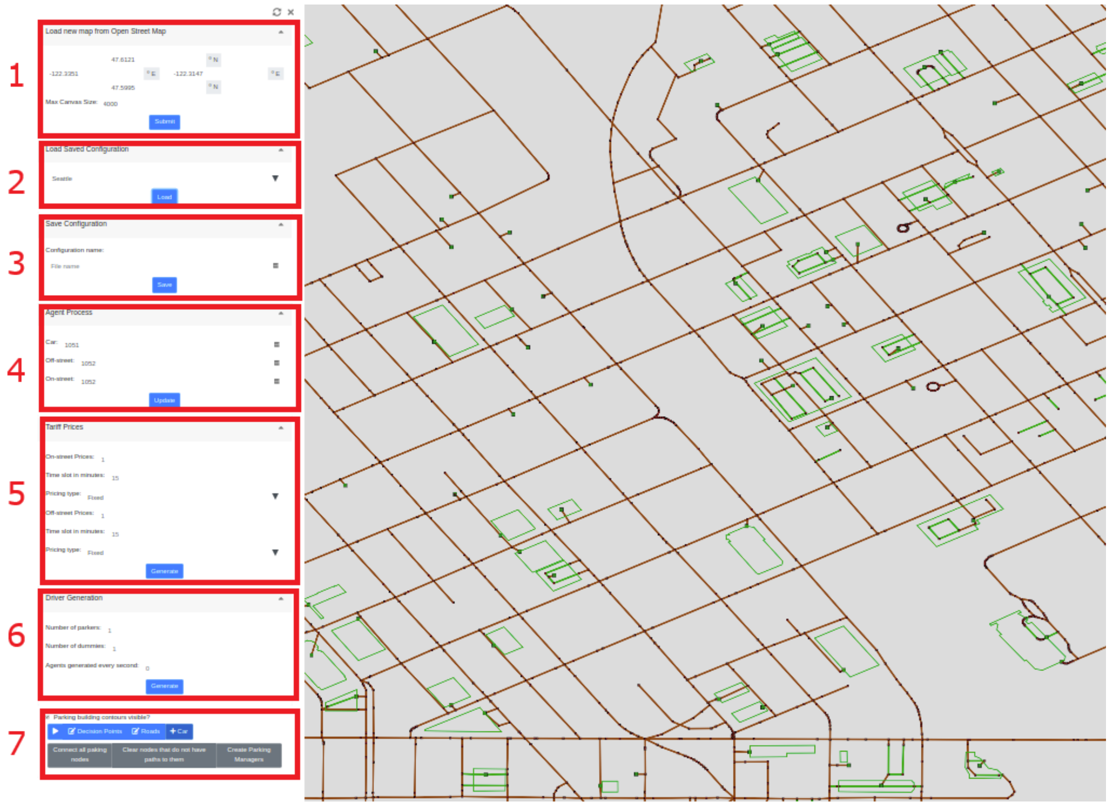


Figure 4.2: Simulation configuration interface with a map based on the city of Seattle

Menu numbered four is responsible for determining the processes used for drivers and managers of both open and closed parking lots. If multiple process identifiers are provided separated by a comma, they are chosen randomly at the time of agent creation. For example, if two processes are specified for driver agents, probabilistic states that half of all driver agents use the first and the other half the second.

Configuration of starting tariffs and pricing policies employed by open and closed parking lots is achieved through menu five. Like the case above if multiple prices are specified, they are assigned randomly to created parking lots. The policies existent determine how the Decision Logic service calculates the rate for parking. Section 4.5 provides further information on how these prices are calculated.

The sixth menu allows the user to populate the simulation automatically. In this context, parkers represent drivers who intend to park their vehicle and, as such, have agents associated with them. The set of possible destinations for these drivers is minimal, only three points by default, so popular demanded areas can be portrayed more accurately in the experiments. On the other hand, dummies are drivers that are forever circulating the environment to mimic normal traffic flow.

In the bottom-left corner, menu seven shows a collection of buttons to run and pause the simulation, as well as editing roads and decision points and adding drivers.

The edition of roads is done by choosing the option with the same name and then clicking on two decision points. If a direct path already exists between these two points, the platform asks for confirmation to remove the road. In case it does not exist, a pop-up window appears asking whether it offers on-street parking and if it is only one-way (from the first point selected to the second) or two-way.

Similarly, the user can edit decision points is accomplished selecting the mode of the same name and then clicking on any spot of the map. If the location clicked is a decision point, the platform asks for confirmation and then remove it. Otherwise, a window emerges to query about whether the decision point is a closed parking lot or just a junction between roads.

To add a driver manually, the user must choose this option on the menu and then select two decision points. The first is the driver's starting point and the second the destination. If there is a path between the two points, the service then creates an agent containing this information and draw the driver on the starting point of the map.

The only action necessary for starting the simulation run is pressing the play button present in the second row from the bottom. From this moment forward, the simulation platform begins regular communication with the APM service, and the movement of the drivers becomes apparent in the screen. As shown in Figure 4.3, drivers represented by yellow circles can be seen moving towards their selected choice for parking location. Parking locations are represented by green lines, in the case of on-street parking, or green squares for off-street lots.

Due to the source of map data, OpenStreetMap, not providing information regarding parking capacity, this platform assumes that parking slots are 5.5 meters wide and use this value to calculate how many slots exist in every street where parking is allowed. For closed lots, the parking capacity was fixed at three, so there are extreme cases of parking scarcity.

4.4 Agent Service

The Agent Process Modelling (APM) service's goal is designing, running and monitoring agent-based solutions using the agent-process model. Therefore, APM's agent behaviours are developed and depicted as business processes. Thus, these processes and can be combined, as sub-processes, to define how the agent react. These behaviours can include calling micro-services that act the agents' capabilities to execute tasks.

Processes are created and stored to be re-utilized by multiple different agents. However, each agent during its execution can take different routes and call various services or sub-processes according to the knowledge it possesses. Agents can also communicate with one another by

Figure 4.3: A simulation run set in a map of a section of Avenida da Boavista

exchanging messages or with other world entities (real or simulated) by invoking external micro-services.

4.4.1 Business Process Model and Notation

Created by Business Process Management Initiative, Business Process Model and Notation (BPMN) is a standard graphical notation for specifying business processes. Considering that, as stated previously, agent behaviours in APM are defined as business processes, it is logical to use this notation for this purpose. With a structure based on a flow-charting technique, BPMN is composed of three types of elements: Events, Activities and Gateways.

4.4.1.1 Events

An Event is drawn as a circle that represents that an event has occurred; they can be broadly divided into two categories, Catch and Throw. Catch Events denote that the event is received, whereas the process sends Throw Events. Details regarding the event can be shown in the middle of the circle. For example, events for both receiving and sending messages have an envelope drawn in the middle. There are three types of Events: Start, Intermediate and End.

Start Events act as process triggers and, as such, can only be Catch. In contrast, End Events represent the termination of the process and are restricted to Throw events. Intermediate Events happen in the middle of the process and are allowed to be of both categories. Figure 4.4 shows a table with icons of all Events, some of which are not available in APM.

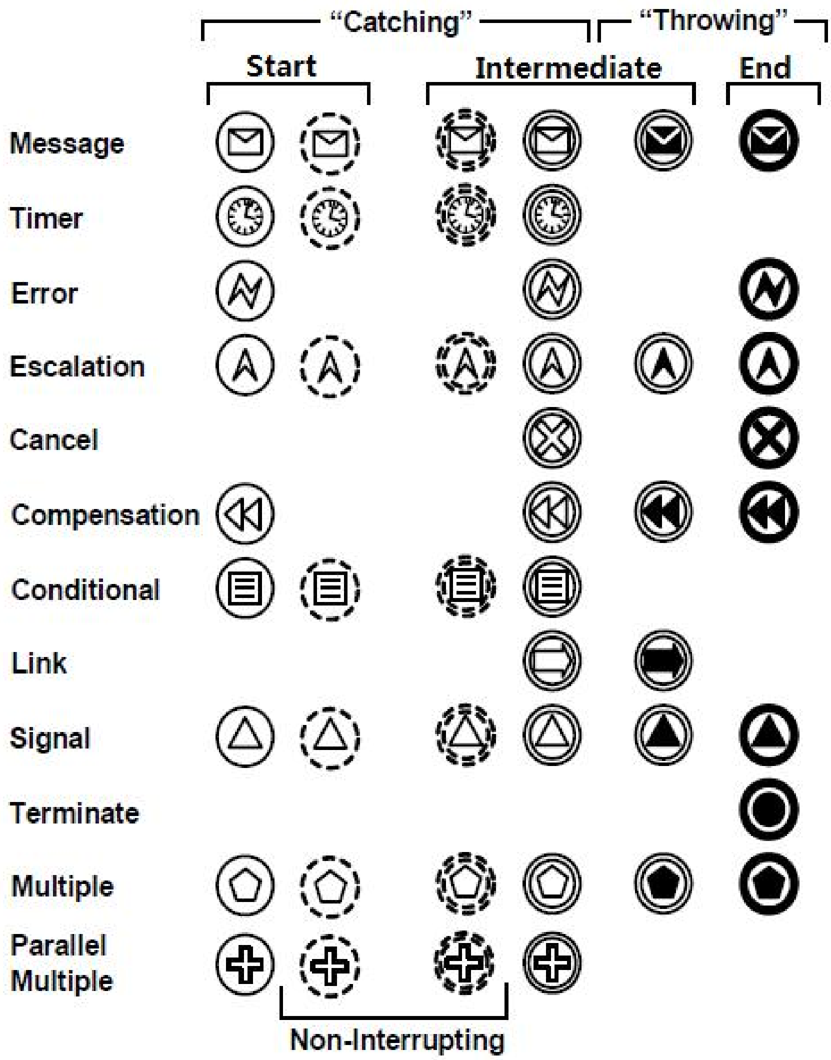


Figure 4.4: BPMN events

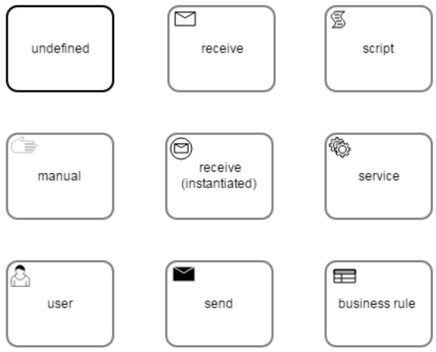


Figure 4.5: BPMN activities

4.4.1.2 Activities

Rounded-corner rectangles represent Activities and denote atomic or compound actions executed by the process. An atomic action or a Task represents a unit that cannot be broken down to a further level of detail. Differently, compound activities are also known as Sub-processes. These can be either explicitly shown as a process within this rounded-corner border or by an icon. Figure 4.5 shows the icons illustrating Activities.

4.4.1.3 Gateways

Represented with a diamond shape, Gateways define forking and merging of paths, depending on the conditions expressed. As illustrate in Figure 4.6, there are four types: Exclusive, Inclusive, Parallel and Event Based.

Parallel gateways create bifurcating paths in the process flow and allow for parallel execution as the name suggests. Exclusive and Event-based gateways create alternative process flows

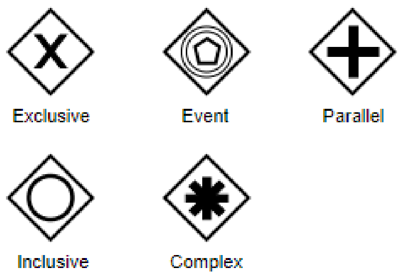


Figure 4.6: BPMN gateways

where only one path is taken according to the conditions, like an XOR computational gate, the only difference is that Event-based gateways “conditions” manifest as which event occurs first. Similarly to an OR gate, Inclusive gateways also create alternate paths according to conditions, but it is possible to take more than one.

4.4.2 APM Elements

APM has some components that allow the modelling and execution of agent-processes. Firstly, this service enables agents to be encapsulated in a specific application domain called environment. This environment permits communications to be self-contained as agents can only interact with those in the same environment. Secondly, there is the notion of roles which represent which type of agent the agent is on that process. A name defines roles, and these can identify a group of agents during execution for, as an example, communication purposes. Thirdly, as mentioned earlier, processes model the agent’s behaviour and interaction with other agents. They are contained in a specific environment and are associated with certain roles. These also have a version to enable agents to continue running even if the process used is updated.

Hence, agents are placed in an environment and have a specific role and process. Besides, agents have variables that are used and modified during its life representing their knowledge. A distinctive execution variable is the “agent” which contains information about the agent himself, such as its identifier, role or historical variables, from within the process. Agents also possess goals that represent their objectives and can be monitored during execution.

4.4.3 Agent Process Models

There are two agents modelled at the simulation at the moment, the drivers and the parking managers. Currently, City Managers are in a way represented by the Decision Logic Service as it imposes the current limits on price signals.

As stated in Section 4.1.2, Driver agents represent drivers or autonomous vehicles that are looking for parking opportunities in the city. Therefore, their decision process, illustrated in Figure[1] 4.7, starts by obtaining a list of possible parking locations sorted by a utility metric and then drive to the best option. This function is a weighted sum of the distance from their final destination and slot price factors. Due to agents having different weights associated with each utility element, the results of applying the same process to two agents, who have the same destination and upper bounds on the price and distance, can start driving towards distinct parking lots.

[1] A full-page size version of this figure can be found in Appendix B.1

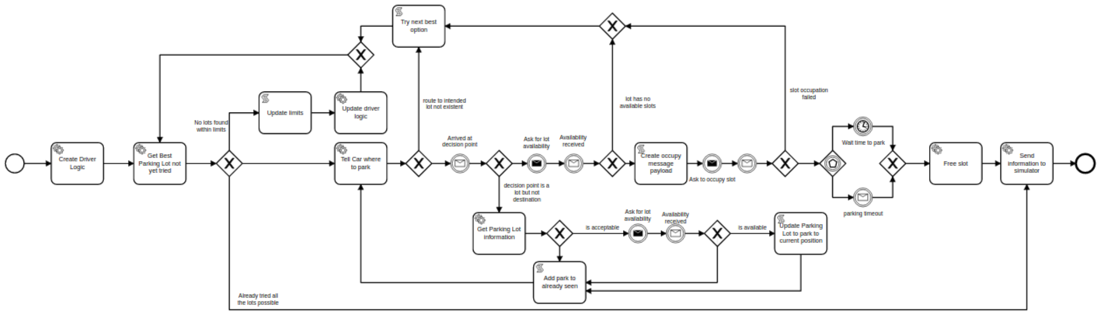


Figure 4.7: Driver behaviour process model

While cruising to the selected parking lot, the driver may find other parking opportunities. When this occurs, the agent requests information about this location, such as price and availability. Should these conditions be deemed acceptable, the driver chooses to park there. If no intermediate parking lots appear, at the time of arrival to the selected parking lot, the driver queries the parking manager for available slots. If they exist, the driver parks there. Otherwise, the parking selection process begins anew by requesting an updated list of sorted parking lots and selects the next best option.

Parking Managers' purpose is to manage the state of the parking lots for which they are responsible. Therefore, in a scenario where parking lot prices' calculation parameters are fixed, their behaviour, shown in Figure[2] 4.8, only include answering queries about availability and enforcing parking time limits. It is relevant to note that parking lot prices are calculated in the

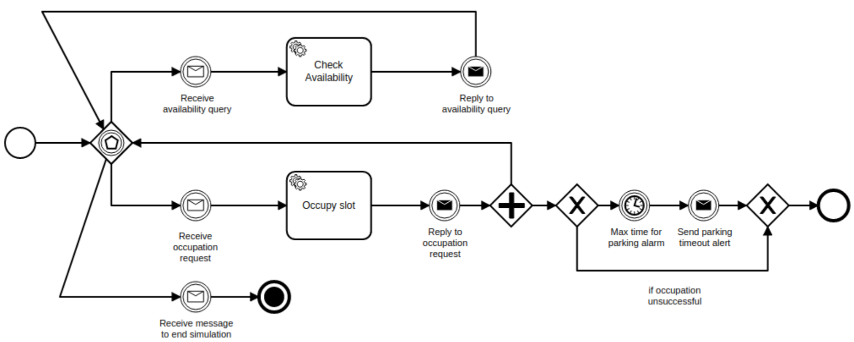


Figure 4.8: Parking manager process model

[2]Appendix B.2 presents a full-page size version of this figure

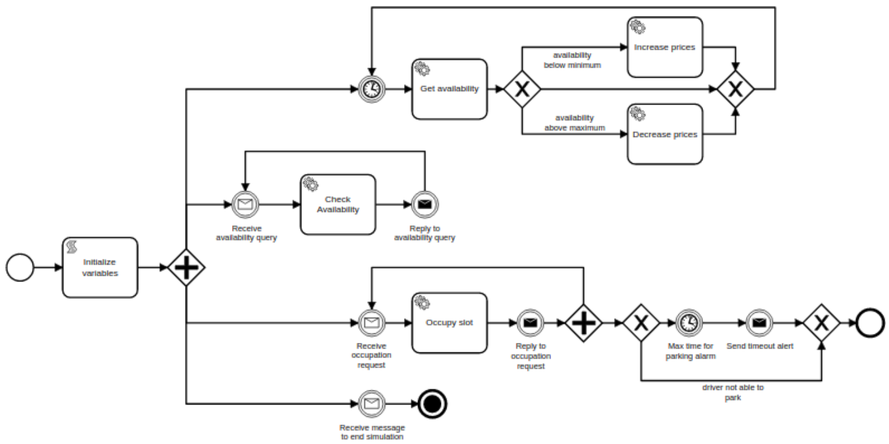


Figure 4.9: Parking manager process model (improved)

Decision Logic Service and can be set to be dynamic in terms of availability, even when this is the process used by the manager.

An updated version of this process, illustrated in Figure[3] 4.9 includes a routinely update on parking lot basic tariffs based on the minimum and maximum intended values for availability. In this case, if a lot has shown to keep occupancy levels below expected, the prices decrease. Likewise, should the opposite occur, the prices rise to discourage drivers from parking there.

4.5 Decision Logic Service

This web service REST, implemented using JHipster[4], maintains and updates the state of the simulation scenario by keeping information about drivers and parking lots. For drivers, it holds information about drivers destination and conditions for parking such as maximum distance from their goal, budget and required parking time. Similarly, it also keeps a record of each parking lot tariffs, location, availability and regulations such as maximum time allowed for parking.

By accessing this information, this service allows drivers to retrieve lists of parking lots, filtered by those which match their requirements or not and ordered according to the agents' preference. The utility function presented in Equation 5.1 specifies drivers' preferences by taking into account the lot's distance from destination, price or a combination of both. Similarly, the requirements represent the maximum values tolerated for these two parameters, as well as the intended parking time.

[3] Appendix B.3 presents a full-page size version of this figure
[4] https:start.jhipster.tech

This service calculates the parking prices according to its manager specification. These prices are calculated both when information about the lot is requested and at the moment of payment. At the moment, three methods are available, fixed, dynamic and regulated.

Equation 4.1 calculates fixed prices, reflecting only the driver's parking time.

$$price_{fixed} = p_s * ts_{used} \tag{4.1}$$

where:

p_s = tariff price per time slot
ts_{used} = number of time slots used

In turn, dynamic prices are obtained by adding a fee dependant on the lot occupation; as such, they are calculated by the formula in Equation 4.2.

$$price_{dynamic} = price_{fixed} + price_{fixed} * occ \tag{4.2}$$

where:

$price_{fixed}$ = price calculated by the formula in Equation 4.1
occ = percentage of occupied slots

Regulated prices, calculated by Equation 4.3, are only available for closed parking lots because they are based on the cost practised in the nearest open parking lot, by adding a percentage, which represents the closed lot's profit.

$$price_{regulated} = (1 + price_{open}) * p + price_{open} \tag{4.3}$$

where:

$price_{open}$ = price of nearest open parking lot
p = percentage of price that represents profit, a value between 0 and 1

Also, this service allows parking managers to update their lot's information by occupying or freeing slots as well as managing how prices are calculated and the tariff price signal.

Chapter 5

Experimental Evaluation

The modelling and execution of the designed models allow the simulation of a Smart Parking System and the study of the impact of new parking pricing dynamics in the city. In this context, all on-street parking is admitted to be open, and every off-street lot as closed. Hence, four different scenarios, with distinct pricing strategies in open and closed parking lots, were designed and evaluated:

1. Both open and closed parking lots have prices that are fixed. As such, initial tariffs are defined, and will not change during the entire run of the simulations.

2. Fixed prices in open parking locations and dynamic prices for closed lots. This price dynamism is independent of open street prices and, therefore, unregulated.

3. Dynamic pricing to on-street parking is introduced in the third experiment. However, on-street parking prices will be used to regulate the off-street price point. Therefore, closed parks will decrease their prices if the street nearest to them does as well.

4. Finally, both on-street and off-street parking lots have dynamic prices. These prices, only regulated by maximum and minimum values provided, provide a possible chaotic scenario.

5.1 Metrics and evaluation

The purpose of experiments in this dissertation is to assess different market dynamics in parking and establish how they impact city-wide traffic. Therefore, the performance of this simulation is assessed by monitoring city traffic flow, parking occupancy rates, parking managers' profit and the allocation utility for drivers.

5.1.1 Driver

On the drivers perspective, the parking metrics evaluated mostly result in the study of a utility function which measures the distance from destination and price paid weighted by the drivers' preference, as shown in Equation 5.1.

$$utility_{parking} = \alpha * \frac{d_{max} - d}{d_{max}} + \beta * \frac{p_{max} - p}{p_{max}} \tag{5.1}$$

where:

α = importance factor for distance
β = importance factor for price $(1-\alpha)$
d = distance in meters from destination
d_{max} = maximum parking distance from destination
p = price paid for parking
p_{max} = price of the most expensive parking lot

Three additional indicators complement this metric. These intend to add information regarding whether or not the driver was able to park at all and if the parking arrangement matched the driver's threshold values for maximum price and distance. As such, driver utility, determined by Equation 5.2, is greater than 3 if the driver is capable of parking within threshold values. Besides, utilities under 1 signify that no parking arrangement was tolerable.

$$utility_{driver} = utility_{parking} + parked + d_{threshold} + p_{threshold} \tag{5.2}$$

where:

$utility_{parking}$ = utility described in 5.1
$parked$ = 1 if driver was able to park, 0 otherwise
$d_{threshold}$ = 1 if parking distance is less than threshold, 0 otherwise
$p_{threshold}$ = 1 if price payed was less than threshold, 0 otherwise

5.1.2 Parking Manager

Literature in this topic shows that Parking managers aim to get maximum profit and keep occupation levels within certain boundaries. As such, those are the metrics employed to measure the satisfaction of these agents during the simulation. Therefore, during each simulation run, the occupancy rates of every parking lot, as well as, instantaneous profit per parking slot owned were registered for each manager at regular, frequent intervals by the formulas shown in Equations 5.3 and 5.4.

$$occupation = \frac{slots_{occupied}}{slots_{total}} \tag{5.3}$$

$$profit = price_{slot} * occupation \tag{5.4}$$

where:

$slots_{occupied}$ = number of slots that are occupied at the moment
$slots_{total}$ = total number of slots in the lot
$price_{slot}$ = price practiced per slot

5.1.3 City

For an overview of the impacts of the parking market on the whole system, it is vital to evaluate some metrics that relate to the good functioning of the city. As such, and based on the studies presented before, traffic flow on every street is one of the performance indicators for this work.

The other indicator is called parking equilibrium and compares the occupancy rates of open and closed parking lots. Calculated as shown in Equation 5.5, *equilibrium* below 1 indicates that closed parking lots are being utilized in detriment of open ones and *equilibrium* above 1 shows that the opposite is true.

$$equilibrium = \frac{occ_{open}}{occ_{closed}} \tag{5.5}$$

where:

occ_{open} = occupancy rate of open parking, a.k.a, on-street
occ_{closed} = occupancy rate of closed parking, a.k.a, off-street

Due to prices in on-street locations usually being closer to most destinations and cheaper as well, it is expected that *equilibrium* levels will be above 1 for most of the simulation runs duration, in every scenario presented above.

5.2 Run Configuration

With the aim of this dissertation in view, four scenarios will be analysed. For each experiment, the simulation is run six times, each with a duration of 25 minutes. Though, five of these minutes are employed as start-up and cool-off periods to collect more information on the drivers who parked.

The runs will start with thirty driver agents with five more being added every fifth second. There are three variants on the driver behaviour, the one shown in Figure 4.7, one more simplistic version which disregards parking opportunities found along the way and a greedy driver who will always try to park in his first choice. The driver order of parking lot choices will be on one of three profiles.

The first profile is distance-oriented. Drivers with this profile do not care about the money spent, so long as they park near their destination. This translates to having α set to 0.95 and β set to 0.05 for $utility_{parking}$ calculations. On the opposite side, the second profile is price-oriented. As such, this profile disregards distance in favour of obtaining a lower parking price. In other words, their α factor is 0.05, and β is 0.95. Lastly, the third profile is a mixture of the two before. By setting α and β both to 0.5, this profile values a balance between price and distance. Therefore, drivers with this profile are more willing to park farther way for smaller discounts than the first profile but not as far as the second.

In addition to these agents, and to give more realistic behaviour to the system, the streets are populated with ten dummy drivers. These drivers exist to emulate the impact on traffic flow of the behaviour of drivers who do not wish to park in the region.

5.3 Experiment 1

In this scenario, both open and closed parking lots have their prices fixed during the entire run. This situation resembles the current parking market found in most cities. As such, this experiment and consequent results serve as a baseline for comparison with the ones that follow.

5.3.1 Configuration

The tariffs practised in this scenario use time slots of 15 seconds. Parking in open parking lots costs from 0.2 to 1, whereas closed parks have prices ranging from 1 to 2.

Due to prices being unchangeable during the whole run, all parking manager processes only deal with parking lot access and are represented by the one shown in Figure 4.8.

5.3.2 Results

Information on driver satisfaction obtained in this experiment can be consulted in Table 5.7. The values $true$ and $false$ in *%Parked* row refer to the percentage of drivers that was able to park their vehicle and those that could not, respectively. Lastly, row $\%Tolerance\ satisfied$ gives an insight into the percentage of drivers whose tolerance parameters, in terms of maximum distance and price, were fulfilled.

By analysing this Table, it can be concluded that in every run there is at least one occurrence of a driver that reaches $utility_{driver}$ over 3.9 which is very near the perfect utility value of 4. Average levels of these metrics also show that, excluding Run 6, overall, drivers could park

Table 5.1: Summary of driver metrics in experiment 1 [1]

		Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Average
Utility	**Max**	3.955	3.978	3.959	3.969	3.989	3.946	3.969
	Average	3.444	3.597	3.569	3.353	3.049	2.974	3.319
	σ	0.946	0.607	0.772	0.77	1.017	1.097	0.882
% Parked	**true**	93.651%	98.950%	96.893%	95.868%	96.627%	94.344%	96.055%
	false	6.349%	1.050%	3.107%	4.132%	3.373%	5.656%	3.945%
% Tolerance satisfied	**distance**	93.651%	89.286%	88.983%	95.868%	95.868%	77.256%	90.152%
	price	93.651%	98.950%	96.893%	71.084%	71.084%	71.480%	83.857%
Average choice		2.762	1.462	1.98	3.917	1.812	1.945	1.953

within tolerance values for both distance and price. In fact, it can be observed that failure to park is only observed in at most 6.4% of drivers and that over 71% can reach a parking allocation that satisfies one of their criteria.

Similarly, Table 5.2 summarizes the results of experiment 1 in the city's perspective. In this Table, the maximum levels of traffic flow and it's variation, as well as the identifier of the road that presents these values, are presented. In addition, the minimum and maximum value of the equilibrium metric, described in Section 5.1, can be consulted. Due to the existence of extreme values (0 and ∞) when either open or closed lots are being used, the average of the equilibrium is calculated from an auxiliary variable that is -1 when closed occupancy is larger, 1 when the opposite occurs and 0 when the equilibrium is 1.

Table 5.2: Summary of city metrics in experiment 1

	Traffic flow				Equilibrium		
	Max	**Road Id**	**Max σ**	**Road Id**	**Average**	**Max**	**Min**
Run 1	19	224645476	4.170	28433727	-0.119	∞	0
Run 2	20	28433727	4.825	40769524	-0.405	∞	0.172
Run 3	13	28433727	2.539	28433727	0.0694	∞	0.086
Run 4	15	224645476	2.775	28433727	0.668	∞	0
Run 5	18	224645476	3.168	28433727	0.983	∞	1
Run 6	22	224645476	3.428	40769524	0.858	∞	0
Run 7	23	28433727	3.304	28433727	0.923	∞	0
Average	18.571		3.459		0.425	∞	0.180

The maximum traffic flow observed in this scenario is of 20 cars with a maximum standard deviation between 2.5 and 4.9 cars. Furthermore, the equilibrium levels in this experiment are, on average, over 1, corroborating the fact that most cars choose to park in on-street locations.

The roads whose identifiers can be found at least one of the Tables 5.2, 5.5, 5.8 and 5.11 are those whose traffic flow can be further studied in Figure 5.1. As such, the values found in the

[1] Detailed information can be found in Table C.1 in Appendix C.1

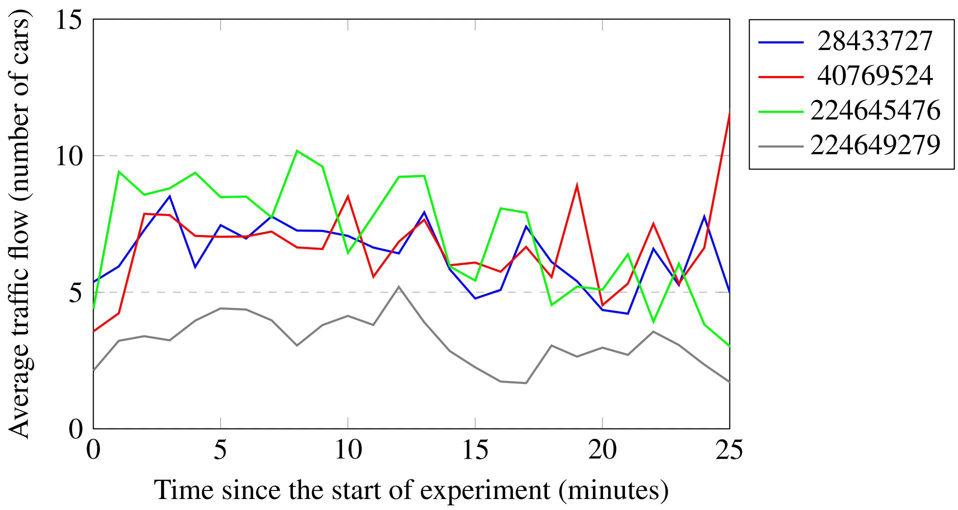


Figure 5.1: Traffic flow in roads with maximum values or variation in experiment 1

legend of this Figure are the road identifier numbers. Also, for readability purposes, the values for traffic flow are averaged per minute.

It must be recalled that these metrics are collected in intervals smaller than a second. Therefore, the traffic flow illustrated in this Figure, and similar ones in the following Sections, will likely yield values distinct from those shown in Tables 5.1 and equivalent. In this context, it can be seen that the average traffic flow is less than 10 for the top 4 roads with the most traffic.

Table 5.3 shows some information about profit and occupancy rates, reflecting the interests of parking managers. These values are shown aggregated by parking lot type, open or closed, and show that in most runs on-street parking has both greater occupancy rates and greater revenue.

Table 5.3: Parking manager metrics in experiment 1 [2]

	Sum of profit			**Average occupancy**		
	Closed	**Open**	**Total**	**Closed**	**Open**	**Total**
Run 1	19.00	75.86	94.86	0.138%	1.019%	0.636%
Run 2	482.40	207.07	689.47	1.985%	2.988%	2.552%
Run 3	177.30	434.23	611.52	1.011%	6.720%	4.238%
Run 4	35.40	559.25	594.65	0.555%	10.122%	5.963%
Run 5	291.60	998.20	1289.80	1.012%	8.402%	5.189%
Run 6	545.20	1253.32	1798.52	1.860%	11.990%	7.586%
Average	258.48	587.99	846.47	1.093%	6.874%	4.360%

[2] More detailed information about these metrics can be found in Appendix C.2 where Table C.5 contains full experimental data by road.

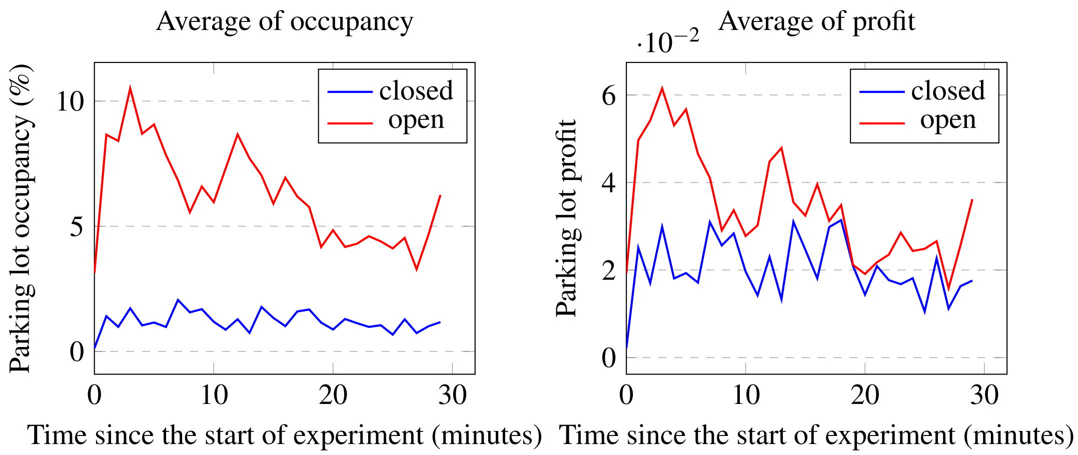


Figure 5.2: Charts of profit and occupancy over time during experiment 1

In Figure 5.2, both the occupancy and profit metrics can be compared between open and closed lots. In this scenario, open parking lots, on average, are above the closed ones in terms of both occupancy and profit.

Another interesting factor in this experiment is the connection between price point and occupancy levels shown in Figure 5.3. In this Figure can be observed that the tariff prices ranging between 1 and 1.2 are the ones that obtain the best occupancy levels on average.

Figure 5.3: Occupancy in terms of price ranges in experiment 1

5.4 Experiment 2

The second scenario has closed lots' prices being changed according to lot's availability. There are two ways for this to be archived. Either the cost is calculated dynamically in the moment of consultation or, it is regularly updated being fixed in between updates.

5.4.1 Configuration

In this experiment, managers of open lots will have the same behaviour explained in Section 5.3 and use the same prices as before.

Similarly, closed parking managers will have the same behaviour as the one used in the first experiment, but the price calculation technique is different. The prices here will be calculated by Equation 2.2 with $price_{base}$ being a value between 0.5 and 1. Therefore, drivers can park in lots with the minimum base price for a price ranging from 0.5 to 1.

The other method of obtaining price dynamism is changing parking manager behaviour to the one shown in Figure 4.9. In this case, the base prices start by being equal to the ones used in Section 5.3, values from 1 to 2. Then, during the simulation, these values are updated rising if occupancy is above manager threshold of 70% and decreasing if this value is below 30%. However, it is important to highlight that the prices are bounded by the logic service which does not allow tariffs to be below 0.1 or over 3 per time slot.

5.4.2 Results

As shown in Table 5.4, this scenario's maximum values of driver utility are still over 3.9. However, the average values of utility drop to an average of 3.1. These results reflect that, while most could still park within threshold parameters, a significant amount of drivers that could not. The

Table 5.4: Summary of driver metrics in experiment 2[3]

		Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Average
Utility	**Max**	3.969	3.981	3.984	3.969	3.961	3.984	3.975
	Average	3.143	3.112	3.134	2.905	3.076	3.267	3.074
	σ	0.916	1.106	1.036	1.329	1.089	0.986	1.0952
% Parked	**true**	93.70%	90.68%	91.68%	84.10%	90.55%	93.14%	90.64%
	false	6.30%	9.32%	8.32%	15.90%	9.45%	6.86%	9.36%
% Tolerance satisfied	**distance**	81.91%	61.55%	76.06%	71.28%	71.28%	76.76%	73.14%
	price	89.34%	87.18%	89.45%	87.79%	87.79%	90.29%	88.64%
Average choice		2.191	4.318	3.016	2.4	3.901	3.01	3.167

[2]More detailed information about driver metrics can be found in Appendix C.1, particularly in Table C.2

percentage of drivers who could not park being around 9% and distance dissatisfaction levels reaching nearly 30% further corroborates this conclusion.

Traffic in this scenario reveals a maximum traffic flow average of over 25 cars with a maximum standard deviation of around 4, as can be observed in Table 5.5. Moreover, parking equilibrium values range from 0.5 to 0.9, indicating that drivers more often choose to park in on-street locations.

Table 5.5: Summary of city metrics in experiment 2

	Traffic flow				Equilibrium		
	Max	**Road**	**Max σ**	**Road**	**Average**	**Max**	**Min**
Run 1	26	224645476	4.670	28433727	0.900	∞	0
Run 2	27	40769524	4.256	40769524	0.687	∞	0
Run 3	22	224645476	3.452	28433727	0.833	∞	0
Run 4	24	28433727	4.754	28433727	0.578	∞	0
Run 5	29	28433727	4.848	28433727	0.866	∞	0.333
Run 6	25	28433727	3.959	28433727	0.519	∞	0
Average	25.5		4.323		0.731	∞	0.056

Roads identified as having the most volatile traffic flow can be analysed in more detail in Figure 5.4. This information shows that three of these roads have, on average, between ten to fifteen cars circulating on them at all times. Road 224649279, however, rarely goes over five cars, but is more stable.

Table 5.6 and Figure 5.6 reveal with certainty that drivers are preferring to park in open lots.

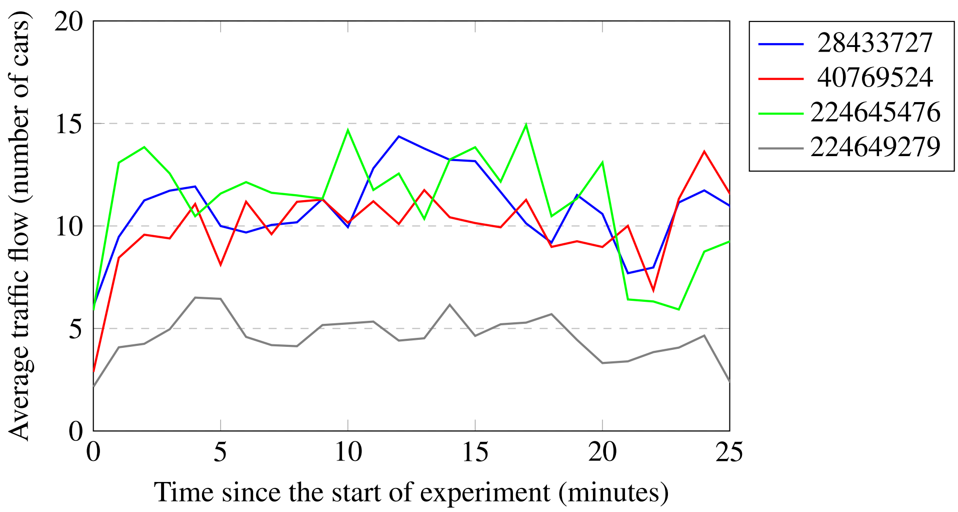


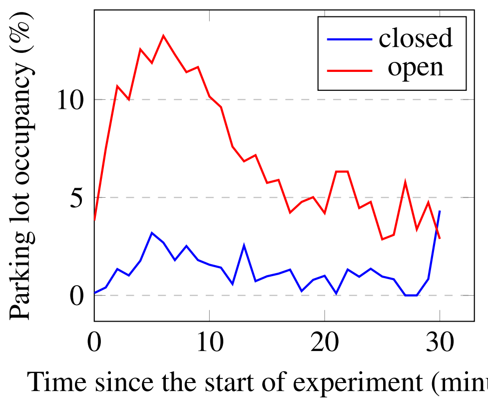
Figure 5.4: Traffic flow in roads with maximum values or variation in experiment 2

In fact, after taking averages of all the runs, these lots have occupancy levels of around double for the most part of the experiment.

Table 5.6: Parking manager metrics in experiment 2 [4]

	Sum of profit			Average occupancy		
	Closed	**Open**	**Total**	**Closed**	**Open**	**Total**
Run 1	235.136	744.075	979.211	1.652%	10.337%	6.561%
Run 2	93.200	427.375	520.575	0.494%	5.910%	3.555%
Run 3	191.160	593.550	784.710	1.259%	8.626%	5.423%
Run 4	61.152	232.275	293.427	1.905%	6.692%	4.611%
Run 5	108.640	426.750	535.390	1.317%	10.890%	6.728%
Run 6	123.136	397.325	520.461	1.609%	5.348%	3.722%
Average	135.404	470.225	605.629	1.373%	7.967%	5.100%

Profit is also, for the most part, greater in on-street parking which can be, partly, due to the lower availability. However, as time progresses off-street managers price updates seem to yield positive results as both profit and occupation, apparently rise towards the end.



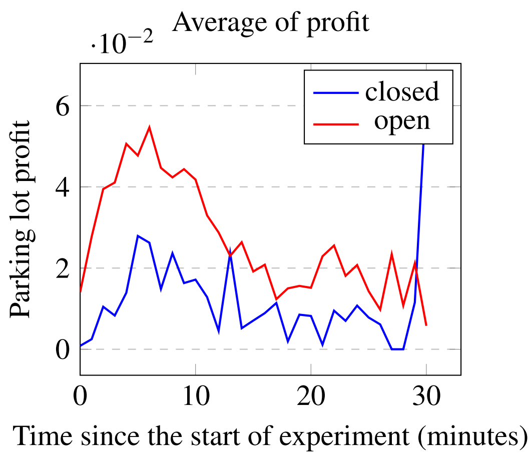


Figure 5.5: Charts of profit and occupancy over time during experiment 2

Figure 5.6 shows that closed lots have greater occupancy levels, around 80% when prices range from 1.4 to 1.8. In contrast, open parking gets less available when the pricing is between 0.2 and 0.6, about 1.2 less than for closed.

[4]More detailed information about these metrics can be found in Appendix C.2 where Table C.6 contains full experimental data by road

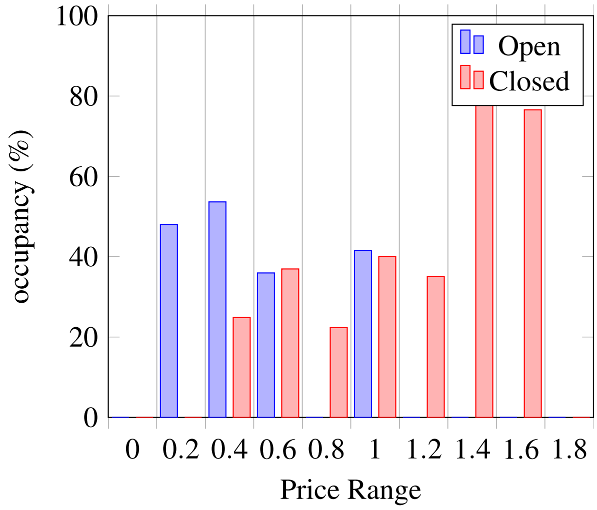


Figure 5.6: Occupancy in terms of price ranges in experiment 2

5.5 Experiment 3

In this scenario, the prices in open lots are dynamic and regulate closed parking prices. As such, this should emulate a city where there is little price disparity between nearby locations.

5.5.1 Configuration

The parking managers of open lots here use a decision process that includes regularly checking the interest shown in lots. If the number of drivers that request lot availability in since the last update is outside a predefined range, the price is changed accordingly. In addition, the price calculation used the formula for dynamic pricing and, as such, takes into account the current availability of slots..

The behaviour of managers of closed lots is very similar to the one used for fixed prices. The only difference is the method used for price calculation, which is shown in Equation 4.3. Hence, the tariffs practised by these agents are regulated by the ones used in open parking and should not differ greatly from them.

5.5.2 Results

In this scenario, average driver utility shows that most drivers are able to park in conditions that match driver requirements of either distance and profit. In fact, as shown in Table 5.7, the mean is around 3.2 with a deviation of a 1, which places utility for the majority of drivers above 2. Hence, it can be inferred that only very few drivers were not able to park respecting at least one decision parameter. The satisfaction of distance thresholds is the one most that most frequently is not obtained. As a result, it can be noted that, in this scenario, drivers respond favourably to dynamic parking prices.

Table 5.7: Summary of driver metrics in experiment 3[5]

		Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Average
Utility	**Max**	3.989	3.991	3.989	3.969	3.962	3.984	3.981
	Average	3.314	3.278	2.945	3.199	3.275	3.434	3.241
	σ	0.863	1.102	1.411	0.839	1.032	0.848	1.016
% Parked	**true**	95.34%	91.03%	82.47%	95.16%	92.24%	95.54%	91.96%
	false	4.66%	8.97%	17.53%	4.85%	7.77%	4.46%	8.04%
% Tolerance satisfied	**distance**	73.58%	79.82%	74.16%	93.67%	80.03%	80.83%	80.35%
	price	91.19%	90.24%	79.33%	79.88%	90.97%	93.89%	87.58%
Average choice		2.509	3.133	5.007	4.935	3.225	2.298	3.518

Table 5.8 shows that the occupancy of open lots is still, on average, greater than the one found in closed lots. However, there still moments where the opposite is true. Additionally, some runs, traffic flow reaches values above 40 cars in some streets with standard deviations of around six.

Table 5.8: Summary of city metrics in experiment 3

	Traffic flow				Equilibrium		
	Max	**Road**	**Max σ**	**Road**	**Average**	**Max**	**Min**
Run 1	26	224649279	0.354	28433689	0.961	∞	0
Run 2	44	28433727	7.690	40769524	0.812	∞	0
Run 3	48	224645476	8.321	40769524	0.810	∞	0
Run 4	29	224645476	4.124	224645476	0.550	∞	0
Run 5	44	224645476	6.914	224645476	0.930	∞	0.75
Run 6	23	28433727	3.544	28433727	0.895	∞	0
Average	35.667		5.158		0.826	∞	0.125

Consequently, Figure 5.7 shows average traffic per minute oscillating between twelve and twenty-eight cars in the most popular streets. In this scenario, traffic flow peaks in the first five minutes and then stabilizes a bit until near the end. Then, around the twenty-minute mark, this streets' flow culminates again. Furthermore, Road 224645476 is the one that is the most populated throughout the experiment. In contrast, Road 224649279 is again, with the exception of the first three minutes when it surpasses Road 40769524, the one with the least traffic flow with around seven cars.

[5]Detailed information about driver metrics in experiment 3 can be found in Appendix C.1 in Table C.3

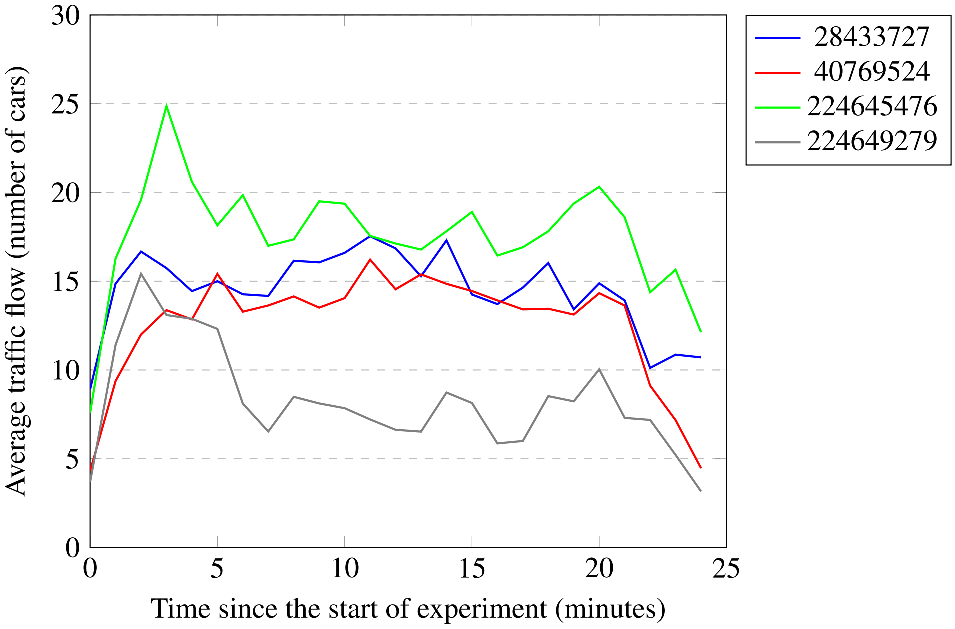


Figure 5.7: Traffic flow in roads with maximum values or variation in experiment 3

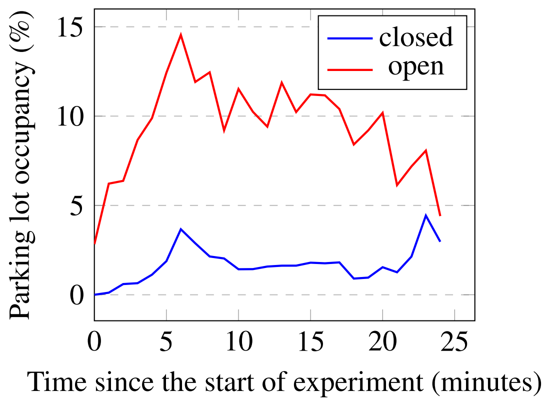
In the parking manager's perspective, occupancy levels in this scenario are about 1.5% and 9.6% for closed and open lots, respectively, as can be observed in Table 5.9.

Table 5.9: Parking manager metrics in experiment 3 [6]

	Sum of profit			**Average occupancy**		
	Closed	**Open**	**Total**	**Closed**	**Open**	**Total**
Run 1	272.409	884.781	1157.19	1.575%	11.802%	7.356%
Run 2	70.873	395.966	466.838	0.930%	8.658%	5.298%
Run 3	70.999	473.131	544.13	0.908%	8.861%	5.403%
Run 4	383.2	1481.5	1864.7	2.943%	8.753%	6.227%
Run 5	61.484	514.616	576.1	0.907%	10.013%	6.054%
Run 6	166.655	659.456	826.111	1.559%	10.488%	6.606%
Average	170.937	734.908	905.845	1.470%	9.762%	6.157%

Figure 5.8 illustrates the regulation in off-street parking prices. The correlation between profit in open and closed parking, which rise and drop almost simultaneously, makes this fact obvious.

[6] More detailed experimental data grouped by road is available in Appendix C.2, in particular in Table C.7 for this experiment.



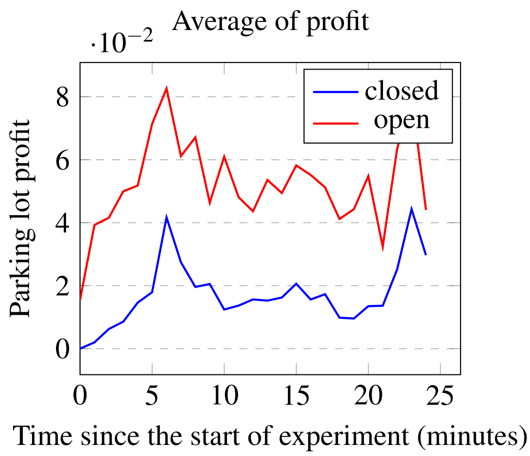


Figure 5.8: Charts of profit and occupancy over time during experiment 3

On the one hand, in this experiment, off-street parking has no availability when prices are on the range of 1.2 to 1.4, getting more reasonable occupancy levels for prices between 0.6 and 1.2. On the other hand, on-street parking lots remain with free slots for every price point. These lots have the best availability, around 60% when prices range from 2.2 to 2.4. These conclusions can be validated from the information in Figure 5.9.

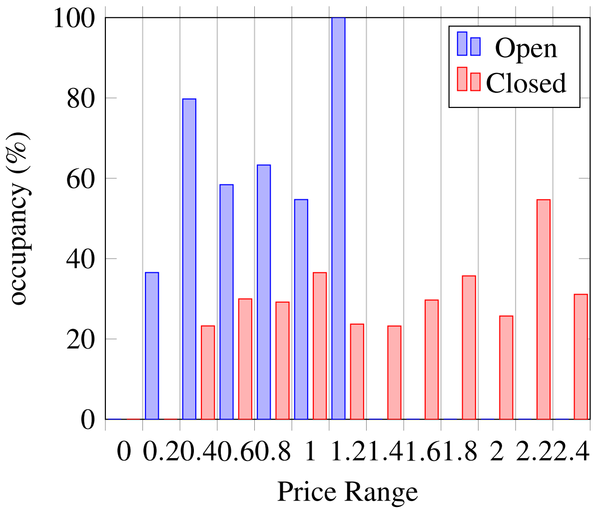


Figure 5.9: Occupancy in terms of price ranges in experiment 3

5.6 Experiment 4

The last scenario includes dynamic pricing in both open and closed lots. With total disconnection between prices in public and private lots in close proximity, the difference between parking prices can benefit a certain type of parking lot creating. Therefore, it has the potential to lead to traffic flow peaks and parking equilibrium far from the ideal value of 1.

5.6.1 Configuration

Both types of parking managers have similar behaviour, the one illustrated in Figure 4.9. The price changes occur every minute by adding or decreasing 0.05 to the price if the availability is not within the already mentioned thresholds of 30% and 70%. However, the prices themselves are also calculated dynamically by the formula in Equation 4.2, so the price changes described are to the $price_{base}$ and can be felt as much as doubled in cases of completely free lots becoming full between updates.

5.6.2 Results

As shown in Table 5.10, in this scenario, driver utility is, on average, of 3.3 with a standard deviation of less than 1.1. As such, it can be concluded that most drivers are still able to park within tolerated parameters for either distance or price. In fact, price thresholds were only disrespected for at most 9.3% of drivers. On the contrary, distance has only a maximum of 84.5% satisfaction rate, which is lower than the minimum registered for price.

Table 5.10: Summary of driver metrics in experiment 4 [7]

		Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Average
Utility	**Max**	3.971	3.985	3.983	3.984	3.978	3.977	3.98
	Average	3.283	3.23	3.361	3.241	3.285	3.3	3.28
	σ	1.103	1.02	0.99	1.135	1.045	1.008	1.0586
% Parked	**true**	90.70%	92.19%	93.04%	90.15%	92.03%	92.56%	91.78%
	false	9.30%	7.81%	6.96%	9.85%	7.97%	7.44%	8.22%
% Tolerance satisfied	**distance**	84.50%	81.29%	83.07%	78.77%	78.77%	82.59%	81.50%
	price	90.70%	92.00%	92.78%	91.51%	91.51%	92.25%	91.79%
Average choice		2.233	2.614	2.248	2.84	2.584	2.552	2.536

In the city perspective, traffic flow in this experiment reaches maximum levels mostly in Road 224645476. This Road is also the one with the highest registered variance in flow, as demonstrated in Table 5.11. Additionally, equilibrium metrics show that, although the first run

[7] More information on experiment four's driver metrics can be found in Table C.4

had, on average, similar occupancy for both open and closed parking, the former were utilized most frequently throughout the experiment.However, in every run, there are moments where all drivers choose to park on the street or all of them opt for closed parking.

Table 5.11: Summary of city metrics in experiment 4

	Traffic flow				Equilibrium		
	Max	**Road**	**Max σ**	**Road**	**Average**	**Max**	**Min**
Run 1	16	224645476	2.697	224645476	0.147	∞	0
Run 2	29	224645476	3.692	40769524	0.856	∞	0
Run 3	25	224645476	3.351	224645476	0.743	∞	0
Run 4	23	224645476	3.653	224645476	0.768	∞	0
Run 5	22	28433727	3.713	224645476	0.863	∞	0
Run 6	19	224645476	3.226	40769524	0.491	∞	0
Average	22.333		3.389		0.645	∞	0

Figure 5.1 illustrates the mean traffic flow per minute in the four roads with the most traffic or most variant flow. In this Figure, it can be observed that Roads 28433727 and 40769524 have a similar traffic flow oscillating between seven and eleven drivers. Also, Road 224649279 remains the one with the less but more stable traffic, around five cars.

As mentioned before, in this experiment, drivers choose to park mostly in on-street locations.

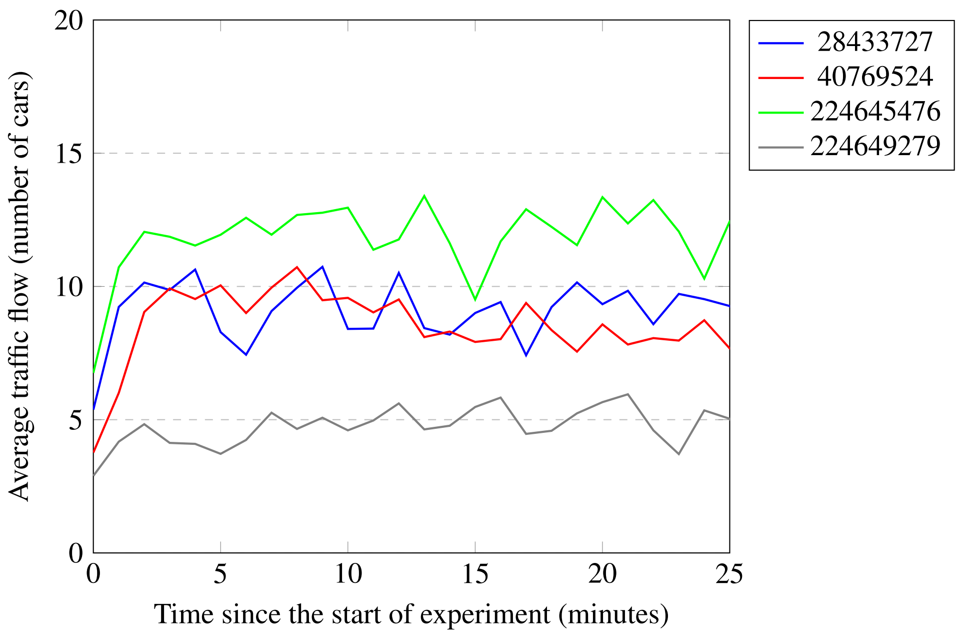


Figure 5.10: Traffic flow in roads with maximum values or variation in experiment 4

This claim is verified by the information present in both Table 5.12 and Figure 5.11. In fact, occupancy of closed parking lots around 2.1% whereas open lots has an average availability almost four times larger.

Table 5.12: Parking manager metrics in experiment 4 [8]

	Sum of profit			Average occupancy		
	Closed	**Open**	**Total**	**Closed**	**Open**	**Total**
Run 1	37.264	88.631	125.895	3.240%	4.989%	4.229%
Run 2	107.52	591.666	699.186	2.380%	9.969%	6.669%
Run 3	68.708	443.359	512.067	1.376%	7.192%	4.664%
Run 4	74.444	760	834.444	1.075%	8.215%	5.110%
Run 5	110.228	648.725	758.953	2.528%	10.946%	7.286%
Run 6	75.172	572.256	647.428	2.241%	7.408%	5.161%
Average	78.889	517.44	596.329	2.140%	8.120%	5.520%

Similarly, managers of off-street parking have profit levels that are highly discrepant from their on-street equivalent. Open parking lots' profit oscillates between 0.02 and 0.06 for each slot owned, while closed receive, at most, around 0.02.

In terms of prices, on-street slots have occupancy near the intended maximum rate of 70% when they are price somewhere between 0.4 and 0.8. For closed lots, the desired level availability is never achieved, but price ranges from 0.4 to 0.6 and 0.8 to 1 present the nearest results, as can be seen from Figure 5.12.

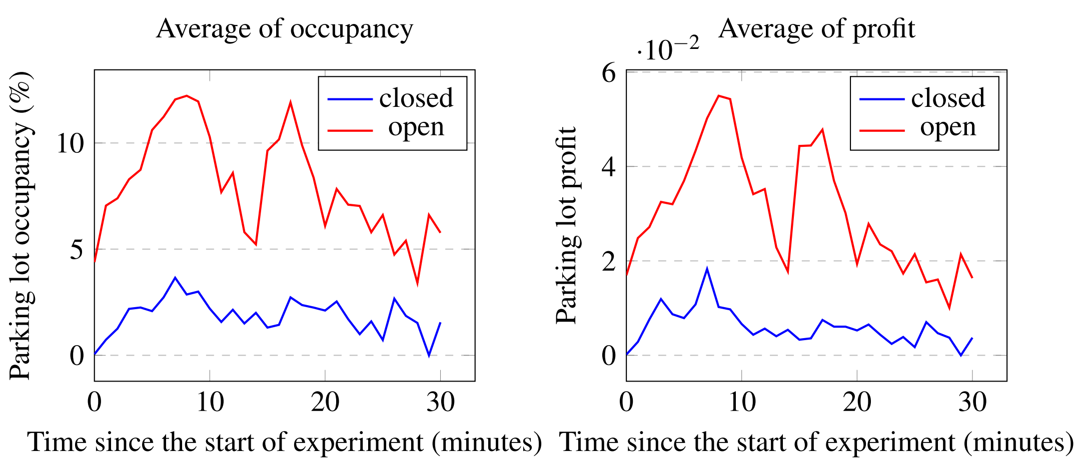


Figure 5.11: Charts of profit and occupancy over time during experiment 4

[8]More detailed information can be found in Appendix C.2, specifically in Table C.8

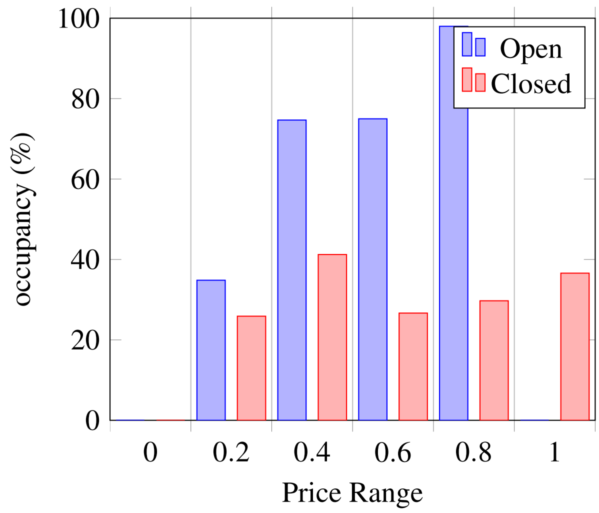


Figure 5.12: Occupancy in terms of price ranges in experiment 4

5.7 Discussion and Remarks

Since different types of metrics have been established accordingly to each agent type on the system, the discussion of results is actor-oriented.

5.7.1 Drivers Results

Table 5.13 presents a comparison between the average driver metrics obtained during each experiment. Here, the third scenario exhibits the maximum utility and parking success rate. However, the combination of dynamic prices in open parking with regulated ones for closed lots does not represent the highest average utility. This apex is found in the scenario where both types of parking opportunities have fixed prices. It could be argued that these outcomes were due to initial prices being the most useful for drivers, but not for the managers.

Furthermore, independent dynamic prices, simulated in experiment 4, has the best results for the rate of drivers who were able to park within their intended price limit, an astounding 91.8%, and the second best for the distance tolerance, 81.5%. However, having these dynamics only present in off-street lots has the worst metrics for the percentage of parking failure and dissatisfaction of maximum distance thresholds. It is difficult to explain this result, but it might be related to the lack of viable closed parking options near the destinations chosen, for instance, cheaper parking lots being farther from the destination than initially tolerated.

Contrary to expectations, although the third scenario has the most successful parking, it also represents the experiment where drivers had to the most trouble finding a satisfactory slot. This

Table 5.13: Comparison of driver metrics between experiments

		Experiment 1	Experiment 2	Experiment 3	Experiment 4
Utility	**Max**	3.969	3.975	3.981	3.98
	Average	3.319	3.074	3.241	3.28
	σ	0.882	1.0952	1.016	1.0586
% Parked	**true**	96.055%	90.644%	91.962%	91.779%
	false	3.945%	9.356%	8.038%	8.221%
% Tolerance satisfied	**distance**	90.152%	73.142%	80.346%	81.501%
	price	83.857%	88.639%	87.581%	91.790%
Average choice		1.953	3.167	3.518	2.536

conclusion can be drawn due to drivers, on average, parking either in their third or fourth choice, whereas, in other scenarios, the mean was closer to the second choice. A possible explanation for this might be that the first options became overly competitive to the point where parks became full for more extended periods.

5.7.2 Parking Managers Results

Analysing the parking managers perspective, Table 5.14 shows that on-street parking always creates the most profit. Furthermore, the managers of this type of lots get the most monetary revenue when their prices are dynamic. In contrast, according to this data, closed lots have more profit with fixed pricing. These differences can be explained in part by the lower occupancy rates in the latter, as these reduce the price of the few occupied slots in off-street lots.

Table 5.14: Comparison of parking manager metrics between experiments

	Sum of profit			Average occupancy		
	Closed	**Open**	**Total**	**Closed**	**Open**	**Total**
Experiment 1	296.700	520.854	817.554	1.139%	6.208%	4.360%
Experiment 2	135.404	470.225	605.629	1.373%	7.967%	5.1%
Experiment 3	170.937	734.908	905.845	1.47%	9.762%	6.157%
Experiment 4	78.889	517.440	596.329	2.14%	8.12%	5.52%

However, in terms of occupancy, having dynamic prices does significantly improve parking occupancy in every experiment. In this context, open parking prices taking into account both traffic flow and occupancy proves to be the most beneficial for this type of lots. However, the price regulation this scenario involved did not prove to be helpful for closed parking that had better results, both in profit and availability, in the fully dynamic prices situation presented in experiment 4. These results are consistent with expectations as price alterations are driven by the increase of parking manager utility.

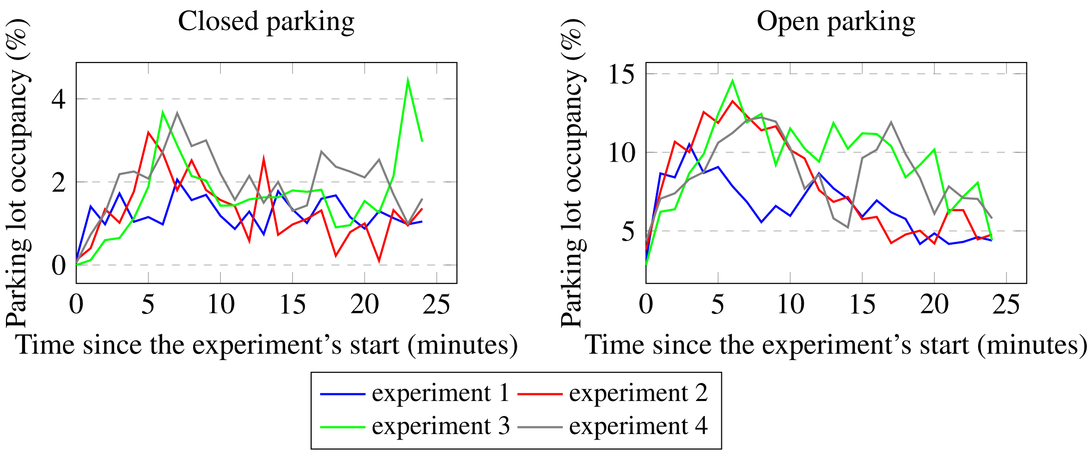


Figure 5.13: Comparison of evolution parking occupancy across experiments

Figure 5.13 shows that experiments 3 and 4 have the best occupancy rates for open parking consistently. As such, in that regard, dynamic prices are concluded to be the best solution for this type of parking lots. This observation may support the hypothesis that price dynamism is capable of aiding managers in regulating their lot's availability.

For closed lots, parking occupancy is very variable and, on average, below 4%. Therefore, the only observation to be noticed is that the fixed price mechanism is the one with the worst results. A possible explanation for this might be that the initial parking rates were too high compared to the ones found in open lots. There are, however, other possible explanations. For instance, these lots not being sufficiently near the desired destinations to be a viable alternative to on-street parking or driver processes not taking into account factors different from price and distance, such as security or other features associated to these type of parking.

From a profit standpoint, as illustrated by Figure 5.14, overall, regulated parking prices in off-street lots are more desirable. In truth, the profit is only comparable to when both types of lots have fixed prices. Additionally, one unanticipated finding was that, according to this chart, a fully dynamic pricing scenario is harmful to closed parking profits. Hence, it could conceivably be hypothesised that external price regulations, seen as a safeguard from drastic differences between both types of parking, has a potential of ensuring that parks in the same area have more equal chances of being chosen. Another possible hypothesis is that the parking market is not self-regulated.

On the one hand, across all the experiments, Figure 5.15 reveals that the best price ranges for closed parking lots' prices seems to be from 0.6 to 1.2 monetary units. However, when parking prices on the street are fixed, these seems to increase to prices between 1.4 and 2, with the exception of range 1.6 to 1.8. As such, it can be deduced that municipal parking prices were initially set to be less expensive than the optimum.

On the other hand, Figure 5.15 also shows that optimal pricing for on-street locations is highly dependent on the pricing mechanisms used for closed lots. Therefore, if prices off-street are dynamic the optimal prices range from 0.2 to 1.2. In the case of closed lots prices being regulated by the on-street ones, this range narrows to include only prices above 0.6.

5.7.3 City Managers Results

From a city-wide perspective, price dynamics are inferred to increase overall traffic flow in the most requested roads, as can be seen in Figure 5.16. Regulating closed parking lot prices seems to be the worst-case scenario in this point of view. This finding was unexpected and suggests that dynamic prices can influence drivers to park in a more restricted set of parking options in a specific area of the city. However, it is essential to bear in mind that most of the roads do not possess on-street parking, and these are the main links connecting critical areas of the map.

These pricing dynamics also seem to benefit on-street parking as shown in Table 5.15 by the significant increase in the average equilibrium metric for experiments 2 and 3. However, fully dynamic prices in both open and closed parks display the capacity to auto-regulate this ratio as values average values tend to get closer to 0 in the fourth experiment.

5.7.4 Overall Results

Together these results provide important insights into the influence of pricing policies in the parking problem. Taken together, they suggest that there is an association between price dynamism and better utility for both drivers and parking managers. However, the most striking result to emerge from the data is that traffic flow does not seem to benefit from these policies.

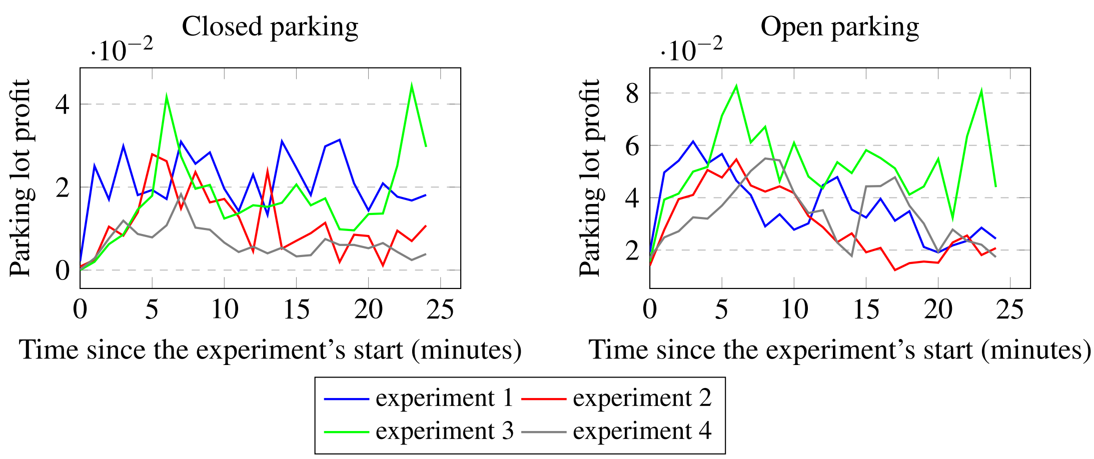


Figure 5.14: Comparison of evolution parking managers' profit across experiments

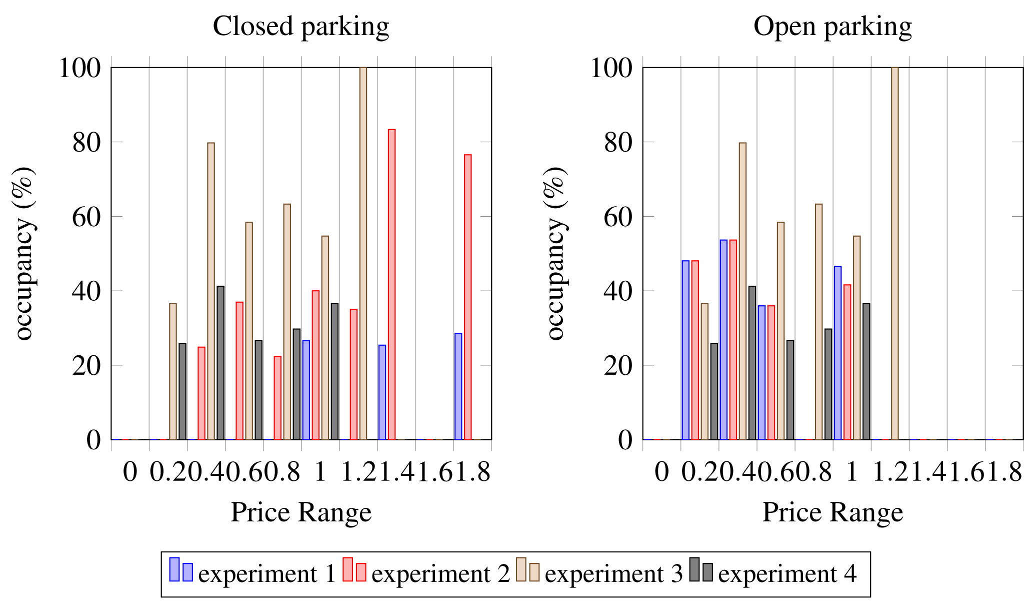


Figure 5.15: Occupancy in terms of price ranges in all experiments

Table 5.15: Comparison of city metrics between experiments

	Traffic flow		**Equilibrium**		
	Max	**Max σ**	**Average**	**Max**	**Min**
Experiment 1	18.571	3.459	0.425	∞	0.18
Experiment 2	25.5	4.323	0.731	∞	0.056
Experiment 3	23	3.544	0.895	∞	0
Experiment 4	22.333	3.389	0.644	∞	0

The next chapter, therefore, moves on to discuss findings in more detail and present the conclusions taken.

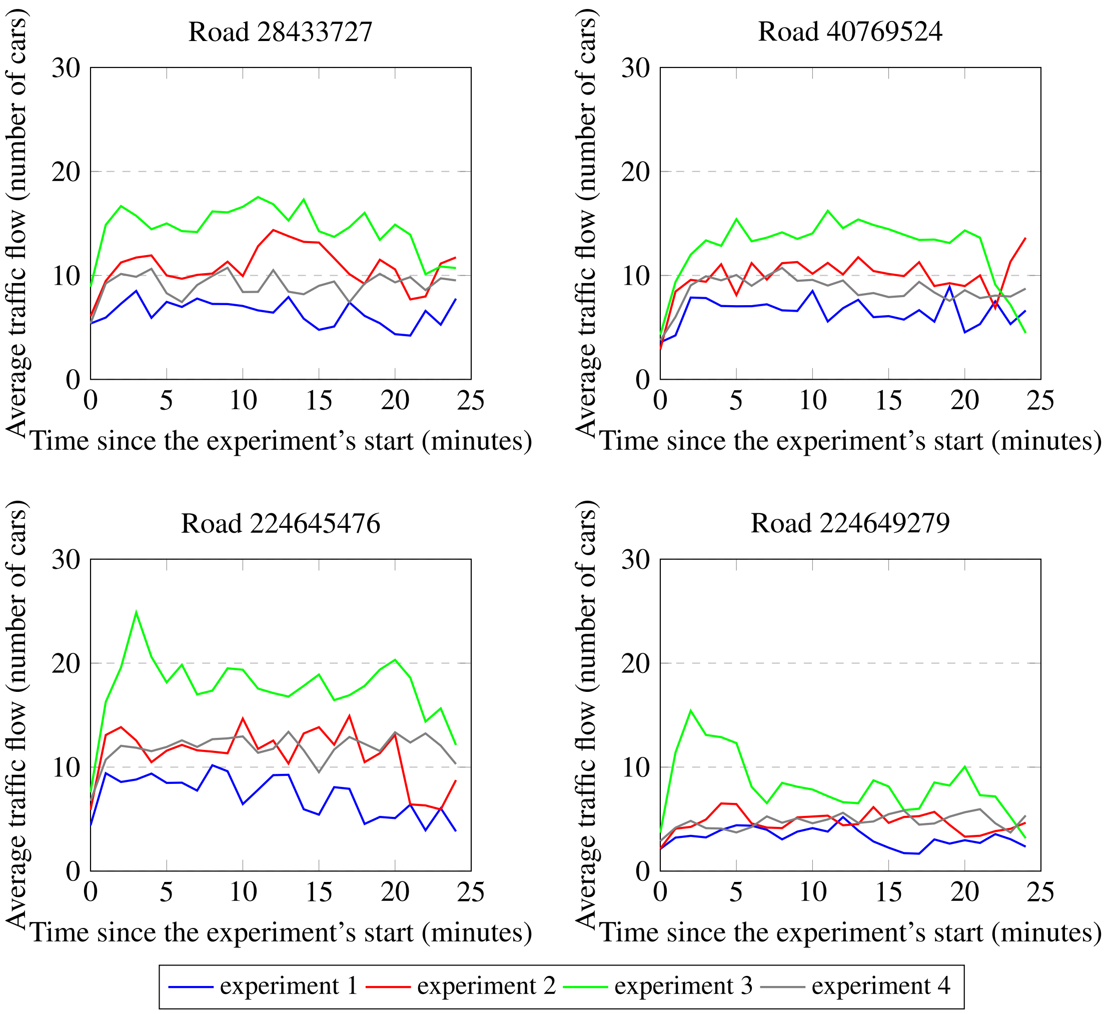


Figure 5.16: Comparison of traffic flow in selected roads across experiments

Chapter 6

Conclusions and Future Work

In conclusion, this thesis attempts to analyse the current parking problem using a simulation approach. By employing a multi-agent system based on micro-services, the simulation model the city's parking layout and the entities involved: drivers, parking and city managers. The agents then negotiate favourable parking conditions amongst themselves.

6.1 Discussion

The present dissertation was designed to determine the effect of different pricing policies in traffic and parking behaviour, assuming a Smart City arrangement. In this context, the simulation of four distinct parking managers operating processes aimed to ascertain whether dynamic prices in city-managed open parking could help mitigate traffic issues, such as congestion in highly demanded locations, and improve slot availability by visibly influencing driver parking decisions.

Additionally, it is assumed that these entities have goals to keep occupancy rates with predetermined thresholds to ensure a profit and not guarantee parking supply for every client. Therefore, the scenarios simulated also aimed to discover if frequent tariff updates could improve parking managers' satisfaction overall.

Furthermore, this study set out to discover a collection of metrics that could indicate the requirement of regulation policies. These measurements should imply the dissatisfaction of one of the entities involved in the parking problem, drivers, parking managers or city. As such, they are the base for investigating the impact of market dynamics in the smart parking scenario.

With these hypotheses in mind, multi-agent simulation was used to expand our understanding of how diverse market strategies influence Smart Parking systems. This approach, combined with the use of micro-services and business processes to design, implement and improve the behaviour of all parking stakeholders, proves useful in creating a more decoupled and efficient environment. Therefore, the same agents with similar processes could be connected to real-world services and act like intelligent, automated, entities to mitigate the parking problem, such as autonomous vehicles and parking management.

To the author's knowledge, this project is the first comprehensive investigation of the effect of dynamic pricing strategies open parking. Thus, it contributes to existing knowledge of Smart Parking by providing insight into the consequences it carries for traffic and the general satisfaction of every entity involved.

According to the experimental results, drivers are more successful when on-street parking has dynamic pricing schemes. Additionally, having closed parking prices be regulated seems to increase both traffic flow and overall parking lot occupancy rates, which is a remarkable result. In fact, in this scenario, on-street parking seems to be benefited with more drivers choosing to park in these locations. This observation may support the hypothesis that market liberalism in parking is not the best solution, as pricing regulations are favourable in improving parking results.

Unlike what happens with driver and parking managers metrics, very little was found in the literature on the question of how to evaluate parking policies in a city-level perspective. As such, the parking equilibrium metric, which measures the balance between occupancy rates in both open and closed parking, was created to illustrate the level of preference drivers were showing for the former. According to the data collected on this metric, different pricing schemes can be inferred to indeed alter driver behaviour and balance availability in nearby parking lots.

Although these findings will doubtless be much scrutinised, there are some immediately reliable conclusions for the relationship between parking equilibrium and traffic flow measurement and the need for further parking regulation. The metrics associated with city managers gain extreme values when chaotic parking scenarios, such as when a significant amount of drivers is unable to park successfully.

This project is a first attempt to model the parking problem and the associated market mechanisms. So, only the fundamental business rules were implemented. Consequently, more complex processes could be tested and would probably impact the results reported. Some improvements would be the inclusion of the possibility to reserve some parking locations or the use of peer-to-peer slot reselling.

Furthermore, the attributes of the development environment and the use of agent-process modelling still being somewhat recent have most likely impacted the obtained results. In truth, the experiments conducted could have benefited from the use of a higher number of driver agents to ensure parking supply shortage. These situations would have great value to assess the performance of the system with the given pricing dynamics.

6.2 Future work

This area would be fruitful for future work. An obvious starting point would be the improvement of the presented agent behaviours and the creation of new ones. It is to be expected that better negotiation models will improve traffic metrics and overall satisfaction of every stakeholder of the parking problem. Hence, upgrading negotiation processes by allowing parking conditions to be more personalised for each parking request would be favourable to better results.

Furthermore, in the scenarios presented, parking managers' knowledge of the world is still relatively limited to their resources. As such, the addition of a slightly more complex learning mechanism for optimal pricing could provide significant improvements to their satisfaction metrics.

Similarly, considerably more work will need to be done to determine the influence of several distinct driver processes. The creation of new behaviours could enrich this simulation by representing a more diverse population and, providing a more accurate view of reality.

Moreover, the natural progression of this work is design and experiment with a broader range of agent roles. These roles could include, for example, city managers who could implement and modify parking regulations. Consequently, the employment of such an entity could shed more light on the impact of these on parking markets.

Finally, another path to continue the research started in this dissertation is to include other market models such as peer-to-peer selling of private parking slots or reselling of parking time not used in open parking lots.

References

[Abar et al., 2017] Abar, S., Theodoropoulos, G. K., Lemarinier, P., and O'Hare, G. M. (2017). Agent Based Modelling and Simulation tools: A review of the state-of-art software. *Computer Science Review*, 24:13–33.

[Anderson and de Palma, 2004] Anderson, S. P. and de Palma, A. (2004). The economics of pricing parking. *Journal of Urban Economics*, 55(1):1–20.

[Andrew Kelly and Peter Clinch, 2006] Andrew Kelly, J. and Peter Clinch, J. (2006). Influence of varied parking tariffs on parking occupancy levels by trip purpose. *Transport Policy*, 13(6):487–495.

[Balac et al., 2017] Balac, M., Ciari, F., and Axhausen, K. W. (2017). Modeling the impact of parking price policy on free-floating carsharing: Case study for Zurich, Switzerland. *Transportation Research Part C: Emerging Technologies*.

[Barile et al., 2017] Barile, F., Bove, L., Napoli, C. D., and Rossi, S. (2017). City Parking Allocations as a Bundle of Society-Aware Deals. In *Agent-Based Modeling of Sustainable Behaviors*, pages 167–186. Springer.

[Barile et al., 2015] Barile, F., Di Napoli, C., Di Nocera, D., and Rossi, S. (2015). Evaluating the Social Benefit of a Negotiation–Based Parking Allocation. *Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science)*.

[Bellifemine et al., 2005] Bellifemine, F., Bergenti, F., Caire, G., and Poggi, A. (2005). Jade — A Java Agent Development Framework. In *Multi-Agent Programming*, pages 125–147. Springer, Boston, MA.

[Bellifemine et al., 2001] Bellifemine, F., Poggi, A., and Rimassa, G. (2001). Developing Multi-agent Systems with JADE. In *ATAL 2000: Intelligent Agents VII Agent Theories Architectures and Languages*, pages 89–103. Springer, Berlin, Heidelberg, Boston, MA, USA.

[Boudali and Ouada, 2017] Boudali, I. and Ouada, M. B. (2017). Smart Parking Reservation System Based on Distributed Multicriteria Approach. *Applied Artificial Intelligence*.

[C-Y Cynthia Lin et al., 2011] C-Y Cynthia Lin, T., Zhang, W., and Umanskaya, V. I. (2011). The Effects of Driving Restrictions on Air Quality: São Paulo, Bogotá, Beijing, and Tianjin. In *Proceedings of the Agricultural \& Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting*, pages 24–27, Pittsburgh, Pennsylvania.

[Cork City Council and QPark, 2018] Cork City Council and QPark (2018). Parking - Datasets - The Home of Open Data in Cork.

[Demary, 2015] Demary, V. (2015). Competition in the Sharing Economy. Technical report, IW policy paper.

[Di Napoli et al., 2014] Di Napoli, C., Di Nocera, D., and Rossi, S. (2014). Agent negotiation for different needs in smart parking allocation. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*.

[Endert et al., 2007] Endert, H., Küster, T., Hirsch, B., and Albayrak, S. (2007). Mapping BPMN to Agents: An Analysis. In MALLOW, editor, *Agents, Web-Services, and Ontologies Integrated Methodologies*, pages 43–58.

[Ferber, 1997] Ferber, J. (1997). *Les systèmes multi-agents: vers une intelligence collective*. InterEditions.

[Fleyeh et al., 2018] Fleyeh, H., Paidi, V. P., Håkansson, J., Nyberg, R. G., and Paidi, V. (2018). Smart Parking Tools Suitability for Open Parking Lots: A Review. In *4th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS)*, Madeira, Portugal.

[Geng and Cassandras, 2013] Geng, Y. and Cassandras, C. G. (2013). New "Smart Parking" System Based on Resource Allocation and Reservations. *IEEE Transactions on Intelligent Transportation Systems*, 14(3):1129–1139.

[Gupta et al., 2017] Gupta, A., Kulkarni, S., Jathar, V., Sharma, V., and Jain, N. (2017). Smart Car Parking Management System Using IoT. *American Journal of Science, Engineering and Technology*, 2(4):112–119.

[Harper et al., 2018] Harper, C. D., Asce, S. M., Hendrickson, C. T., Asce, M., Samaras, C., and Asce, A. M. (2018). Exploring the Economic, Environmental, and Travel Implications of Changes in Parking Choices due to Driverless Vehicles: An Agent-Based Simulation Approach. *Journal of Urban Planning and Development*, 144(4).

[Houissa et al., 2017] Houissa, A., Barth, D., Faul, N., and Mautor, T. (2017). A learning algorithm to minimize the expectation time of finding a parking place in urban area. In *2017 IEEE Symposium on Computers and Communications (ISCC)*, pages 29–34. IEEE.

[Kaspi et al., 2016] Kaspi, M., Raviv, T., Tzur, M., and Galili, H. (2016). Regulating vehicle sharing systems through parking reservation policies: Analysis and performance bounds. *European Journal of Operational Research*.

[Kong et al., 2018] Kong, X. T., Xu, S. X., Cheng, M., and Huang, G. Q. (2018). IoT-Enabled Parking Space Sharing and Allocation Mechanisms. *IEEE Transactions on Automation Science and Engineering*.

[Kotb et al., 2017] Kotb, A. O., Shen, Y. C., and Huang, Y. (2017). Smart Parking Guidance, Monitoring and Reservations: A Review. *IEEE Intelligent Transportation Systems Magazine*.

[Kotb et al., 2016] Kotb, A. O., Shen, Y.-C., Zhu, X., and Huang, Y. (2016). iParker—A New Smart Car-Parking System Based on Dynamic Resource Allocation and Pricing. *IEEE Transactions on Intelligent Transportation Systems*, 17(9):2637–2647.

[Kravari and Bassiliades, 2018] Kravari, K. and Bassiliades, N. (2018). A Rule-Based eCommerce Methodology for the IoT Using Trustworthy Intelligent Agents and Microservices. In *Rules and Reasoning*, pages 302–309. Springer, Cham.

[Krivic et al., 2018] Krivic, P., Skocir, P., Kusek, M., and Jezic, G. (2018). Microservices as Agents in IoT Systems. In *Agent and Multi-Agent Systems: Technology and Applications*, pages 22–31. Springer, Cham.

[Küster et al., 2014] Küster, T., Heßler, A., and Albayrak, S. (2014). Towards Process-Oriented Modelling and Creation of Multi-Agent Systems. In *EMAS 2014: Engineering Multi-Agent Systems*, pages 163–180. Springer, Cham.

[Lamersdorf et al., 2011] Lamersdorf, W., Braubach, L., Pokahr, A., and Lamersdorf, W. (2011). Jadex: A short overview. Technical report, Distributed and Information Systems Group, University of Hamburg, Hamburg, Germany.

[Leitão and Rückemann, 2013] Leitão, P. and Rückemann, C.-P. (2013). *Parallelising Multi-agent Systems for High Performance Computing*. IARIA.

[Leon et al., 2015] Leon, F., Paprzycki, M., and Ganzha, M. (2015). A Review of Agent Platforms. Technical report, Systems Research Institute, Polish Academy of Sciences.

[Leurent and Boujnah, 2014] Leurent, F. and Boujnah, H. (2014). A user equilibrium, traffic assignment model of network route and parking lot choice, with search circuits and cruising flows. *Transportation Research Part C: Emerging Technologies*.

[Lin et al., 2017] Lin, T., Rivano, H., and Le Mouel, F. (2017). A Survey of Smart Parking Solutions. *IEEE Transactions on Intelligent Transportation Systems*, 18(12):3229–3253.

[Liu et al., 2018] Liu, K. S., Gao, J., Wu, X., and Lin, S. (2018). On-Street Parking Guidance with Real-Time Sensing Data for Smart Cities. In *2018 15th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON)*, pages 1–9. IEEE.

[Mangwani, 2018] Mangwani, P. (2018). Smart Parking System Based on Internet of Things. *International Journal of Applied Engineering Research*, 13:10281–10285.

[Manville et al., 2018] Manville, M., Chatman, D. G., and Chatman, D. G. (2018). Market-Priced Parking in Theory and Practice. In *Parking and the City*, pages 354–360. Routledge, First edition. | New York, NY : Routledge, 2018.

[Markus et al., 2008] Markus, J., Andrews, P. S., Sampson, A. T., Markus Bjørndalen, J., Stepney, S., Timmis, J., Warren, D. N., and Welch, P. H. (2008). Investigating Patterns for the Process-Oriented Modelling and Simulation of Space in Complex Systems. In *Artificial Life XI: Proceedings of the Eleventh International Conference on the Simulation and Synthesis of Living Systems*, pages 17–24. MIT Press, Cambridge, MA, USA.

[Melo et al., 2019] Melo, S., Macedo, J., and Baptista, P. (2019). Capacity-sharing in logistics solutions: A new pathway towards sustainability. *Transport Policy*, 73:143–151.

[Nocera et al., 2014] Nocera, D. D., Napoli, C. D., and Rossi, S. (2014). A social-aware smart parking application. In *CEUR Workshop Proceedings*.

[Olus Inan et al., 2019] Olus Inan, M., Inci, E., and Robin Lindsey, C. (2019). Spillover parking. *Transportation Research Part B: Methodological*, 125:197–228.

[Patel et al., 2018] Patel, A. S., Ojha, M., Rani, M., Khare, A., Vyas, O. P., and Vyas, R. (2018). Ontology-based multi-Agent smart bike sharing system (SBSS). In *Proceedings - 2018 IEEE International Conference on Smart Computing, SMARTCOMP 2018*.

[Pham et al., 2015] Pham, T. N., Tsai, M. F., Nguyen, D. B., Dow, C. R., and Deng, D. J. (2015). A Cloud-Based Smart-Parking System Based on Internet-of-Things Technologies. *IEEE Access*.

[Polycarpou et al., 2013] Polycarpou, E., Lambrinos, L., and Protopapadakis, E. (2013). Smart parking solutions for urban areas. In *2013 IEEE 14th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*, pages 1–6. IEEE.

[Qiu et al., 2018] Qiu, J., Tian, J., Chen, H., and Lu, X. (2018). Prediction Method of Parking Space Based on Genetic Algorithm and RNN. In *Advances in Multimedia Information Processing – PCM 2018*, pages 865–876, Hefei, China.

[Rajabioun and Ioannou, 2015] Rajabioun, T. and Ioannou, P. (2015). On-Street and Off-Street Parking Availability Prediction Using Multivariate Spatiotemporal Models. *IEEE Transactions on Intelligent Transportation Systems*, 16(5):2913–2924.

[Rizvi et al., 2018] Rizvi, S. R., Zehra, S., and Olariu, S. (2018). ASPIRE: An Agent-Oriented Smart Parking Recommendation System for Smart Cities. *IEEE Intelligent Transportation Systems Magazine*.

[Robertson, 2005] Robertson, D. A. (2005). Agent-Based Modeling Toolkits NetLogo, RePast, and Swarm. Technical report, University of Warwick, UK.

[Rousset et al., 2016] Rousset, A., Herrmann, B., Lang, C., and Philippe, L. (2016). A survey on parallel and distributed multi-agent systems for high performance computing simulations. *Computer Science Review*, 22:27–46.

[Rúbio et al., 2017] Rúbio, T. R., Kokkinogenis, Z., Cardoso, H. L., Oliveira, E., and Rossetti, R. J. (2017). ResMAS - A conceptual MAS model for resource-based integrated markets. In *Communications in Computer and Information Science*.

[Rúbio et al., 2019] Rúbio, T. R. P. M., Lopes Cardoso, H., and Oliveira, E. (2019). Agent Process Modelling. In Demazeau Yves, , Matson, E., and Corchado Juan Manuel, and and De la Prieta Fernando, editors, *Advances in Practical Applications of Survivable Agents and Multi-Agent Systems: The PAAMS Collection*, pages 277–280, Cham. Springer International Publishing.

[Shaheen and Cohen, 2012] Shaheen, S. A. and Cohen, A. P. (2012). Carsharing and Personal Vehicle Services: Worldwide Market Developments and Emerging Trends. *International Journal of Sustainable Transportation*.

[Shin and Jun, 2014] Shin, J. H. and Jun, H. B. (2014). A study on smart parking guidance algorithm. *Transportation Research Part C: Emerging Technologies*.

[Smolnicki and Sołtys, 2016] Smolnicki, P. M. and Sołtys, J. (2016). Driverless Mobility: The Impact on Metropolitan Spatial Structures. In *Procedia Engineering*.

[Stephany, 2015] Stephany, A. (2015). *The business of sharing : making it in the new sharing economy*. Springer.

[Tjoa et al., 2008] Tjoa, S., Jakoubi, S., and Quirchmayr, G. (2008). Enhancing Business Impact Analysis and Risk Assessment Applying a Risk-Aware Business Process Modeling and Simulation Methodology. In *2008 Third International Conference on Availability, Reliability and Security*, pages 179–186. IEEE.

[Vasirani and Ossowski, 2012] Vasirani, M. and Ossowski, S. (2012). A Market-Inspired Approach for Intersection Management in Urban Road Traffic Networks. *Journal of Artificial Intelligence Research*, 43:621–659.

[Wang, 2011] Wang, H. (2011). A Reservation-based Smart Parking System. *Computer Science and Engineering: Theses, Dissertations, and Student Research*.

[Yan et al., 2011] Yan, T., Hoh, B., Ganesan, D., Tracton, K., Iwuchukwu, T., and Lee, J.-S. (2011). CrowdPark: A crowdsourcing-based parking reservation system for mobile phones. Technical report, University of Massachusetts, Amherst.

[Zhang et al., 2018] Zhang, C., Chen, J., Li, Z., and Wu, Y. (2018). Predicting Owners' Willingness to Share Private Residential Parking Spots. *Transportation Research Record: Journal of the Transportation Research Board*, page 036119811877294.

Appendix A

Gap Analysis

Table A.1: Gap Analysis of Literature in Smart Parking

Title	PGI / PRS / SP	Agents / Entities	Reservations	Markets	Goals
Modelling the impact of parking price policy on free-floating carsharing: Case study for Zurich, Switzerland [Balac et al., 2017]	PGI and Carsharing	Agents who will choose a plan of activity and Carsharing Managers	×	Dynamic Prices and Carsharing	analyse the impacts of parking price policies in carsharing use and generally in the city of Zurich
Evaluating the Social Benefit of a Negotiation–Based Parking Allocation [Barile et al., 2015]	SP	Drivers and Parking Managers	✓	×	Optimize parking allocation to maximize utility for all agents
Smart Parking Reservation System Based on Distributed Multicriteria Approach [Boudali and Ouada, 2017]	SP	Vehicle, Geographic Information System, Locality and Park	✓	×	Aid drivers find the best parking spot that matches their multi-criteria preferences

Title	PGI / PRS / SP	Agents / Entities	Reservations	Markets	Goals
New "Smart Parking" System Based on Resource Allocation and Reservations [Geng and Cassandras, 2013]	SP	Driver Request Processing Center and Smart Parking Allocation Center	✓	×	dynamically change reservation until the car is physically parked to ensure overall maximum efficiency
A learning algorithm to minimize the expected time of finding a parking place in an urban area [Houissa et al., 2017]	PGI	Intersections	×	×	Minimizes expected time for a driver to find an available parking spot
Regulating vehicle sharing systems through parking reservation policies: Analysis and performance bounds [Kaspi et al., 2016]	PRS	Vehicle sharing users and Renting stations	✓	×	Study the impact of introducing partial reservation policies for parking vehicle sharing systems
IoT-Enabled Parking Space Sharing and Allocation Mechanisms [Kong et al., 2018]	SP	Drivers and Parking platform	✓	Parking Space Peer-to-Peer Exchange and Auctions	Encourage drivers to exchange their private parking spots during working hours and obtain grater welfare
iParker—A New Smart Car-Parking System Based on Dynamic Resource Allocation and Pricing [Kotb et al., 2016]	SP	Parkers, Parking managers, local smart allocation systems and central request centre	✓	Dynamic Pricing	increase parking success with minimal cost to the drivers and highest revenue for parking managers

Title	PGI / PRS / SP	Agents / Entities	Reservations	Markets	Goals
A user equilibrium, traffic assignment model of network route and parking lot choice, with search circuits and cruising flows [Leurent and Boujnah, 2014]	PGI	Parking lots, roadway network and customers	$\times$	$\times$	Macroscopic simulation of parking route and search choices with stochastic parking lot conditions
On-Street Parking Guidance with Real-Time Sensing Data for Smart Cities [Liu et al., 2018]	PGI	Drivers and a Cloud Server	$\times$	$\times$	recommend parking locations based on availability prediction
Capacity-sharing in logistics solutions: A new pathway towards sustainability [Melo et al., 2019]	SP	Drivers and parking spots with variable parking restrictions	$\times$	$+/-$	Increase traffic efficiency by sharing parking spots reserved for city logistics during specific periods of the day for short-term use.
A Cloud-Based Smart-Parking System Based on Internet-of-Things Technologies [Pham et al., 2015]	PGI	Driver and Parking System	$\times$	$\times$	Decrease the number of cars that fail to find parking as well as minimize the time spent searching for the car park
ASPIRE: An Agent-Oriented Smart Parking Recommendation System for Smart Cities [Rizvi et al., 2018]	PRS	Local Agent, Parker's Agent, Resource Allocation Management Center, Park Unit	$\checkmark$	$\times$	Building a strategy for finding the parking allocation based on drivers' preferences

Title	PGI / PRS / SP	Agents / Entities	Reservations	Markets	Goals
Carsharing and Personal Vehicle Services: Worldwide Market Developments and Emerging Trends [Shaheen and Cohen, 2012]	Carsharing	Users and Carsharing organisations	×	✓	Survey carsharing business models from 2006 to 2015 which are highly dependent on free or reduced-price parking
CrowdPark: A Crowdsourcing-based Parking Reservation System for Mobile Phones [Yan et al., 2011]	PRS	Parking Sellers and Buyers.	✓	✓	aid drivers to "loosely" reserve parking spots by crowd-sourcing their availability, and detect malicious users
Agent negotiation for different needs in smart parking allocation [Di Napoli et al., 2014]	SP	User and Parking Manager Agents	✓	Negotiation	Use automated negotiation to select parking spaces by fulfilling all entities' different needs
A Social-Aware Smart Parking Application [Nocera et al., 2014]	SP	User and Parking Manager Agents	✓	Dynamic pricing	Based on [Di Napoli et al., 2014], negotiate parking conditions between all entities with dynamic pricing related to distance from red zones and availability
City Parking Allocations as a Bundle of Society-Aware Deals [Barile et al., 2017]	SP	Driver and Parking Manager Agents	✓	Dynamic pricing	Use negotiation to increase global utilitarian social welfare of the system, simulating the city of Naples

Appendix B

Full Page Process Models

B.1 Driver Process Model

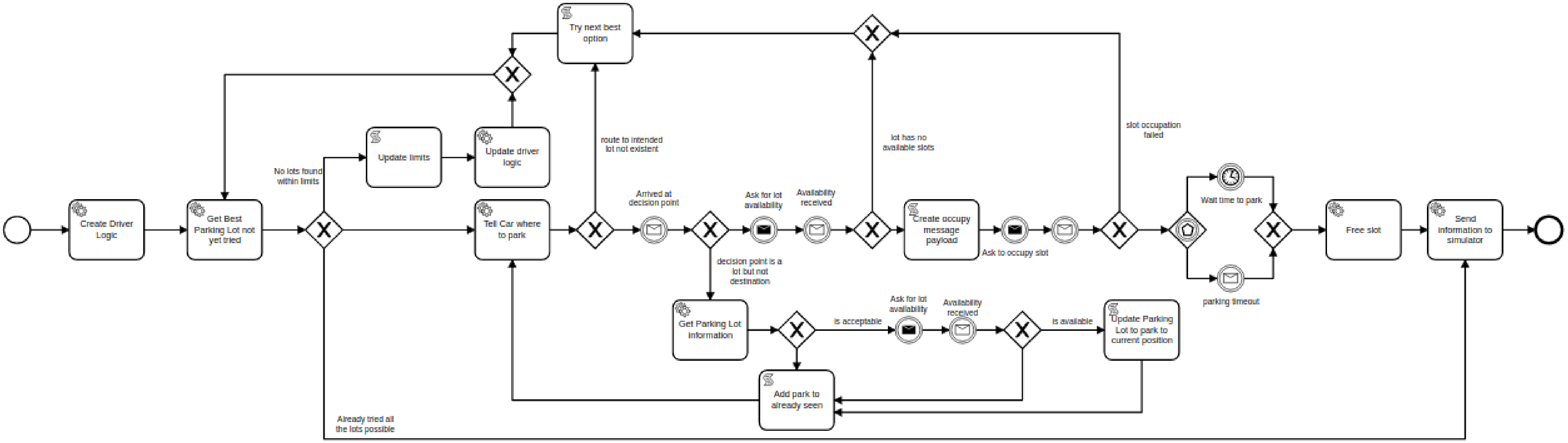


Figure B.1: Driver behaviour process model

B.2 Parking Manager Process Model

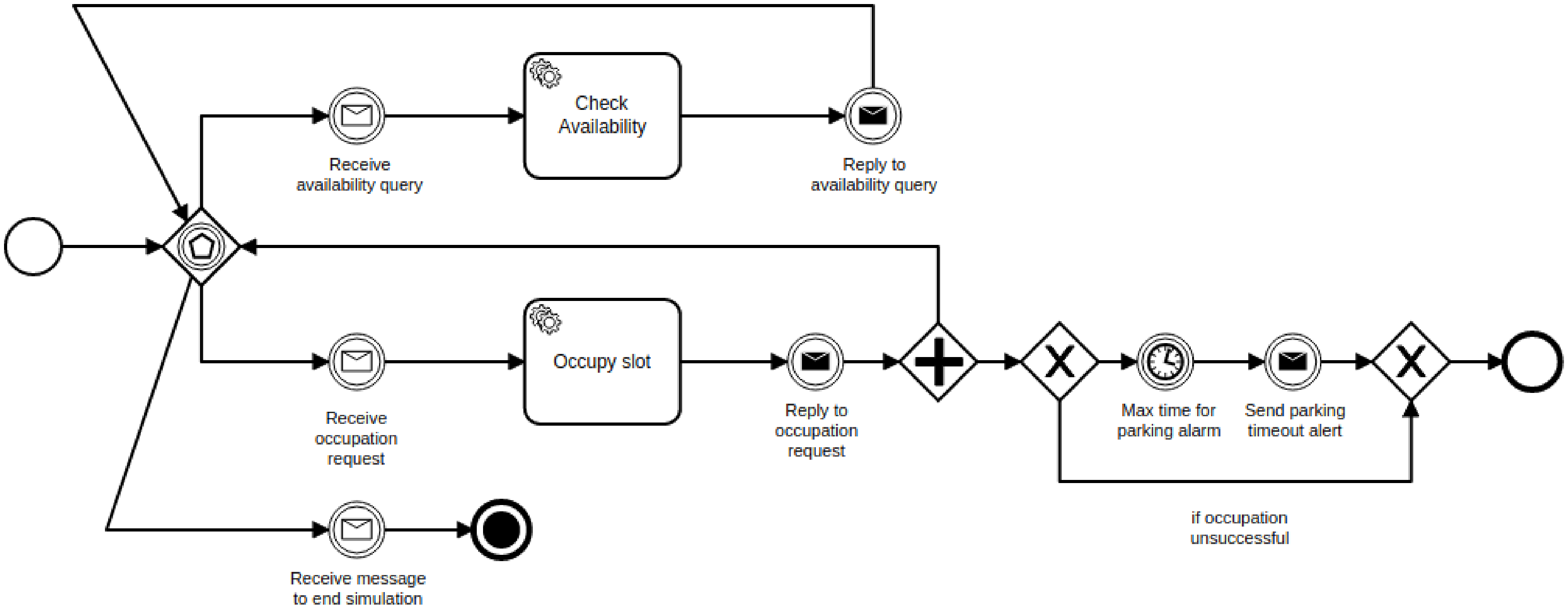


Figure B.2: Parking manager process model

B.3 Improved Parking Manager Process Model

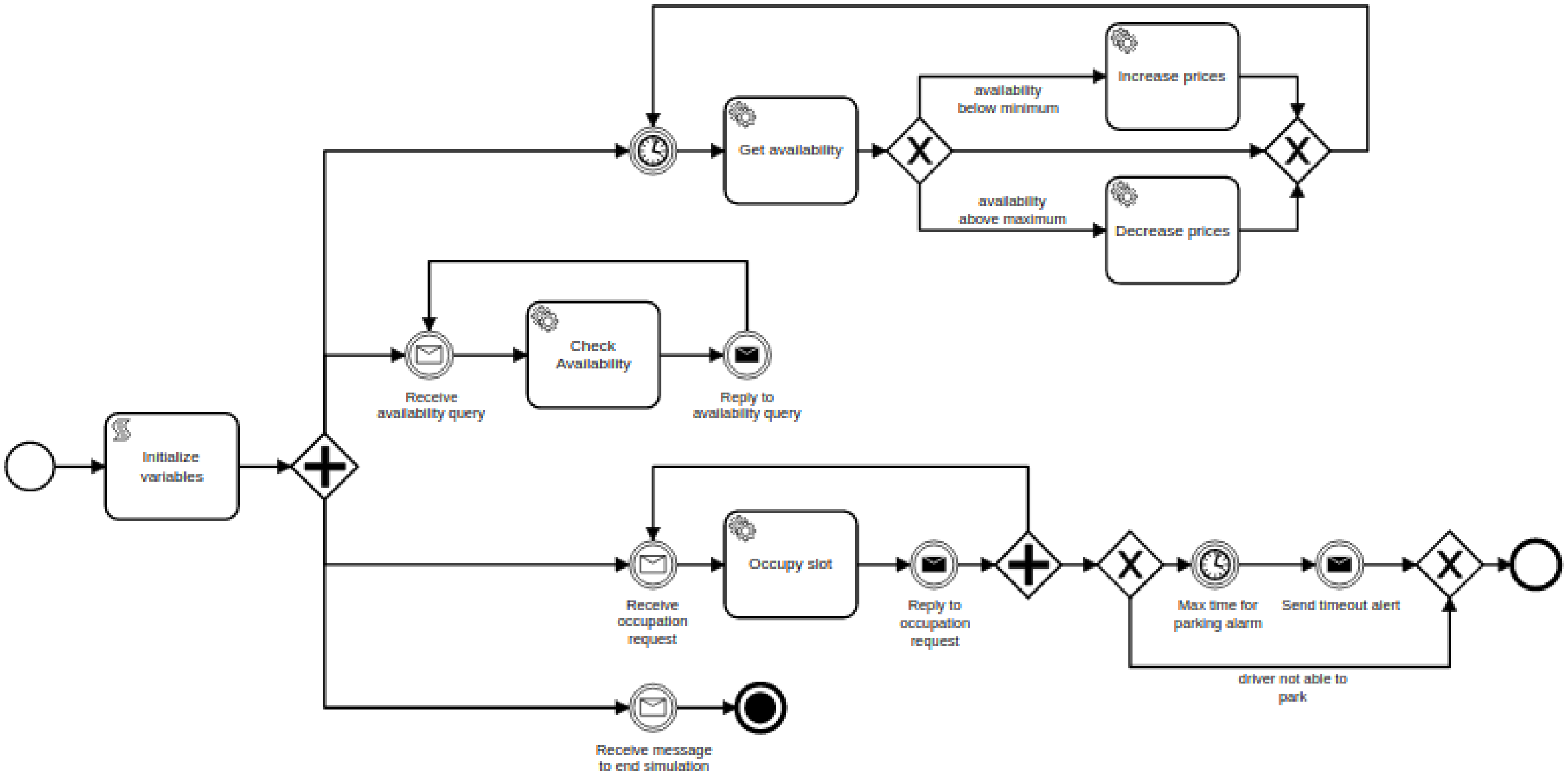


Figure B.3: Parking manager process model (improved)

Appendix C

Complete tables

C.1 Driver evaluation metrics

Table C.1: Driver metrics in experiment 1

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
Run 1	**63**	**3.444**	**0.924**	**137.594**	**2.762**
1147	7	3.741	1.571	96.350	1.143
1149	1	3.000	1.500	37.778	2.000
2051	1	3.784	3.000	30.161	1.000
2054	3	3.318	1.633	199.474	1.333
2058	3	3.897	0.333	46.033	1.000
2059	18	3.636	0.300	203.526	1.778
2061	21	3.767	1.000	122.412	1.143
2062	1	3.000	0.700	26.449	4.000
2068	4	3.692	1.500	94.643	1.000
Not parked	4	0.000	—	—	23.000
Run 2	**476**	**3.597**	**0.895**	**160.904**	**1.462**
1101	48	3.745	1.563	93.431	1.146
1104	5	3.000	1.000	176.738	2.400
1107	168	3.671	0.373	207.128	1.101
1111	2	3.489	1.500	26.477	3.000
1112	26	3.278	0.408	186.986	1.500
1113	50	3.736	2.670	96.350	1.160

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
1115	23	3.274	1.248	182.493	1.130
1116	56	3.854	0.400	187.882	1.000
1117	64	3.791	0.992	94.643	1.063
1118	23	3.000	0.409	195.285	2.435
1121	5	3.145	1.500	60.427	2.200
1122	1	3.000	0.200	318.417	9.000
Not parked	5	0.000	—	—	23.000
Run 3	**354**	**3.569**	**0.995**	**162.122**	**1.980**
1128	28	3.749	1.821	94.643	1.464
1130	1	3.720	0.700	37.778	1.000
1133	43	3.626	3.000	96.350	1.326
1135	31	3.748	1.839	88.457	1.419
1138	1	3.743	0.200	320.827	10.000
1139	2	3.472	3.000	11.927	4.000
1140	79	3.824	0.339	168.631	1.380
1142	135	3.644	0.360	213.393	1.526
1143	3	3.890	0.667	36.167	1.000
1144	15	3.191	0.967	216.605	2.667
1146	5	3.685	1.100	40.574	2.200
Not parked	11	0.000			15.545
Run 4	**121**	**3.353**	**1.897**	**126.347**	**3.917**
1124	2	3.639	1.000	168.631	7.000
1126	8	3.845	2.625	96.350	1.625
1128	26	3.522	2.038	94.643	2.385
1130	1	3.000	2.000	51.829	2.000
1132	62	3.463	1.742	127.722	2.968
1133	1	3.620	2.000	165.341	14.000
1134	1	3.000	3.000	332.115	8.000
1136	1	3.000	2.000	318.417	13.000
1137	1	3.000	1.000	38.711	8.000
1139	9	3.678	1.889	212.503	2.778
1140	1	3.719	2.000	64.745	2.000
1143	3	3.000	2.333	95.031	4.667

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
Not parked	5	0.000	—	—	23.000
Run 5	**415**	**3.049**	**1.347**	**134.207**	**1.812**
1101	1	3.000	2.000	0.000	6.000
1104	4	3.673	0.500	29.839	3.000
1105	1	3.000	1.000	37.778	2.000
1106	1	3.982	1.500	5.562	1.000
1107	116	3.233	1.267	115.536	1.526
1110	56	2.559	3.143	96.350	1.375
1112	23	3.351	0.409	129.658	1.957
1113	106	3.390	0.372	212.290	1.547
1117	6	3.599	1.167	254.203	1.500
1119	76	2.986	1.908	94.643	1.921
1122	3	3.307	2.500	155.246	2.000
1123	8	3.454	0.300	23.451	3.625
Not parked	14	0.000	—	—	5.571
Run 6	**831**	**2.974**	**1.330**	**139.186**	**1.945**
1124	106	2.546	3.717	96.350	1.349
1125	3	3.000	0.700	65.082	4.000
1127	1	3.000	1.000	188.508	4.000
1128	26	3.560	0.354	145.436	1.115
1129	200	3.297	0.361	199.553	1.360
1130	2	2.364	2.000	57.144	3.500
1132	25	3.426	0.920	118.233	2.080
1136	138	3.202	1.359	94.643	2.188
1137	100	3.297	0.396	187.882	2.250
1138	2	3.000	2.000	44.450	5.000
1140	2	3.309	0.700	194.369	2.000
1144	10	3.848	0.380	27.424	2.100
1145	168	3.103	1.768	113.138	1.530
1146	1	3.195	4.000	155.246	2.000
Not parked	47	0.000	—	—	5.872
Grand Total	**2260**	**3.246**	**1.205**	**145.864**	**1.953**

Table C.2: Driver metrics in experiment 2

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
Run 1	**619**	**3.143**	**0.937**	**144.004**	**2.191**
1101	18	3.135	1.028	202.589	2.056
1102	173	3.377	0.375	223.500	1.775
1107	7	3.851	0.343	24.821	1.000
1111	2	3.458	0.700	3.781	3.500
1112	17	3.425	0.306	167.483	1.706
1114	23	3.409	0.804	196.250	1.435
1116	122	3.266	1.302	105.270	1.557
1118	113	3.332	1.559	96.350	1.460
1119	105	3.422	0.929	94.643	3.181
Not parked	39	0.000	—	—	6.333
Run 2	**515**	**3.112**	**0.760**	**179.926**	**4.318**
1501	42	3.619	2.019	96.350	1.976
1509	175	3.210	0.368	254.593	2.034
1511	12	3.560	0.917	119.826	2.583
1513	41	3.623	2.122	94.643	2.098
1515	42	3.000	0.357	200.538	5.929
1516	2	3.482	1.250	24.538	4.500
1517	50	3.818	1.050	85.316	1.980
1520	103	3.631	0.367	168.631	2.010
Not parked	48	0.000	—	—	23.000
Run 3	**493**	**3.134**	**0.789**	**151.251**	**3.016**
1103	10	3.521	0.400	31.178	2.800
1106	4	2.770	0.350	268.157	37.000
1108	3	3.000	1.400	33.644	2.000
1110	2	3.463	1.400	1.813	3.000
1111	165	3.352	0.365	207.349	1.697
1112	2	3.254	1.500	238.299	1.000
1115	49	3.412	1.653	87.303	1.224
1116	64	3.560	0.969	94.643	1.641
1117	1	3.000	1.000	168.631	2.000
1119	22	3.554	0.318	124.445	1.500

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
1120	68	3.407	0.382	187.882	2.838
1121	60	3.488	1.698	96.350	1.133
1122	2	3.000	1.000	194.369	12.000
Not parked	41	0.000	—	—	12.976
Run 4	**195**	**2.905**	**0.691**	**151.312**	**2.400**
1101	1	3.885	1.000	11.927	1.000
1103	16	3.383	2.000	94.643	1.125
1104	29	3.451	0.366	188.653	2.138
1107	4	3.864	0.300	21.846	1.000
1109	3	3.854	0.667	32.625	1.000
1110	48	3.254	0.296	230.719	1.479
1114	37	3.631	0.735	96.350	1.162
1121	19	3.528	1.179	85.316	1.211
1122	7	3.406	0.400	196.053	2.000
Not parked	31	0.000	—	—	7.387
Run 5	**434**	**3.076**	**0.647**	**142.824**	**3.901**
1102	22	3.383	0.355	141.739	2.636
1103	120	3.567	0.390	94.643	5.500
1107	1	3.000	1.500	169.748	8.000
1110	53	3.325	1.360	96.350	1.151
1113	1	3.276	1.500	37.778	1.000
1118	72	3.562	0.944	94.783	1.389
1119	11	3.525	1.336	93.000	2.000
1121	113	3.141	0.370	252.149	2.124
Not parked	41	0.000	—	—	13.244
Run 6	**525**	**3.267**	**0.767**	**153.160**	**3.010**
1102	6	3.315	1.050	172.232	1.000
1105	6	3.605	0.933	238.299	1.000
1108	3	3.738	0.800	35.595	1.000
1109	108	3.764	0.800	96.350	1.287
1110	56	3.765	0.839	94.643	1.607
1111	3	3.627	1.167	4.437	1.333
1113	1	3.000	1.000	188.508	45.000

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
1114	26	3.694	0.338	131.663	1.731
1116	60	3.547	2.150	85.316	1.383
1118	217	3.278	0.372	219.703	2.493
1120	2	3.962	1.000	13.517	1.000
1121	1	3.321	2.100	172.869	1.000
Not parked	36	0.000	—	—	17.083
Grand Total	**2781**	**3.132**	**0.785**	**153.931**	**3.167**

Table C.3: Driver metrics in experiment 3

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
Run 1	**579**	**3.314**	**1.199**	**189.620**	**2.509**
1104	34	3.607	0.521	208.977	1.324
1106	46	3.340	0.744	215.568	1.717
1107	4	3.937	0.575	19.261	1.000
1108	1	3.000	0.950	188.508	2.000
1110	20	3.610	0.393	145.483	1.650
1112	87	3.252	0.398	233.924	2.356
1117	106	3.649	1.578	110.119	1.406
1118	31	3.199	0.381	436.099	2.581
1119	87	3.671	1.130	94.643	2.540
1120	4	3.000	0.912	182.410	5.000
1122	81	3.600	3.263	96.350	1.247
1123	51	3.137	0.375	434.559	1.608
Not parked	27	0.000	—	—	16.000
Run 2	**758**	**3.278**	**0.591**	**132.299**	**3.133**
1103	155	3.677	0.593	94.643	3.400
1104	246	3.710	0.555	114.608	1.740
1105	14	3.693	0.400	62.999	1.929
1106	85	3.741	1.188	96.350	1.176
1110	35	3.584	0.341	148.875	1.714
1116	3	3.548	0.200	39.974	2.667
1120	97	3.263	0.404	238.919	2.660

Lot id	Number of drivers	Average			
		Utility	**Price**	**Distance**	**Choice**
1121	37	3.048	0.384	249.989	2.378
1122	18	3.733	0.386	88.661	1.444
Not parked	68	0.000	—	—	12.544
Run 3	**445**	**2.945**	**0.930**	**135.175**	**5.007**
1102	2	3.988	0.660	0.000	1.000
1104	47	3.552	2.011	96.350	1.468
1106	4	3.699	1.120	172.232	1.000
1109	5	3.629	0.430	203.216	1.200
1114	4	3.303	0.613	236.178	1.750
1115	11	3.739	1.010	51.502	2.091
1116	4	3.735	0.937	17.217	2.000
1117	24	3.391	0.354	186.217	2.000
1118	128	3.723	1.153	121.071	1.375
1121	138	3.447	0.474	158.183	6.138
Not parked	78	0.000	—	—	13.308
Run 4	**805**	**3.199**	**1.805**	**91.543**	**4.935**
1150	3	2.559	2.667	155.246	34.333
1502	239	3.427	1.757	85.316	3.368
1505	1	3.000	1.000	189.464	4.000
1507	238	3.486	1.857	96.350	2.206
1508	56	3.239	1.786	122.832	2.696
1511	191	3.227	1.770	94.643	6.335
1512	23	3.055	1.957	15.854	4.609
1513	3	2.727	2.667	165.341	41.000
1516	5	3.136	1.600	19.857	5.400
1517	6	3.372	1.667	31.892	3.333
1518	1	3.523	3.000	37.778	2.000
Not parked	39	0.000	—	—	23.000
Run 5	**631**	**3.275**	**0.835**	**136.838**	**3.225**
1103	78	3.712	1.462	96.350	1.385
1112	6	3.312	1.025	72.596	4.833
1113	29	3.384	0.618	212.407	1.828
1114	3	3.381	0.317	240.103	2.000

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
1117	138	3.586	0.705	94.643	4.790
1118	206	3.619	0.862	121.241	1.786
1120	110	3.315	0.520	232.148	1.518
1122	12	3.633	1.249	102.985	3.250
Not parked	49	0.000	—	—	12.327
Run 6	**965**	**3.434**	**0.614**	**141.516**	**2.298**
1108	5	3.264	0.360	188.098	3.200
1109	33	3.361	0.379	224.665	1.152
1110	143	3.350	0.389	215.054	1.741
1111	220	3.769	0.709	104.791	1.350
1112	1	3.866	0.400	38.523	4.000
1113	64	3.124	0.384	237.224	4.594
1114	20	3.660	0.373	81.763	1.700
1115	12	3.817	0.325	31.462	1.583
1116	86	3.627	0.391	170.642	1.977
1118	106	3.615	1.441	96.350	1.396
1120	35	3.381	0.391	207.876	2.257
1122	164	3.780	0.569	94.643	1.811
1123	33	3.709	0.318	102.951	1.424
Not parked	43	0.000	—	—	12.233
Grand Total	**4183**	**3.268**	**0.992**	**135.552**	**3.414**

Table C.4: Driver metrics in experiment 4

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
Run 1	**129**	**3.283**	**0.400**	**119.229**	**2.233**
1101	29	3.682	0.384	92.032	1.379
1102	2	3.895	0.500	15.261	1.000
1103	1	3.000	0.350	40.883	3.000
1104	1	3.510	0.200	238.299	1.000
1106	14	3.811	0.554	94.643	1.571
1107	17	3.483	0.329	157.244	1.647
1108	7	3.248	0.450	187.882	4.143

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
1112	2	3.310	0.600	27.206	5.500
1113	1	3.957	0.200	24.538	1.000
1114	3	3.887	0.350	32.369	1.333
1116	6	3.164	0.425	226.245	3.167
1117	1	2.512	0.200	165.341	2.000
1120	8	3.591	0.350	193.776	1.375
1121	25	3.785	0.386	96.350	1.440
Not parked	12	0.000	—	—	6.583
Run 2	**1037**	**3.230**	**0.501**	**133.041**	**2.614**
1102	56	3.371	0.371	133.194	1.679
1103	54	3.320	0.381	238.299	1.519
1105	28	3.558	0.407	45.886	2.036
1106	54	3.208	0.414	187.882	2.963
1107	5	3.839	0.600	17.812	1.400
1108	96	3.255	0.390	189.408	1.375
1110	159	3.709	0.723	96.350	1.465
1111	6	3.354	0.333	193.453	1.667
1112	238	3.615	0.550	105.364	1.601
1113	5	2.856	0.320	256.496	1.000
1114	4	3.515	0.460	1.942	1.500
1115	40	3.639	0.400	168.631	1.225
1117	76	3.253	0.342	161.057	1.474
1118	1	2.668	0.600	257.203	1.000
1119	23	3.266	0.339	188.508	2.609
1120	2	3.534	0.600	22.634	1.000
1122	6	3.143	0.317	156.315	2.333
1123	103	3.702	0.569	94.643	1.903
Not parked	81	0.000	—	—	13.704
Run 3	**762**	**3.361**	**0.479**	**132.608**	**2.248**
1520	139	3.752	0.407	94.643	1.626
1522	3	3.866	0.267	32.267	1.667
1523	26	3.484	0.373	127.524	1.846
1524	213	3.720	0.433	112.746	1.315

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
1525	50	3.377	0.368	195.554	1.420
1526	32	3.225	0.341	237.224	2.438
1527	83	3.716	1.189	96.350	1.265
1528	43	3.548	0.330	168.631	1.326
1530	6	3.576	0.367	16.859	3.167
1534	2	3.305	0.400	268.157	3.000
1535	47	3.473	0.283	206.676	1.319
1538	2	3.889	0.300	93.593	1.000
1540	22	3.439	0.345	187.882	2.091
1541	20	3.522	0.310	57.155	2.350
1542	21	3.189	0.362	238.299	1.476
Not parked	53	0.000	—	—	11.887
Run 4	**457**	**3.241**	**0.556**	**131.835**	**2.840**
1101	10	3.541	0.390	214.683	1.200
1104	40	3.650	1.532	96.350	1.200
1105	1	3.975	0.300	0.000	1.000
1108	34	3.570	0.341	168.631	1.324
1113	134	3.702	0.499	118.017	1.537
1114	86	3.684	0.529	94.643	2.756
1116	1	3.761	0.400	20.104	1.000
1117	1	3.760	0.600	204.199	1.000
1118	22	3.595	0.386	133.129	1.364
1119	12	3.276	0.383	220.985	2.167
1120	3	3.845	0.333	6.006	1.000
1121	60	3.265	0.353	205.329	1.567
1122	4	3.650	0.350	24.836	2.500
1123	4	3.343	0.450	96.487	2.250
Not parked	45	0.000	—	—	12.778
Run 5	**577**	**3.285**	**0.533**	**142.156**	**2.584**
1125	44	3.373	0.405	208.802	1.614
1126	1	3.734	0.400	187.882	1.000
1127	26	3.354	0.371	200.415	2.692
1130	125	3.754	0.489	106.349	1.328

Lot id	Number of drivers	Average			
		Utility	Price	Distance	Choice
1131	3	3.564	0.200	21.791	3.000
1134	104	3.775	0.650	96.350	1.279
1135	17	3.473	0.774	141.505	1.412
1136	68	3.415	0.388	200.625	1.397
1137	50	3.618	1.012	94.643	2.340
1139	7	3.677	0.436	76.442	1.000
1140	7	3.178	0.507	150.720	3.143
1141	16	3.209	0.381	247.345	2.375
1142	14	3.117	0.393	207.066	3.786
1143	1	3.473	1.050	238.299	1.000
1144	45	3.416	0.346	168.631	1.444
1146	3	3.708	0.333	155.246	3.000
Not parked	46	0.000	—	—	13.261
Run 6	**632**	**3.300**	**0.566**	**129.147**	**2.552**
1102	60	3.525	0.383	169.784	1.483
1103	78	3.398	0.382	158.077	1.385
1105	98	3.709	0.668	94.643	1.786
1106	2	3.187	0.200	231.436	1.000
1107	5	3.343	0.360	19.481	4.200
1109	18	3.364	0.422	180.502	1.667
1112	40	3.216	0.351	238.299	3.150
1113	3	3.580	0.483	12.104	2.000
1114	4	3.155	0.400	44.513	4.000
1116	13	3.599	0.277	86.569	1.231
1118	7	3.548	0.343	168.631	1.000
1119	10	3.387	0.340	231.666	1.500
1122	82	3.745	0.794	96.350	1.305
1123	165	3.622	0.676	107.152	1.933
Not parked	47	0.000	—	—	12.255
Grand Total	**3594**	**3.282**	**0.516**	**133.084**	**2.536**

C.2 Parking Manager evaluation metrics

Table C.5: Parking manager metrics in experiment 1

	Run 1		**Run 2**		**Run 3**		**Run 4**		**Run 5**		**Run 6**		**Average**	
Road Ids	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**profit**	**Occupancy**
Closed	**19.00**	**0.138%**	**482.40**	**1.985%**	**177.30**	**1.011%**	**35.40**	**0.555%**	**291.60**	**1.012%**	**545.20**	**1.860%**	**258.48**	**1.093%**
2ca1egzvj	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
3662m23xu	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
3cz5rurcs	19.00	1.376%	482.40	19.852%	177.30	10.111%	35.40	5.553%	283.60	9.759%	531.20	17.886%	254.82	10.756%
4g5eo749w	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
bgcnenw9y	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
c2nii9l2q	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
jobl1mgw3	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
kvsi32e0u	0	0%	0	0%	0	0%	0	0%	7.20	0.330%	6.80	0.229%	2.33	0.093%
m7mnatybo	0	0%	0	0%	0	0%	0	0%	0.80	0.028%	7.20	0.485%	1.33	0.085%
wzma72mga	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Open	**75.86**	**1.019%**	**207.07**	**2.988%**	**434.23**	**6.720%**	**559.25**	**10.122%**	**998.20**	**8.402%**	**1253.32**	**11.990%**	**587.99**	**6.874%**
1725588183	0	0%	2.20	0.679%	0.20	0.086%	0	0%	83.35	28.682%	3.15	0.303%	14.82	4.958%
1788788609	1.17	0.084%	0	0%	8.50	0.727%	4.75	1.118%	3.55	1.222%	6.85	2.306%	4.14	0.910%
1788788622	0.42	0.061%	15.19	1.875%	0.35	0.043%	0.50	0.118%	2.25	0.155%	2.28	0.219%	3.50	0.412%
1788788626	32.38	1.920%	25.95	3.940%	16.63	1.422%	20.25	2.382%	6.95	0.860%	17.40	2.929%	19.93	2.242%
4468836872	1.81	0.187%	11.17	0.985%	29.25	5.004%	41.50	9.765%	20.15	6.934%	36.75	4.949%	23.44	4.637%
4598151009	4.17	0.302%	80.63	9.954%	152.00	13.003%	254.00	59.765%	568.50	39.126%	530.95	51.077%	265.04	28.871%
4598151018	0	0%	38.09	11.757%	87.95	37.618%	4.75	1.118%	14.38	1.979%	112.70	37.946%	42.98	15.070%
4598151026	19.44	2.813%	18.00	1.111%	92.25	7.891%	219.00	51.529%	299.08	29.405%	481.00	32.391%	188.13	20.857%
4720649125	0	0%	1.17	0.072%	47.10	20.145%	3.25	0.765%	0	0%	0	0%	8.59	3.497%
4720649127	0	0%	14.67	4.528%	0	0%	0	0%	0	0%	61.75	20.791%	12.74	4.220%
4720649129	0	0%	0	0%	0	0%	6.75	1.588%	0	0%	0	0%	1.13	0.265%
4720649131	16.47	5.964%	0	0%	0	0%	4.50	1.059%	0	0%	0.50	0.034%	3.58	1.176%
Total	**94.86**	**0.636%**	**689.47**	**2.552%**	**611.52**	**4.238%**	**594.65**	**5.963%**	**1289.80**	**5.189%**	**1798.52**	**7.586%**	**846.47**	**4.360%**

Table C.6: Parking manager metrics in experiment 2

	Run 1		**Run 2**		**Run 3**		**Run 4**		**Run 5**		**Run 6**		**Average**	
Road Ids	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**Profit**	**Occupancy**
Closed	**235.136**	**1.652%**	**93.2**	**0.494%**	**191.16**	**1.259%**	**61.152**	**1.905%**	**108.64**	**1.317%**	**123.136**	**1.609%**	**135.404**	**1.373%**
2ca1egvj	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
3662m23xu	0	0%	0	0%	0.36	0.028%	0	0%	0	0%	1.632	0.260%	0.332	0.048%
3c5rurcs	235.136	16.522%	93.2	4.945%	190.8	12.566%	61.152	19.055%	108.64	13.175%	103.648	14.087%	132.096	13.392%
4g5eo749w	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
bgcnenw9y	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
c2nii9l2q	0	0%	0	0%	0	0%	0	0%	0	0%	5.712	0.519%	0.952	0.087%
jobl1mgw3	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
kvsi32e0u	0	0%	0	0%	0	0%	0	0%	0	0%	10.416	0.947%	1.736	0.158%
m7mnatybo	0	0%	0	0%	0	0%	0	0%	0	0%	1.728	0.275%	0.288	0.046%
wma72mga	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Open	**744.075**	**10.337%**	**427.375**	**5.910%**	**593.55**	**8.626%**	**232.275**	**6.692%**	**426.75**	**10.890%**	**397.325**	**5.348%**	**470.225**	**7.967%**
1725588183	0	0%	91.65	31.647%	4.75	0.662%	26.4	24.000%	79.7	33.829%	0	0%	33.75	15.023%
1788788609	4.45	1.759%	21.5	7.424%	0	0%	0.5	0.091%	12.15	5.157%	5.375	0.821%	7.329	2.542%
1788788622	0	0%	2.25	0.311%	11.2	1.116%	0	0%	3.375	0.573%	0	0%	2.804	0.333%
1788788626	10.1	1.848%	0	0%	15.2	1.778%	8.8	4.000%	4.5	0.382%	8.4	0.458%	7.833	1.411%
4468836872	29.25	4.625%	17.75	2.452%	13.95	4.864%	3.375	1.227%	26.95	3.268%	8.65	3.304%	16.6542	3.290%
4598151009	310.25	49.051%	195	13.467%	248.5	34.658%	130.5	23.727%	184.7	78.396%	108.5	16.578%	196.242	35.979%
4598151018	33.75	5.336%	0	0%	115.2	40.167%	0	0%	0	0%	0	0%	24.825	7.584%
4598151026	251.125	28.360%	51.625	5.093%	133.25	9.292%	41.65	10.818%	115.375	19.588%	174	13.293%	127.836	14.407%
4720649125	105.15	41.561%	47.6	16.436%	0.5	0.035%	0	0%	0	0%	0	0%	25.541	9.672%
4720649127	0	0%	0	0%	49.85	17.381%	0	0%	0	0%	0	0%	8.308	2.897%
4720649129	0	0%	0	0%	1.15	0.401%	21.05	19.136%	0	0%	90.15	34.435%	18.725	8.995%
4720649131	0	0%	0	0%	0	0%	0	0%	0	0%	2.25	0.172%	0.375	0.029%
Total	**979.211**	**6.561%**	**520.575**	**3.555%**	**784.71**	**5.423%**	**293.427**	**4.611%**	**535.39**	**6.728%**	**520.461**	**3.722%**	**605.629**	**5.100%**

Table C.7: Parking manager metrics in experiment 3

	Run 1		Run 2		Run 3		Run 4		Run 5		Run 6		Average	
	∑profit	Average occupancy	∑profit	Average occupancy	∑profit	Average occupancy	∑profit	Average occupancy	∑profit	Average occupancy	∑profit	Average occupancy	Profit	Occupancy
Closed	**272.409**	**1.57%**	**70.873**	**0.93%**	**70.999**	**0.91%**	**383.200**	**2.94%**	**61.484**	**0.91%**	**166.655**	**1.56%**	**170.937**	**1.47%**
2ca1egvj	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
3662m23xu	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
3c5rurcs	272.409	15.75%	70.873	9.30%	59.263	7.43%	376.000	28.88%	61.484	9.07%	166.655	15.59%	167.781	14.34%
4g5eo749w	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
bgcnenw9y	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
c2nii9l2q	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
jobl1mgw3	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
kvsi32e0u	0	0%	0	0%	9.604	1.26%	7.200	0.55%	0	0%	0	0%	2.801	0.30%
m7mnatybo	0	0%	0	0%	2.132	0.40%	0	0%	0	0%	0	0%	0.355	0.07%
wma72mga	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Open	**884.781**	**11.80%**	**395.966**	**8.66%**	**473.131**	**8.86%**	**1481.500**	**8.75%**	**514.616**	**10.01%**	**659.456**	**10.49%**	**734.908**	**9.76%**
1725588183	47.250	13.14%	0	0%	0	0%	0	0%	29.903	10.01%	40.741	10.88%	19.649	5.67%
1788788609	2.688	0.94%	8.100	3.18%	0	0%	5.000	0.38%	0	0%	5.975	1.93%	3.627	1.07%
1788788622	60.225	19.13%	0	0%	0	0%	8.750	0.67%	0.438	0.18%	0	0%	11.569	3.33%
1788788626	30.241	4.87%	11.150	2.01%	21.950	3.93%	75.750	2.91%	32.072	3.94%	12.025	1.85%	30.531	3.25%
4468836872	19.875	7.49%	17.825	6.81%	16.716	3.74%	90.500	6.95%	13.594	2.18%	11.788	3.80%	28.383	5.16%
4598151009	371.212	52.42%	188.713	49.95%	258.900	67.47%	815.500	62.63%	230.250	58.07%	221.675	45.27%	347.708	55.97%
4598151018	66.391	15.48%	0	0%	0	0%	22.250	1.71%	0	0%	47.025	13.94%	22.611	5.19%
4598151026	268.566	28.89%	150.166	41.10%	174.128	35.55%	463.250	35.58%	208.359	51.86%	249.509	37.09%	252.330	38.35%
4720649125	0	0%	0	0%	1.438	0.57%	0	0%	0	0%	24.313	7.05%	4.292	1.27%
4720649127	0	0%	20.013	7.48%	0	0%	0	0%	0	0%	44.969	12.21%	10.830	3.28%
4720649129	16.850	6.09%	0	0%	0	0%	0	0%	0	0%	0	0%	2.808	1.01%
4720649131	1.484	0.12%	0	0%	0	0%	0.500	0.04%	0	0%	1.438	0.47%	0.570	0.11%
Total	**1157.190**	**7.36%**	**466.838**	**5.30%**	**544.130**	**5.40%**	**1864.700**	**6.23%**	**576.100**	**6.05%**	**826.111**	**6.61%**	**905.845**	**6.16%**

Table C.8: Parking manager metrics in experiment 4

	Run 1		**Run 2**		**Run 3**		**Run 4**		**Run 5**		**Run 6**		**Average**	
Road Ids	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**∑profit**	**Average occupancy**	**Profit**	**Occupancy**
Closed	**37.264**	**3.240%**	**107.520**	**2.380%**	**68.708**	**1.376%**	**74.444**	**1.075%**	**110.228**	**2.528%**	**75.172**	**2.241%**	**78.889**	**2.140%**
2ca1egvj	0.384	0.369%	28.464	8.236%	0	0%	0	0%	1.728	0.569%	7.632	2.574%	6.368	1.958%
3662m23xu	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
3c5rurcs	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
4g5eo749w	5.504	4.931%	0	0%	21.728	5.906%	8.800	2.137%	0	0%	0	0%	6.005	2.162%
bgcnenw9y	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
c2nii9l2q	11.744	10.323%	0.192	0.060%	0	0%	0	0%	0.048	0.016%	26.928	8.680%	6.485	3.180%
jobl1mgw3	0.240	0.230%	0	0%	0	0%	0.192	0.051%	0	0%	3.984	1.346%	0.736	0.271%
kvsi32e0u	0	0%	1.584	0.493%	0	0%	0	0%	0	0%	0	0%	0.264	0.082%
m7mnatybo	19.392	16.544%	77.280	15.007%	46.980	7.856%	65.452	8.562%	108.452	24.692%	36.628	9.807%	59.031	13.745%
wma72mga	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Open	**88.631**	**4.989%**	**591.666**	**9.969%**	**443.359**	**7.192%**	**760.000**	**8.215%**	**648.725**	**10.946%**	**572.256**	**7.408%**	**517.440**	**8.120%**
1725588183	0	0%	4.813	1.439%	0	0%	0	0%	72.363	16.133%	8.238	2.712%	14.235	3.381%
1788788609	4.313	3.975%	1.563	0.467%	1.625	0.450%	1.125	0.286%	1.125	0.355%	0	0%	1.625	0.922%
1788788622	0.438	0.230%	3.844	0.934%	0.563	0.156%	3.750	0.954%	12.613	3.890%	8.738	2.839%	4.991	1.501%
1788788626	8.663	3.946%	28.453	4.083%	16.038	2.204%	8.375	1.066%	20.838	3.189%	2.500	0.421%	14.144	2.485%
4468836872	3.081	2.650%	19.991	5.624%	16.919	4.478%	20.313	4.882%	30.869	7.405%	8.159	2.271%	16.555	4.552%
4598151009	32.225	20.507%	191.538	34.978%	173.088	32.123%	340.075	40.872%	216.738	31.793%	224.225	38.394%	196.315	33.111%
4598151018	0.188	0.173%	67.900	17.265%	0	0%	64.109	13.311%	76.438	21.011%	5.013	1.661%	35.608	8.903%
4598151026	32.988	23.502%	151.206	28.999%	167.041	34.129%	273.691	32.729%	135.956	32.089%	310.784	46.110%	178.611	32.926%
4720649125	0	0%	46.772	12.126%	21.813	5.861%	31.750	7.761%	41.262	11.592%	4.600	1.472%	24.366	6.469%
4720649127	6.738	5.933%	53.187	13.472%	8.800	2.282%	0	0%	1.125	0.355%	0	0%	11.642	3.674%
4720649129	0	0%	0	0%	2.750	0.761%	1.688	0.429%	27.400	7.622%	0	0%	5.306	1.469%
4720649131	0	0%	22.400	6.129%	34.725	8.852%	15.125	3.435%	12.000	3.673%	0	0%	14.042	3.681%
Total	**125.895**	**4.229%**	**699.186**	**6.669%**	**512.067**	**4.664%**	**834.444**	**5.110%**	**758.953**	**7.286%**	**647.428**	**5.161%**	**596.329**	**5.520%**