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**PARKING POLICIES AND THEIR
IMPACTS ON URBAN NETWORKS**

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presented by

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Foreword

Parking is an intrinsic component of urban systems. Moreover, its relation to the traffic system is undeniable, yet often overlooked. Parking policies affect the traffic system as much as they affect the parking system, potentially leading to higher or lower levels of traffic performance, as a function of the share of traffic that is cruising for parking. The work of Mr. Jakob uses a macroscopic framework to evaluate multiple parking policies paying special attention to such interactions. Such macroscopic framework is computationally very efficient and has very low data requirements. As such, he can then use it to determine the short-term impacts of different parking policies, and the resulting interactions between the parking and traffic systems. Moreover, he proposes a number of extensions to the framework in order to (i) capture the competition between on-street and off-street parking, (ii) illustrate the potential use of parking pricing as an alternative to the more controversial congestion pricing, (iii) introduce a new dynamic pricing scheme that is a function of both, the parking demand and the parking supply, and (iv) estimate the optimal parking occupancy with and without differentiate parking.

Mr. Jakob's work is not only relevant from a scientific perspective, but also timely from a practical perspective. To illustrate the value and importance of each of the extensions mentioned above, Mr. Jakob uses a case study based on real data from the city of Zurich, Switzerland. Moreover, he discusses and evaluates the tradeoffs between the revenue generated by a policy and the benefits it provides for the users. He also develops the tools so city governments can analyze these tradeoffs in response to changes to demand, supply, and other aspects related to the parking and traffic systems. As a result, many of his insights are directly implementable by local governments aiming to improve parking while minimizing traffic disruptions.

On behalf of the Traffic Engineering research group at the Swiss Federal Institute of Technology, Zurich, I thank Mr. Jakob for his extreme motivation and work ethics. Even while working full-time in a private company, and clearly progressing on his role within that company, Mr. Jakob has managed to be very active on his PhD studies, publishing four articles in scientific journals. I cannot imagine a better testament to his hard work than this very thesis.

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Abstract

Parking policies and their interactions with the urban traffic and parking systems can have significant impacts on the traffic performance and the congestion in an urban area. These impacts have a long-term component affecting the travel demand and the travelers' preferences, and a short-term component affecting the traffic and parking operations. This dissertation studies multiple parking policies focusing on pricing and occupancy aspects and analyzes their short-term impacts on the parking searchers and the performance of the traffic and parking systems, which, in turn, might impact the efficiency of the parking policies themselves. In other words, we investigate the interdependencies between different parking policies and parking-caused traffic issues. In particular, we evaluate the influences on the searching-for-parking traffic, the congestion in the network, the total driven distance, and the revenue created by parking, park and ride (P+R) fees, and/or congestion tolls for the city. We show the results for the different parking policies in some case studies of a central area within the city of Zurich, Switzerland. Our easy to implement model uses a dynamic macroscopic framework which saves on data collection efforts and reduces the computational costs significantly as all values correspond to aggregations at the network level over time. Our work clusters the parking policies into two types. First, we study static and dynamic parking pricing strategies and second, we investigate parking occupancy related strategies.

- i. At the beginning of this dissertation, we focus on a macroscopic on-street and garage parking framework which allows us to model the drivers' decision between searching for an on-street parking space or driving to a parking garage instead. Different static on-street and garage parking fee ratios are analyzed with respect to the impacts on the traffic system and the parking search model over time. Our framework shows how traffic performance issues might influence the drivers' decision between on-street and garage parking in the short-term. This decision is faced by multiple user groups with respect to their value of time (VOT). We study the impacts of different parking policies, including the availability of real-time garage usage information, and the conversion of on-street parking to garage parking spaces. The recovered on-street curb can then be used for other activities (e.g., bike lanes) in order to improve the quality of life for the city's residents.

Another strategy for cities might be to establish a P+R facility outside the city in order to reduce the searching-for-parking traffic in the central area. We analyze a P+R policy with static fares and compare it to a congestion pricing scenario and/or parking pricing policy in the network. In case the area consists of a high number of public parking spaces, parking pricing could be considered as a viable alternative to congestion pricing in terms of improving the performance of the traffic and parking system (i.e., traffic performance, parking availability, revenue for the city, etc.). Different parking fees or traffic conditions might, however, affect

the drivers' decision between entering the network by car or using P+R instead. We propose a decision model with respect to the drivers' VOT and integrate it into a multimodal macroscopic traffic and parking framework focusing on parking and congestion pricing. We evaluate the distributional effects of our heterogeneous VOT model on the drivers' decision of which mode (P+R or car) to use when entering the area. Additionally, the proposed methodology can be used by city councils to find the trade-offs between the parking fee and the congestion toll when looking to reduce the average cruising time in the network, or increase the total revenue for the city.

Moreover, we study a dynamic responsive parking pricing scheme which takes the parking search phenomenon and the parking occupancy into account. This macroscopic pricing policy maximizes the parking revenue for a city while minimizing the searching-for-parking time simultaneously. In different words, our pricing algorithm changes in response to the parking occupancy rate and the number of searching vehicles on the network. It checks whether the cost of paying the current parking fee is lower than the cost of keep on searching for another available parking space depending on the drivers' VOT. The latter cost includes paying the predicted parking fee for the next available parking space at a future time slice under consideration of the driving and penalty costs to get there. We show the short-term impacts of the proposed dynamic parking pricing scheme on the urban traffic and parking systems, including the financial benefits of the pricing scheme and the benefits (or disbenefits) for the traffic performance in the area.

- ii. As the second type of parking policies, we study parking occupancy strategies in this dissertation. Here, we model the optimal parking occupancy rate over, e.g., the peak hours of the day, to guarantee an optimal trade-off between an efficient usage of the parking infrastructure and a high likelihood of finding parking to improve the traffic performance in a central area. In other words, our framework tries to find the optimal equilibrium between a high occupancy rate and a low average searching time in the network. It is based on the same macroscopic traffic and parking model that we used in the first part of the thesis. We extend it to include multiple vehicle types allowing us to generate insights about the parking occupancy's dependency on specific vehicle types (e.g., fuel and electric vehicles). We evaluate a differentiated and a hierarchical parking policy for parking supply with and without battery chargers, and compare the results to a parking scheme without any parking differentiation. Our optimal parking occupancy strategy allows local governments to evaluate how to react towards a constantly varying parking demand (e.g., a modal shift towards electric vehicles), and how much parking supply to dedicate to electric vehicles in order to have the best balance between traffic performance, optimal parking occupancies, social impacts, and a high parking revenue for the city. Additionally, we provide cities a tool to analyze the influences on the optimal parking occupancy rate caused by a change in parking demand, supply, or parking duration in the area.

In general, we discuss various parking policies in this dissertation and develop the tools

for cities to evaluate the short-term impacts on the traffic and parking system when applying such policies. We show how to evaluate them macroscopically with the minimum amount of data requirements and costs, as our algorithms can easily be implemented with a simple numerical solver. Parking planners, traffic managers, consultants, practitioners, and local authorities can then use the new insights about these parking policies to develop the best fit for their city.

Zusammenfassung

Parkrichtlinien und ihre Wechselwirkungen mit dem städtischen Verkehr und den Parksyste men können erhebliche Auswirkungen auf die Verkehrsleistung und den Stau in einem städtischen Gebiet haben. Diese Auswirkungen wirken sich langfristig auf die Reisenachfrage und die Vorlieben der Reisenden aus, und kurzfristig auf den Verkehrs- und Parkbetrieb. Diese Dissertation untersucht mehrere Parkrichtlinien, die sich auf Preis- und Belegungsaspekte konzentrieren, und analysiert deren kurzfristige Auswirkungen auf die Parksucher und die Leistung der Verkehrs- und Parksyste me, die sich wiederum auf die Effizienz der Parkrichtlinien selbst auswirken können. Mit anderen Worten, wir untersuchen die Abhängigkeiten zwischen verschiedenen Parkrichtlinien und parkbedingten Verkehrsproblemen. Insbesondere bewerten wir die Einflüsse auf den Parkplatzsuchverkehr, die Überlastung des Netzwerks (Stau), die gesamte zurückgelegte Fahrtstrecke, und die Einnahmen aus Park-, P+R-, und/oder City-Mautgebühren für die Stadt. Wir zeigen die Ergebnisse für die verschiedenen Parkrichtlinien in einigen Fallstudien in einem zentralen Gebiet innerhalb der Stadt Zürich, Schweiz. Unser einfach zu implementierendes Modell verwendet ein dynamisches makroskopisches Bezugssystem, das Datenerfassungsaufwand spart und die Rechenkosten erheblich reduziert, da alle Werte im Zeitablauf Aggregationen auf Netzwerkebene entsprechen. Unsere Arbeit gliedert die Parkrichtlinien in zwei Typen. Erstens untersuchen wir statische und dynamische Parkpreisstrategien, und zweitens untersuchen wir Strategien zur Parkplatzbelegung.

- i. Zu Beginn dieser Dissertation konzentrieren wir uns auf ein makroskopisches Straßenpark- und Garagenparksystem, mit dem wir die Entscheidung der Fahrer zwischen der Suche nach einem Parkplatz auf der Straße oder der Fahrt zu einem Parkhaus modellieren können. Unterschiedliche statische Parkgebührenverhältnisse auf der Straße und in der Garage werden im Hinblick auf die Auswirkungen auf das Verkehrssystem und das Parksuchmodell im Zeitverlauf analysiert. Unser Rahmen zeigt, wie sich Probleme mit der Verkehrsleistung kurzfristig auf die Entscheidung der Fahrer zwischen Parken auf der Straße und in der Garage auswirken können. Diese Entscheidung wird von mehreren Benutzergruppen in Bezug auf ihren Wert der Zeit (VOT) getroffen. Wir untersuchen die Auswirkungen verschiedener Parkrichtlinien, einschließlich der Verfügbarkeit von Echtzeit-Informationen zur Garagennutzung und der Umwandlung von Parkplätzen auf der Straße in Garagenparkplätze. Der zurückgewonnene Straßenrand kann dann für andere Aktivitäten (z.B. für Radwege) verwendet werden, um die Lebensqualität der Einwohner in der Stadt zu verbessern.

Eine andere Strategie für Städte könnte darin bestehen, eine P+R-Einrichtung

außerhalb der Stadt einzurichten, um den Verkehr auf der Suche nach Parkplätzen im zentralen Bereich zu verringern. Wir analysieren eine P+R-Richtlinie mit statischen Tarifen und vergleichen sie mit einem City-Mautszenario und/oder einer Parkpreisstrategie im Netzwerk. Wenn das Gebiet aus einer großen Anzahl öffentlicher Parkplätze besteht, könnte die Parkgebühr als praktikable Alternative zur City-Maut angesehen werden, um die Leistung des Verkehrs- und Parksystems zu verbessern (d.h. die Verkehrsleistung, die Parkverfügbarkeit, die Einnahmen für die Stadt, usw.). Unterschiedliche Parkgebühren oder Verkehrsbedingungen können jedoch die Entscheidung des Fahrers beeinflussen, ob er mit dem Auto in den Stadtkern fährt oder stattdessen P+R verwendet. Wir stellen ein Entscheidungsmodell in Bezug auf den Wert der Zeit der Fahrer vor und integrieren es in einen multimodalen makroskopischen Verkehrs- und Parkrahmen, der sich auf Park- und City-Mautpreise konzentriert. Wir analysieren die Verteilungseffekte unseres heterogenen Modells der Wert der Zeit auf die Entscheidung der Fahrer, welche Verkehrsform (P+R oder Auto) sie zum Erreichen des Stadtkerns verwenden möchten. Darüber hinaus kann die vorgeschlagene Methodik von den Stadträten verwendet werden, um die Austauschbeziehungen zwischen der Parkgebühr und der City-Maut zu ermitteln, wenn die durchschnittliche Reisezeit im Verkehrsnetz verringert oder die Gesamteinnahmen für die Stadt erhöht werden sollen.

Darüber hinaus untersuchen wir ein dynamisches, reagierendes Parkpreisschema, welches das Phänomen der Parksuche und der Parkplatzbelegung berücksichtigt. Diese makroskopische Preispolitik maximiert die Parkeinnahmen für eine Stadt und minimiert gleichzeitig die Zeit für die Suche nach Parkplätzen. Mit anderen Worten, unser Preisalgorithmus ändert sich in Abhängigkeit von der Parkplatzbelegungsrate und der Anzahl der suchenden Fahrzeuge im Netzwerk. Es wird geprüft, ob die Kosten für die Zahlung der aktuellen Parkgebühr niedriger sind als die Kosten für die Suche nach einem anderen verfügbaren Parkplatz, abhängig von dem Wert der Zeit des Fahrers. Die letzteren Kosten beinhalten die Zahlung der prognostizierten Parkgebühr für den nächsten verfügbaren Parkplatz zu einem späteren Zeitpunkt, unter Berücksichtigung der Fahrt- als auch der bereits zurückgelegten Parkplatzsuchkosten. Wir analysieren die kurzfristigen Auswirkungen des vorgestellten dynamischen Parkpreissystems auf das städtische Verkehrs- und Parksystem, einschließlich der finanziellen Vorteile der Preispolitik und der Vorteile (oder Nachteile) für die Verkehrsleistung in der Region.

- ii. Als zweite Art von Parkrichtlinien untersuchen wir in dieser Dissertation Strategien zur Parkplatzbelegung. Hier modellieren wir die optimale Parkplatzbelegungsrate über z.B. die Stoßzeiten eines Tages, um einen optimalen Kompromiss zwischen einer effizienten Nutzung der Parkinfrastruktur und einer hohen wahrscheinlichen Parkplatzverfügbarkeit zu finden, sodass die Verkehrsleistung im Stadtkern verbessert werden kann. Mit anderen Worten, unser Bezugssystem versucht das optimale Gleichgewicht zwischen einer hohen Belegungsrate und einer niedrigen durchschnittlichen Parkplatzsuchzeit im

Netzwerk zu finden. Es basiert auf demselben makroskopischen Verkehrs- und Parkmodell, welches wir im ersten Teil der Arbeit verwendet haben. Wir erweitern es um mehrere Fahrzeugtypen, sodass wir Einblicke in die Abhängigkeit der Parkplatzbelegung von bestimmten Fahrzeugtypen (z.B. von Kraftstoff- und Elektrofahrzeugen) gewinnen können. Wir analysieren eine differenzierte und eine hierarchische Parkplatzrichtlinie für die Parkversorgung mit und ohne Batterieladegerät, und vergleichen diese Ergebnisse mit einer Parkplatzstrategie ohne jegliche Parkdifferenzierung. Unsere optimale Parkplatzbelegungsstrategie ermöglicht es den Lokalbehörden zu bewerten, wie sie auf eine sich ständig ändernde Parknachfrage (z. B. eine Verlagerung des Autoverkehrs auf Elektrofahrzeuge) reagieren können. Hierbei ist für die Behörden interessant wie viel Parkangebot für Elektrofahrzeuge bereitgestellt werden sollte, sodass ein bestmögliches Gleichgewicht zwischen der Verkehrsleistung, der optimalen Parkplatzbelegung, der soziale Auswirkungen und der hohen Parkeinnahmen erzielt wird. Darüber hinaus bieten wir Städten ein Tool zur Analyse der Einflüsse auf die optimale Parkplatzauslastung, die durch eine Änderung der Parknachfrage, des Parkangebots oder der Parkdauer in der Region verursacht werden kann.

Im Allgemeinen diskutieren wir in dieser Dissertation verschiedene Parkrichtlinien und entwickeln Tools für Städte, um die kurzfristigen Auswirkungen auf das Verkehrs- und Parksystem bei der Anwendung solcher Richtlinien zu bewerten. Wir zeigen, wie Sie diese makroskopisch mit minimalem Datenbedarf und minimalen Kosten auswerten können, da unsere Algorithmen leicht mit einem einfachen numerischen Löser implementiert werden können. Parkplaner, Verkehrsmanager, Berater, Praktiker und lokale Behörden können dann die neuen Erkenntnisse über diese Parkrichtlinien nutzen, um die beste Lösung für ihre Stadt zu entwickeln.

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I want to dedicate this Ph.D. dissertation to my mum, Monika Jakob, who unfortunately passed away in August 2017. She supported me to start this Ph.D. journey at ETH Zurich. Even though she cannot be there to see me finish it, she will always stay with me in my heart and will never be forgotten.

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Chapter 1:

Introduction

1.1 Motivation

Parking is an essential component at both ends of each private car journey. An average car spends over 80 % of its time parked at home, and about 16 % parked somewhere else, which results in only about 4 % actual usage time of the car ([RAC Foundation \(2004\)](#)). The travel to work is the most frequent reason for parking. For example, outside London, U.K., 70 % of the drivers commute to work by car leading to regular traffic congestion during peak hours. The highest parking demand is then usually around midday, when the non-workplace related parking activities add about 44 % to the base demand resulting from workplace parking activities ([Bates and Leibling \(2012\)](#)). Most drivers experience daily difficulties finding legal and available parking spaces. 29 % of all drivers have even given up their journeys and gone home because they could not find an available parking space in an area ([RAC Foundation \(2004\)](#)). Illegal parking with shares of about 40 % to 50 % of the total parking activities is a widespread issue in inner cities and residential areas ([Topp \(1991\)](#)). Thus, policies about parking should be integral parts of transport and traffic policies. Parking policies and the time spent on searching for parking are often neglected by both individual travelers and planning authorities. This is unfortunate, as taking cruising-for-parking into account can not only assist drivers to better plan their trips (including departure time and mode choice); but it can also reduce the local environmental impacts from traffic. However, learning about cruising conditions in urban areas can be difficult, since the cruising vehicles are hidden within the normal driving traffic. So, cities should concentrate on various parking policies which might positively influence the traffic performance

- reducing cruising-for-parking traffic,
- relieving the parking demand pressure, and
- increasing the parking availability in central areas, although this might be controversial as it might lead to higher parking demands in the long-term.

Additionally, parking policies might also lead to

- a raise in revenue for local authorities and governments,
- an option to regain curb space and make it available for other activities (e.g., creating pedestrian zones or bicycle lanes) by removing on-street parking spaces or converting them into concentrated parking garages, and
- a chance to manage the parking demand (e.g., reducing the car usage, deterring visitors from using the car in central areas, and controlling the transportation and delivery demand).

In this dissertation, we analyze different parking policies and their impacts on the parking and traffic systems which are relevant components of the overall transportation system in nearly all urban areas. Compared to methodologies concentrating on long-term demand management strategies, we focus on the short-term interactions between these two components, i.e., we analyze how parking

policies might affect traffic operations in the network, and vice versa. We evaluate different parking policies showing their short-term influences on the performance of both the urban parking and traffic systems, e.g., how these policies can impact the traffic performance, the congestion, the parking revenue, the parking occupancy, or the parking availability in the area.

Urban parking policies affect the travel demand and the traffic system in the long-term. Drivers can change their travel behavior such that they are no longer entering an urban area by car, and change to public transportation (PT) instead. These decisions can arise due to a change in travelers' parking choice which might be caused by, e.g., an increase in parking pricing, congestion, strict parking time controls, limited parking availability or higher walking times after parking. In comparison to studies analyzing the parking policy impacts on the travel demand based on microscopic models or agent-based simulation tools ([Axhausen \(1990\)](#), [Axhausen and Polak \(1990, 1991\)](#), [Axhausen et al. \(1989\)](#), [Weis et al. \(2012\)](#)), our dissertation presents a macroscopic traffic and parking framework focusing on short-term interactions between the urban parking and traffic systems. We evaluate the interdependencies between different parking policies (focusing on parking pricing and parking occupancy) and parking-caused traffic issues with the aid of limited aggregated data. Note that this dissertation focuses on improving car traffic. The introduced parking policies try to establish a better traffic performance by reducing the drivers' time searching for parking in an urban area. Even if high cruising-for-parking times might force drivers to change to other transportation modes which, in turn, changes the demand, reduces the car traffic and might lead to significant traffic performance improvements, these demand changes are not intended by our parking policies. Long-term changes in the travel demand and the drivers' travel behavior are out of the scope of this research.

Our macroscopic methodology has several advantages. The framework is based on very limited data inputs, while most of the models used nowadays to analyze parking policies and parking-related traffic require a lot of detailed data that is hard to get. Our model saves on data collection efforts and reduces the computational costs significantly as all values correspond to aggregations at the network level over time. These efficiencies are useful and can especially be applied in real-time control algorithms or when the data is scarce. A simple numerical solver such as Excel or Matlab can be used to easily solve our methodology without the use of complex simulation software. Moreover, our macroscopic model provides additional insights that cannot be delivered by microscopic models (e.g., insights into the mathematical relation between traffic properties and parking policies with respect to a minimal total cruising time in the area).

Our macroscopic traffic and parking methodology uses the parking-state-based matrix, and the methodology to determine the likelihood of finding parking from [Cao and Menendez \(2015a\)](#). Input data for the used case studies is based on prior data collections and an agent-based model in MATSim ([Waraich and Axhausen \(2012\)](#)). That data includes the time stamps of all cars arriving to the area, and the times they leave the area after parking, as well as the parking occupancy in the area at the start

of our simulation. The original model from [Cao and Menendez \(2015a\)](#) was calibrated and validated with real data from the city of Zurich, Switzerland in [Cao et al. \(2019\)](#), using the parking occupancy data over a working day based on a local monitoring system (PLS Zurich), and the cruising time based on survey results that were conducted during May 2016. The results were all found to be reasonable. Our parking policy applications are based on such conditions. [Cao and Menendez \(2018\)](#) extended the methodology to quantify the potential cruising time savings associated with intelligent parking services. We enhance and combine the macroscopic traffic and parking model from [Cao and Menendez \(2015a\)](#) with the multimodal extension of the macroscopic fundamental diagram (MFD ([Geroliminis and Daganzo \(2008\)](#), [Geroliminis \(2009, 2015\)](#))), the 3D-MFD framework from [Loder et al. \(2019\)](#) and [Zheng and Geroliminis \(2016\)](#) when capturing the system dynamics of urban car, PT and P+R traffic. The latter is relevant when evaluating whether parking pricing can be considered as an alternative to the more controversial congestion pricing schemes. Additionally, further improvements of the parking-state-based matrix from [Cao and Menendez \(2015a\)](#) are analyzed in this study (e.g., covering on-street and garage parking, dynamic parking pricing and different vehicle types as electric and fuel vehicles). Within the frame of this dissertation, we develop a macroscopic concept to analyze the impact of parking policies on an urban network considering its cruising-for-parking traffic in the short-term. The policies are mostly used for operational purposes, e.g., for traffic management and control within an area. We focus on two specific parking aspects – parking pricing and parking occupancy – that can potentially affect the traffic performance and the congestion in an area:

i. Parking pricing:

We differentiate this part into static and dynamic macroscopic parking pricing policies.

First, we develop on-street and garage parking policies with static parking fees using a macroscopic traffic and parking framework. It allows us to model the driver's decision to use on-street or garage parking over time. Here we determine several cost factors influencing the on-street/garage parking decision which is embedded into our on-street and garage parking-state-based matrix describing the system dynamics of urban traffic based on multiple parking-related states. Our model can be used to analyze the relationship between on-street and garage parking, and we can get valuable insights on the interdependency between cruising-for-parking traffic and traffic performance with respect to different parking fees. Additionally, it allows us to study parking policies in city center areas, e.g., the short-term effects of converting on-street to garage parking spaces on the traffic system can be simulated, and recommendations for city councils can be made.

Second, we study the influences of different parking pricing and congestion pricing policies on the traffic system. We develop a multimodal macroscopic traffic and parking search model that allows us to evaluate whether parking pricing can be considered as an alternative to the more controversial

congestion pricing schemes, especially in areas with a high parking demand for public parking spaces. Our methodology investigates the short-term interdependencies between traffic congestion, P+R and parking pricing within the area. The static congestion or parking pricing schemes allow us to analyze, for example, how the cars searching for parking or the drivers deciding to enter the area using P+R affect the traffic performance and the congestion in the area. Our framework can also be used to find the best relation between the parking fee and the congestion toll in order to improve the traffic performance in the network or the total revenue for the city.

Third, instead of static pricing policies cities can use dynamic parking pricing schemes. We propose a macroscopic responsive pricing scheme, taking the available parking supply and the parking search phenomenon into consideration. Parking pricing is modeled as an optimization problem to maximize revenue while minimizing the cruising time in the urban area. The framework is integrated into an existing parking-state-based matrix to account for the driver's parking decision between using the first available parking space or searching for another one. The latter might be interesting for some drivers in case of lower costs. Our methodology can be used to analyze the interdependency between responsive parking pricing and searching-for-parking traffic in urban traffic and parking systems. When introducing a dynamic responsive parking pricing scheme, our research can help cities to efficiently evaluate their short-term impacts over time.

ii. Parking occupancy:

We propose a framework to determine the optimal parking occupancy rate with and without differentiated parking for multiple vehicle types based on a macroscopic traffic and parking model for an urban area. The parking occupancy is defined to be optimal when minimizing the cruising time over a given time horizon. The results help cities setting the optimal parking occupancy rate in order to guarantee an optimal trade-off between an efficient usage of the parking infrastructure and a high likelihood of finding parking. The latter ensures that the traffic performance is improved in the network. We evaluate policies including a modal shift towards a specific vehicle type (e.g., electric vehicles). This will lead to new challenges for cities establishing the required parking supply (e.g., parking spaces with battery charging opportunities for electric vehicles) in the area. Our model allows us to evaluate the impacts of different vehicle type proportions (e.g., fuel and electric vehicles) in demand and supply on the traffic performance, the optimal parking occupancy rates and the society. That way, cities can react towards a constantly varying parking demand for, e.g., electric vehicles over time and can reserve some dedicated parking supply in the area. We investigate a non-differentiated parking scheme, a differentiated parking policy, covering vehicle type dependent parking spaces (e.g., fuel vehicles park at fuel vehicle parking spaces, and electric vehicles park at their dedicated parking spaces), and a hierarchical parking policy, considering no

parking space restrictions for some vehicle types (e.g., electric vehicles can park at any parking space).

In this dissertation, we present the analytical models for all parking policies using the macroscopic traffic and parking framework presented in chapter 2. Chapters 3 to 5 concentrate on parking pricing policies, and chapter 6 on parking occupancy policies. We show how they can be applied on a real urban network, e.g., an area within the city of Zurich. Here we discuss the findings and analyze their impacts on the traffic performance, the congestion, the environmental conditions and the total revenue for the city which can consist of, e.g., parking fees, congestion tolls, P+R fees, and/or PT fares. More details on the dissertation outline are given in section 1.6.

1.2 Literature Review

The following literature review is divided into sections about parking pricing, and parking occupancy.

1.2.1 Parking pricing

Attractive parking pricing schemes are often based on empirical or modelling approaches. Empirical approaches usually collected data by using parking meters for on-street parking spaces, e.g., Xerox[®] (implemented in Los Angeles's LA ExpressPark[™]), [SFpark \(2009\)](#). The latter used its responsive pricing scheme to leave between 20 and 40 percent of on-street parking spaces open on every block in San Francisco, and [Pierce et al. \(2015\)](#) introduced parking pricing to have open spaces available in public garages at all times. Other garage parking models are based on questionnaires, e.g., [Auchincloss et al. \(2015\)](#), [Bianco \(2000\)](#), or they use dynamic information to predict real-time garage parking availability ([Caicedo et al. \(2012\)](#)). Moreover, several companies have invested heavily in their "smart parking" technologies (e.g., Deteq, Fybr, Streetline, Libelium, etc.). In our macroscopic model, however, we have the advantage that we do not require very specific parking data. Without any physical devices nor large data collection efforts, we provide general results regarding the effects of parking pricing on a dynamic traffic network under realistic conditions.

Some modelling approaches do not differentiate between on-street and garage parking. In [Lei and Ouyang \(2017\)](#) a demand-driven dynamic location-dependent parking pricing and reservation strategy was used to improve the system-wide performance of an intelligent parking system. The drivers were allowed to make parking reservations prior to their trips and secure parking spaces for a future time period. These models provide a long-term demand management strategy capturing user competition and considering market equilibrium, while our model provides an aggregate parking pricing methodology focusing on the short-term effects on traffic performance. [Ayala et al. \(2012\)](#) worked on a pricing model that sets the parking fees such that the total driving distance is minimized in the system. A static parking

demand is assumed, i.e., the model cannot replicate a dynamic real-world environment. [Zhang and Van Wee \(2011\)](#) introduced a duration dependent parking fee regime based on daily travel cost in a linear city. [Arnott and Rowse \(1999\)](#) presented a nonlinear model of parking congestion focusing on the searching-for-parking phenomenon for an available on-street parking space in a homogeneous metropolis. [Arnott and Inci \(2006\)](#) analyzed the influences of on-street parking pricing on cruising-for-parking and [Arnott and Rowse \(2013\)](#) studied the effects of on-street parking time limits on traffic performance, but it did not consider garage parking. [Arnott et al. \(1991\)](#) explored optimal location-dependent parking fees in comparison to time-varying road tolls concentrating on commuter parking and their arrival times during the morning rush hour. They proposed different parking meter rates across time at different locations during the morning rush-hour in a downtown area to be able to control the order in which on-street parking spaces are occupied. They used network equilibrium models to regulate traffic and parking usage with the help of their parking fee policy. Because of the use of a parking fee policy to control the congestion of the city, low-income workers would try to avoid paying high parking fees and park further away from their destination in the city center. Their model, however, did not take into account traffic performance, i.e., the traffic performance parameters (e.g., travel speed) were assumed as fixed for all conditions in the model. [Arnott and Inci \(2010\)](#) investigated how an increasing demand affects the traffic dynamics for a uniform road network with on-street parking. [Wang et al. \(2019\)](#) derived a bi-modal traffic equilibrium model to investigate the optimal parking supply considering the scale economy of transit. [Kladeftras and Antoniou \(2013\)](#) focused on the effects of illegal parking (double parking) on traffic and environmental conditions using a microscopic simulation.

For modeling both on-street and garage parking and the associated parking fees, [Arnott \(2006\)](#) and [Inci and Lindsey \(2015\)](#) illustrated how the actual full price of parking contains both the interaction between garage operators and the cruising costs for on-street parking. They developed a spatial competition model to eliminate cruising by allocating excess cruising demand to garage parking and focused on social optimum suggestions concerning the relationship between curbside and garage fares. [Shoup \(2019\)](#) showed that underpriced on-street parking creates an incentive for drivers to cruise. The microeconomic model explained why a driver would rather choose to cruise for free on-street parking than paying for garage parking. The decision model between on-street and garage parking in [Shoup \(2019\)](#) was based on the garage parking fee, the driver's intended parking duration, the time spent cruising, the cost of petrol while cruising-for-parking, the number of people in the car, and the driver's and his passengers' VOT. Our parking decision, instead, is based on a macroscopic modeling approach. [Kobus et al. \(2013\)](#) estimated the effect of on-street parking fees on drivers' choice between on-street and garage parking. [Gragera and Albalade \(2016\)](#) analyzed how garage parking demand is affected by on-street parking regulations. [Mackowski et al. \(2015\)](#) modeled variable on-street and garage pricing in real-time for effective parking access and space utilization by using a dynamic Stackelberg leader-follower game theory approach. [Van Nieuwkoop \(2014\)](#)

combined a traffic assignment model ([Wardrop \(1952\)](#)) and a parking search model into one single dynamic link-based methodology that is formulated as a mixed complementarity problem (MCP). By making a distinction between curbside and garage parking spaces and a differentiation of user classes with respect to their VOT, the model aimed to analyze the efficiency and distributional effects of different parking fee policies and to impose a demand-responsive pricing scheme for parking. This agent-based MCP model has interesting results regarding the impact of parking fee policies on cruising and congestion. Our proposed model has similar goals, but from a macroscopic perspective with much less data requirements and lower computational costs. [Anderson and de Palma \(2004\)](#) analyzed the parking pricing economics more formally and showed that the social optimum can be achieved if the parking garages are owned privately. In comparison with these approaches, our proposed model requires very limited data, as we do not need individual vehicle or parking spaces information. [Benenson et al. \(2008\)](#) developed an agent-based parking model for a city by simulating the behavior of each driver in comparison to our macroscopic framework based on aggregated data. Further studies used this agent-based parking model to analyze different parking policies ([Martens and Benenson \(2008\)](#)), estimated city parking patterns ([Levy and Benenson \(2015\)](#)), explored cruising-for-parking ([Levy et al. \(2013\)](#), [Martens et al. \(2010\)](#)) and evaluated parking planning projects for large parking garages ([Levy et al. \(2015\)](#)). [Wang et al. \(2015\)](#) studied P+R networks with multiple origins and one destination and focused on an optimal parking pricing strategy. They only focused on setting optimal parking fees for P+R terminals and did not consider the interaction with on-street parking. [Arnott et al. \(2015\)](#) studied how much curbside to allocate to parking when the private sector provides garage parking. [Arnott and Rowse \(2009\)](#) analyzed parking in a spatially homogeneous downtown area where the drivers choose between on-street and garage parking. Cruising for parking contributed to congestion, such that the price of the initially cheaper on-street parking was increased until it equaled the price of garage parking. Then increasing the on-street parking fee may generate an efficiency gain through the reduction of cruising. These models focused on social optimum and user equilibrium methodologies.

[Zheng and Geroliminis \(2016\)](#) modeled multi-modal traffic with limited on-street and garage parking and dynamic pricing based on a congestion- and cruising-responsive feedback parking pricing scheme. The proposed framework was based on the MFD reflecting the dynamics of parking flows in an urban network ([Geroliminis \(2009, 2015\)](#) and [Geroliminis and Daganzo \(2008\)](#)). The model from [Zheng and Geroliminis \(2016\)](#) used feedback pricing controllers to realize a congestion- and cruising-responsive parking pricing scheme. It was assumed that drivers start to cruise-for-parking after they arrive at their destinations. This assumption is not needed in our methodology, as the vehicles might start to search for parking before they arrive at their destination. The system dynamics with MDF representation in [Zheng and Geroliminis \(2016\)](#) required a regional route choice model to be integrated between origin-destination (OD) pairs or the sequence of regions for specific ODs should be known priori. Our model is only interested in the destination of the drivers who are

searching for a parking space, and assumes such destinations are all within our area of interest. As long as the vehicles are already in the network looking for a parking space, their origin is irrelevant. We do not compute the total distance driven for their whole trip, but just the portion of the trip that happens within the area of interest. This simplifies the model without the need for tracking individual vehicles. The aggregated and dynamic pricing strategies in [Zheng and Geroliminis \(2016\)](#) were developed for large-scale network applications. These pricing strategies include a congestion- and cruising-responsive feedback parking pricing scheme, and optimization strategies that minimize the total passenger cost or the total travel time. However, the optimization problems are highly non-linear and are solved by sequential quadratic programming, hence cannot be easily implemented in real-time. Our dynamic macroscopic pricing framework in chapter 5, in comparison, builds on a convex optimization problem minimizing the total travel time in a homogenous network environment. Our dynamic pricing model combines several characteristics from the strategies presented in [Zheng and Geroliminis \(2016\)](#). It incorporates responsive characteristics based on the parking occupancy and the number of searching vehicles, and it can be implemented in real-time. Another advantage of our model is that the parking pricing optimization strategy can easily be switched between parking pricing set to change in response to both the parking occupancy and the number of searching vehicles, or only to the parking occupancy while still minimizing the total travel time in the network. Additionally, our dynamic pricing model can be easily solved with a simple numerical solver such as Excel or Matlab without the use of complex simulation software. [Zheng et al. \(2016\)](#) proposed a time-dependent area-based pricing scheme for congested multimodal urban networks considering user heterogeneity in an agent-based environment. The level of congestion is described by an MFD at the network level. [Liu and Geroliminis \(2016\)](#) used an MFD approach to investigate how cruising-for-on-street-parking influences the commuters' morning peak and developed a dynamic parking pricing model to reduce total social cost. However, it did not consider garage parking in its framework. [Leclercq et al. \(2017\)](#) only included on-street parking to their trip-based MFD model evaluating the on-street parking search process with respect to different vehicle parking strategies. They analyzed the relationship between the aggregated travel distance before parking and the on-street parking occupancy in an urban network. Based on a trip-based MFD formulation using experimental data from the city of Lyon, France, parking search laws were investigated to understand how the distance to park behaves when the parking occupancy rate changes dynamically.

All the congestion pricing methodologies implemented so far are based on the principle of marginal cost pricing. A comprehensive literature summary of congestion pricing models can be found in [Yang and Huang \(2005\)](#). Some models determine the congestion charge focusing on the time loss externalities for drivers not entering the network ([Anas and Lindsey \(2011\)](#), [Small et al. \(2007\)](#), [Vickrey \(1969\)](#)). If a city introduces congestion pricing, alternative transportation options should also be offered. Therefore, it is reasonable for cities to reinvest the income from congestion pricing onto other modes. [Leape \(2006\)](#) and [Prud'homme and Bocarejo \(2005\)](#)

investigated the impact on the traffic performance and the changes in congestion driven by the changes in modal split triggered by the congestion pricing. These studies used aggregated traffic indicators, but did not take into account any parking related phenomena. The methodology we propose in chapter 4 allows us to model the decision of entering the area and paying the congestion charge or not entering and changing the transportation mode at a P+R facility outside the area. In the latter case the drivers then use some form of PT to enter the protected area, e.g., buses, trams and/or trains. [Albert and Mahalel \(2006\)](#) examined the sensitivity of drivers' attitudes towards parking fees and congestion tolls and their effect on travel habits such as demand changes for the considered network. In comparison to our macroscopic methodology, a numerical simulation model is developed in [Calthrop et al. \(2000\)](#) to study the efficiency gains from various parking policies with and without a simple cordon pricing scheme. [Ambühl et al. \(2018\)](#) used empirical data from loop detectors and automated vehicle location (AVL) devices from May 2016 to analyze the impacts of London's congestion pricing using the multimodal extension of the MFD ([Geroliminis and Daganzo \(2008\)](#), [Geroliminis \(2009, 2015\)](#)), the 3D-MFD ([Dakic et al. \(2020\)](#), [Loder et al. \(2017\)](#), [Paipuri and Leclercq \(2020\)](#), [Zheng et al. \(2014\)](#)). [Ambühl et al. \(2018\)](#), [Gu et al. \(2018b\)](#), [Smeed \(1968\)](#) and [Yang et al. \(2019\)](#) accounted for bi-modal interactions such that a macroscopic traffic analysis inside and outside the congestion pricing area could be made. Our research, in comparison, studies the short-term interdependencies between traffic congestion, P+R and parking pricing within the area (chapter 4). The aggregated bi-modal interactions in [Ambühl et al. \(2018\)](#) were observed for a large-scale network, and they did not account for the parking impacts within the area nor any P+R. In contrast, our methodology considers networks with traffic and parking systems that are affected by the drivers entering the area and searching for a parking space to get to their desired destination. These destinations can be within or outside our area of interest and since the cars start to search for parking within the area, their origin is irrelevant. Additionally, our macroscopic model can be easily solved with a simple numerical solver such as Excel or Matlab without the use of complex simulation software.

1.2.2 Parking occupancy

Other literature used the parking occupancy rate to determine their parking pricing strategy. [Qian and Rajagopal \(2013\)](#) developed a real-time pricing approach for a parking lot based on its occupancy rate as a system optimal parking flow minimization problem. They assumed a user equilibrium travel behavior and only focused on garage parking without analyzing its interdependency with on-street parking in the network. [Qian and Rajagopal \(2014\)](#) presented a parking pricing model that minimizes the total travel time of the system according to real-time occupancy collected by parking sensors. This parking pricing problem under stochastic demand was later extended to investigate both departure time choices and parking location choices ([Qian and Rajagopal \(2015\)](#)). The resulting stochastic control problem managed the parking demand by adjusting the parking prices based on the occupancy rate. [Zhang et al. \(2008, 2011\)](#) and [Qian et al. \(2012\)](#) investigated agent-

based parking pricing models or alternative downtown parking policies incorporating on-street parking occupancy rates in order to improve the traffic performance. Our dynamic parking pricing model in chapter 5, however, uses both, parking occupancy and searching traffic to maximize the revenue for a city while simultaneously minimizing the total searching time on the network.

The stochasticity of vacant on-street parking spaces and their impact on the traffic performance is often underestimated. Even if on-street parking spaces in an area might have low occupancy rates at specific times of the day, there might be times when drivers must spend a considerable amount of time cruising for parking ([Shoup \(1999, 2005, 2006\)](#)). [Vickrey \(1954\)](#) was the first to discuss the possibilities of achieving a specific on-street parking occupancy rate such that there is a parking space on each block available at almost all times. His proposal decreases congestion and the cruising-for-parking time on the network, and it could be achieved through smart on-street parking pricing policies. However, the required technology was beyond the means at that time. [Zakharenko \(2016\)](#) developed a uniform parking pricing scheme for all parking sites focusing on the parkers' arrival rates and the parking occupancy rate in a heterogenous parking environment. He showed that the purpose of pricing methods affects more the parking departures than the arrivals. [Tamrazian et al. \(2015\)](#) proposed efficient learning algorithms to predict parking occupancy rates using historical and real-time data. [Javale et al. \(2019\)](#) developed a smart parking pricing algorithm using electronic IoT-based sensors to determine the optimal parking fee depending on various factors including the current occupancy rate, the time of day and the parking space locations within the network. This agent-based methodology can also be used to predict the future occupancy rate in the area.

As real-time pricing schemes require a lot of information, they are harder and more expensive to implement compared to policies setting the parking meter rate ex ante by block and time of day to achieve a target on-street parking occupancy rate. [Shoup \(1999, 2005, 2006\)](#) developed an on-street parking scheme according to a target parking occupancy rate and suggested setting this rate to 85 %. We confirm these findings using our model in chapter 6 and discuss how these rates might change depending on various demand and supply relationships following different parking policies. A modified version of his proposed scheme has been implemented in San Francisco using empirical data collected by parking meters for on-street parking spaces ([SFpark \(2009\)](#); [Millard-Ball et al. \(2014\)](#); [Pierce and Shoup \(2013\)](#)). [Arnott \(2014\)](#) developed a simple, structural model for steady-state on-street parking to determine the optimal on-street parking occupancy rate on a block in the network. The static results show that the optimal occupancy and parking meter rates are dependent on the parking demand, i.e., at busier blocks with a higher parking demand the target parking occupancy rate should be set to a higher value. [De Vos and van Ommeren \(2018\)](#) focused on the effects of parking occupancy rates on walking distances towards the drivers' destinations in a residential area in Amsterdam, Netherlands. The drivers' walking distances only increase when the parking occupancy rate exceeds 85 % in the area. [Zakharenko \(2019\)](#) used the information from parking occupancy sensors to help drivers during their search for

an available parking space. Increasing the parking price in congested areas can lead to a higher turnover rate for parking spaces. To do this, it is not necessary to install parking sensors for all parking spaces. By considering price discrimination and by pricing parking locations differently, it is possible to set the optimal parking fee for sensed parking lower compared to non-sensed parking spaces. [Zakharenko \(2020\)](#) enhanced this work by investigating when it is more reasonable to steer heterogeneous drivers away from available parking in order to reserve privileged parking spaces. This framework uses second-best pricing policies and is extended by studying parking for drivers with special needs. As electric vehicles require long charging periods, they can be counted as vehicles with special needs. [Zakharenko \(2020\)](#) used the binomial approximation parking search model by [Arnott and Williams \(2017\)](#) which is based on a stochastic simulation of cruising for curbside parking. The binomial approximation, however, leads to an underestimation of cruising-for-parking time, especially at high occupancy rates. In addition, it does not account for competition between cars searching for parking, and the parking search strategy is assumed to be trivial with drivers searching for parking as soon as they enter the network. Our model in chapter 6, however, accounts for non-searching vehicles, as (i) not all drivers search for parking, and (ii) even those that do, usually do not start searching for parking directly after entering a central area. The non-searching traffic in our methodology can also influence the traffic performance and in turn, the likelihood of finding parking. Moreover, our macroscopic framework uses average values and some probability distributions to model searching for parking traffic taking into account the competition across the demand in a dynamic manner ([Cao and Menendez \(2015a\)](#)). [Zakharenko \(2020\)](#) differentiated between standard and specially designed parking bays, and considered two parking policies covering exclusive special-needs parking and an optimal policy which makes special needs parking available to anyone for an extra fee. He stated that the desired parking duration can vary, but for simplicity, it was assumed to be exogenous for each parking searcher and it did not respond to policy or aggregate equilibrium conditions. Our macroscopic framework allows us to investigate different parking space policies for cities analyzing the impacts of changes in parking demand, supply, and parking durations for different vehicle types in the area. Cities can use these results to react to these changes by modifying the supply of parking spaces with battery charging possibilities, by limiting their charging durations while parking, or by pricing in order to achieve different target occupancy rates.

1.3 Research Objectives

The primary objective of this dissertation is to provide insights into macroscopic modelling of parking policies. First, we present the foundations of our macroscopic parking and traffic framework. Then, we concentrate on the parking policies including static and dynamic parking pricing (Part I), and parking occupancy (Part II). Specific objectives for all dissertation parts are listed as follows:

I. Parking pricing

- i. Analyze the effects of on-street and garage parking policies on the traffic and parking system (e.g., traffic performance, searching-for-parking traffic), and how the traffic and parking system can affect the decision to use on-street or garage parking in an urban area.
- ii. Investigate the short-term influences of parking and congestion pricing policies on the traffic and parking system, and how the traffic and parking system can impact the number of cars deciding between entering the network by car or using P+R instead.
- iii. Evaluate the influences of dynamic responsive pricing on the traffic and parking system, and how different traffic conditions (e.g., number of vehicles searching for parking, and available parking spaces in the network) can affect the responsive parking pricing.

II. Parking occupancy

- i. Determine the optimal parking occupancy rate for different vehicle types with the opportunities of evaluating traffic and parking impacts (e.g., average searching time for parking, total revenue from parking pricing, optimal parking occupancy rates) of a modal shift towards a specific vehicle type, such as electric vehicles with differentiated and hierarchical parking space policies.

1.4 Scope

This dissertation studies different parking policies focusing on parking pricing and parking occupancy, and their short-term impacts on the urban parking and traffic system. Here, we concentrate not only on the financial benefits of the parking policies, but also on the benefits (or disbenefits) that this might bring to the area's traffic system. Long-term effects and demand changes (e.g., drivers avoiding paying high on-street or garage parking fees and quitting their journeys) are considered out-of-scope in this dissertation. Our parking demand does not change over time with respect to the choice of travelers as a result of the parking policies and the local conditions of the study area (i.e., residents' and commuters' preferences, culture, or travel behavior). Additionally, we do not account for traffic disruptions caused by parking maneuvers ([Cao and Menendez \(2015b\)](#), [Cao et al. \(2016\)](#)), as we focus on the influence of the number of vehicles searching for on-street parking on the overall traffic performance.

The applicability of our macroscopic model is limited to compact urban areas as relatively homogeneous networks. It has been proven that the model represents a very good compromise between accuracy and efficiency for such networks ([Cao et al. \(2019\)](#)). The network should not be too large such that the drivers' preference of parking location can be more or less neglected, and not be too small either such that

the traffic flow on it can be viewed macroscopically. Even though the scale of the network might sound restrictive, it allows us to analyze the problem with a new and comprehensive methodology, that, above all, has very limited data requirements and rather low computational costs. Non-homogeneous environments are out of the scope of this dissertation. However, we could use our homogeneous network as the first building block; with which further analysis can be developed for more complex situations (e.g., where the parking spaces or the parking prices are not homogeneously distributed). For a case where there are different areas each with a different distribution of parking spaces or parking prices, for example, one can use different subnetworks connected to each other. Each subnetwork could be modelled as in this building block, i.e., would have identical parking fees but different subnetworks would have different parking fees. More research would be needed, however, to determine the connections between those subnetworks.

In the following chapters, our parking policies are applied using a case study for an area within the city of Zurich, Switzerland. The traffic properties (i.e., free-flow speed, maximum traffic throughput, critical traffic density, jam density, coefficients capturing PT traffic properties) are considered as inputs to our research based on the MFD or the 3D-MFD of the city of Zurich, respectively. Changes to the traffic properties are out-of-scope in this dissertation. We refer to chapter 2 showing further modelling assumptions and restrictions for our macroscopic framework.

1.5 Contributions

The main contributions of this dissertation are listed below.

- i. We develop macroscopic decision models and integrate them into a macroscopic traffic and parking framework. These models include the drivers' decisions between different on-street and garage parking fees, or between entering the network by car or using P+R instead. These decisions are faced by multiple user groups with respect to their VOT. Our framework provides valuable insights into different on-street and garage parking fee ratios and their impacts on cruising-for-parking traffic as well as the overall traffic performance. In addition, we study the influences of the traffic performance on the drivers' decision between on-street and garage parking. Our multimodal macroscopic traffic and parking framework focusing on parking and congestion pricing allows cities to evaluate how parking and congestion pricing affect the traffic and parking system, and how the traffic and parking system affect the drivers' decision between entering the network by car or using P+R instead. Our methodology allows us to investigate the distributional effects of different VOTs on this drivers' decision.
- ii. Our frameworks provide the tools to study the trade-off between the parking revenue and the cruising-for-parking traffic. These tools are based on aggregated data at the network level over time that can be easily solved with low computational costs using a simple numerical solver. City councils or

- private agencies can use this study to find reasonable hourly on-street and garage parking fees such that the average vehicle time/distance is not negatively affected and additionally, acceptable financial revenues are obtained. Moreover, our parking and congestion pricing policy can be used to find the best relation between the parking fee and the congestion charge in order to improve the traffic performance in the network or the total revenue for the city (which could be used to improve the P+R facilities).
- iii. We simulate different on-street and garage parking policies in a central area within the city of Zurich, e.g., the short-term effects of converting on-street to garage parking spaces on the traffic system, or the availability of garage usage information to all drivers. Based on our results, recommendations for city councils can be made.
 - iv. We show that parking pricing is indeed a viable alternative to congestion pricing, potentially leading to traffic performance improvements inside the protected network. This is valid in areas with a high parking demand for public parking spaces.
 - v. We develop a responsive parking pricing scheme taking into account the parking search phenomenon by changing in response to the number of searching vehicles, and the parking occupancy rate in the area. The parking fee is then updated over time in response to the parking demand and the supply. Here, we formulate an optimization model to maximize the parking pricing revenue to the highest level, while simultaneously minimizing the negative impacts on the traffic system (i.e., minimizing total cruising time on the network). In the short-term, this optimal parking pricing policy has neither negative influences on traffic performance nor environmental conditions, but it significantly increases the total revenue. This could lead to major improvements for city councils or private agencies in the area.
 - vi. We propose a framework to compute the optimal parking occupancy rate over a given time horizon for an area within a city based on a macroscopic traffic and parking model. The extension of our macroscopic model to include multiple vehicle types allows us to generate insights about the parking occupancy's dependency on specific vehicle types (e.g., fuel and electric vehicles).
 - vii. We investigate a differentiated parking policy with exclusive parking spaces (e.g., fuel vehicles park at fuel vehicle parking spaces, and electric vehicles park at spaces with battery chargers), and a hierarchical parking policy, considering no parking space restrictions for some vehicle types (e.g., electric vehicles can park at both parking spaces for fuel and electric vehicles). We compare both policies to a parking scheme without any parking differentiation. Our framework allows cities to evaluate how to react towards a constantly varying parking demand and how much parking supply to dedicate to electric vehicles in order to have the best balance between traffic performance, optimal parking occupancies, and a high parking pricing

revenue. Additionally, we can use our methodology to quickly evaluate the impacts on the optimal parking occupancy rate caused by a change in parking demand, supply, or parking duration in the area.

1.6 Dissertation Outline

This dissertation presents two main parts, and seven chapters in total. The overall structure is illustrated in Fig. 1.1. An overview of each chapter is given below:

Chapter 2 shows the macroscopic model of an urban parking and traffic system which is used as a foundation for the following chapters.

Part I:

Chapter 3 provides insights into a macroscopic framework of on-street and garage parking using static parking fees and analyzing their impacts on the traffic performance in an urban area.

Chapter 4 presents a macroscopic methodology which allows cities to evaluate the introduction of new parking and congestion pricing policies in an urban area, and analyzes their impacts on the traffic and parking system, and the potential revenue over a defined time horizon.

Chapter 5 introduces a dynamic macroscopic parking pricing framework focusing on the short-term effects of congestion and traffic performance. The scheme not only uses the parking occupancy but also the searching traffic to maximize the revenue for a city while simultaneously minimizing the total searching time in the area.

Part II:

Chapter 6 concentrates on the parking occupancy, and proposes a model to determine the optimal parking occupancy rate for multiple vehicle types based on a macroscopic traffic and parking model over a given time horizon for an urban area. It considers differentiated and hierarchical parking space policies and compares them to a non-differentiated parking scheme.

Chapter 7 concludes this dissertation, highlights the main findings and discusses open questions for future research.

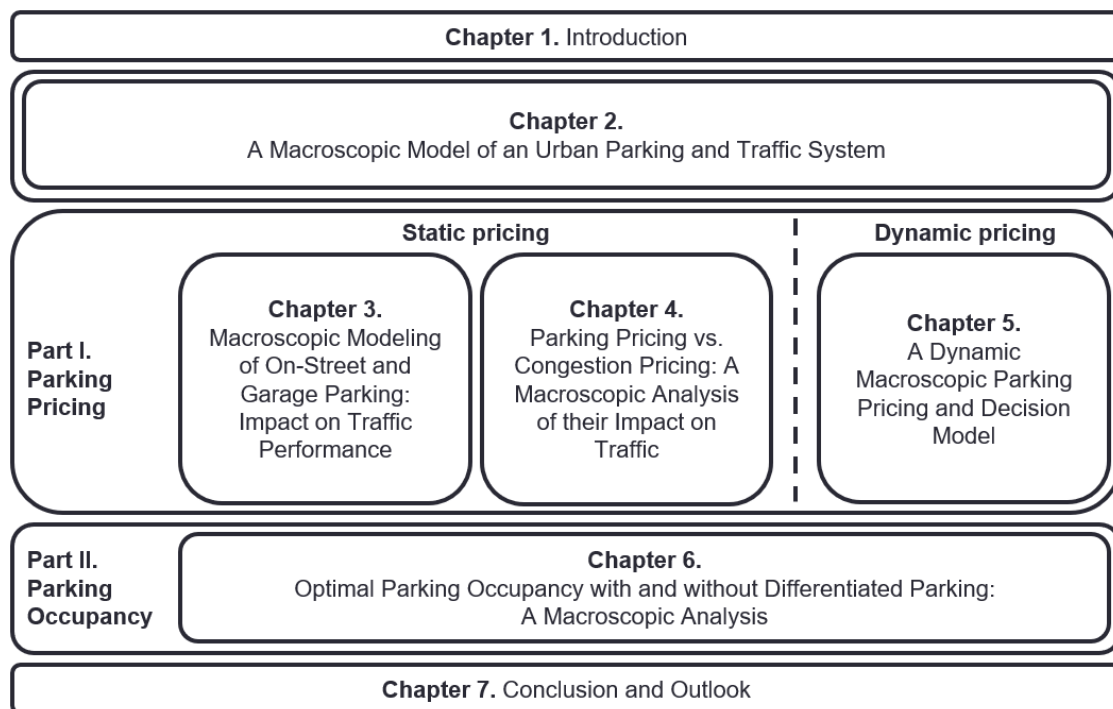


Fig. 1.1. Structure of the dissertation.

This dissertation is based on the following refereed archival journal articles, and conference contributions by the author. All articles below are original work and first-authored by the doctoral candidate:

Journal papers:

- Jakob, M.,** M. Menendez, J. Cao. 2018. "A dynamic macroscopic parking pricing and parking decision model". *Transportmetrica B: Transport Dynamics*, Vol. 8 (2020), Issue 1, pp. 307–331, doi: 10.1080/21680566.2018.1488226.
- Jakob, M.,** and M. Menendez. 2019. "Macroscopic Modeling of On-Street and Garage Parking: Impact on Traffic Performance". *Journal of Advanced Transportation*, Volume 2019, Article ID 5793027, 20 pages, doi: 10.1155/2019/5793027.
- Jakob, M.,** and M. Menendez. 2020. "Parking pricing vs. congestion pricing: a macroscopic analysis of their impact on traffic". *Transportmetrica A: Transport Science*, doi: 10.1080/23249935.2020.1797924.
- Jakob, M.,** and M. Menendez. 2020. "Optimal Parking Occupancy with and without Differentiated Parking: A Macroscopic Analysis". Submitted to *Transport Policy*.

Conference contributions:

- Jakob, M.,** M. Menendez, J. Cao. 2016. "A dynamic macroscopic parking pricing model", *Transportation Research Procedia*, Proceedings of the 14th World Conference on Transportation Research (WCTR 2016), Shanghai, China, July 2016. Paper received Best Paper Award Topic Area C.

Jakob, M., and M. Menendez. 2016. "A macroscopic off-street parking decision model".
Proceedings of the 16th Swiss Transport Research Conference (STRC 2016), Ascona,
Switzerland, May 2016.

Chapter 2:

A Macroscopic Model of an Urban Parking and Traffic System

2.1 Introduction

This chapter describes the macroscopic foundation of our parking policies which is based on a macroscopic model of an urban parking and traffic system. A central element of this methodology is the parking-state-based matrix describing how vehicles transition from one parking-related state to another over time. The matrix consists of transition events and traffic states, accounting for the system dynamics of urban traffic and its interactions with the parking system over time. We present the model inputs and assumptions for this matrix, which – as an output of our methodology – estimates the proportion of cars cruising-for-parking and the cruising time, as well as the traffic conditions and parking usage over time. Additionally, we highlight the advantages of our macroscopic framework compared to microscopic approaches.

2.2 Model inputs and general assumptions

Our macroscopic parking and traffic framework is based on the model in [Cao and Menendez \(2015a\)](#). Modified and enhanced versions build the foundations for our parking pricing and parking occupancy policies. For the readers' convenience, the core parts of the basic model including the macroscopic network setup are summarized again here.

- **Network:** The study considers a compact urban area as a relatively homogeneous network. Following the same idea as the original model, here the urban network is abstracted as one ring road with cars driving in a single direction. Such ring road abstraction has been proven to be reasonable for small, homogeneous traffic networks ([Daganzo \(2011\)](#); [Daganzo et al. \(2011\)](#); [Gayah and Daganzo \(2011\)](#); [Cao and Menendez \(2015a\)](#)).
- **Time:** The total time domain is split into small time slices (e.g., 1 minute), and the traffic/parking conditions are assumed steady within each time slice, although they can change over multiple time slices.
- **Parking demand:** The parking demand is homogeneously distributed over the network, and the parking searchers are homogeneously distributed within the overall driving traffic. This is reasonable for small compact areas where parking is also more or less homogeneously distributed. Thus, we assume that vehicles do not prefer parking possibilities in a specific street or area of the network, i.e., drivers are indifferent across parking locations and can park anywhere in the area. No drivers cancel their trip towards their internal destinations. Since the traffic demand is independent of vehicles travelling in a single direction or two, the assumption of a single travel direction simplifies the model without affecting the model results. All the assumed trips in this network are exclusively made by car (i.e., the mode choice has been previously made). The total demand includes two types of vehicles, those that

might search for parking at some point, and through traffic. Although parking maneuvers have been proven to influence traffic flow ([Cao and Menendez \(2015b\)](#), [Cao et al. \(2016\)](#)), here we do not account for them, as we focus on the influence of the number of vehicles searching for on-street parking on the overall traffic performance. Additionally, we assume no overtaking takes place. Although this seems unrealistic, it does not affect the model results: even if vehicles can overtake each other, for any given number of available parking spaces and searchers the average number of cars finding parking spaces in a time slice will not change.

- **Parking supply:** This analysis includes identical on-street and garage parking spaces. However, vehicles that use parking garages, private parking spaces or have parking permit reservations do not typically search for parking, as they treat their parking location as their target destination. Hence, it is not realistic to model them as searching traffic. Considering that, we define a portion of travel demand as through-traffic which represents trips that do not search for parking. This portion includes drivers with an off-street or dedicate/private parking facility destination, or drivers simply moving through the area. A differentiation between on-street and garage parking is, however, added to our framework in chapter 3. All existing parking spaces (not only the available ones) are on average uniformly distributed on the network. This is reasonable for small areas with standard parking policies/provision (e.g., downtown areas or portions thereof). By looking into the number of available parking spaces (which also can be zero in some instances) at the beginning of each time slice, we take parking restrictions and capacity constraints of parking spaces into account. Thus, it is possible to analyse the limitation of parking resources with our framework for a central part of the city. The number of available parking spaces on the network is deterministic at the beginning of each time slice, but this is not valid for the locations of such spaces, as we assume they are randomly located on the network. Hence, even though at any given iteration the available parking spaces are randomly distributed in the network, in the long run, the locations of all the available parking spaces obey a uniform distribution. Additionally, we assume double and delivery parking activities do not cause any issues in the network.

These assumptions aim at replicating typical conditions in a small downtown area, where traffic and parking spaces are more or less homogeneously distributed. The demand is considered as an inelastic input to the model and known at the beginning of each time interval. Further inputs to this model are the size and the traffic properties of the network, the amount of parking supply, and the distribution of parking durations. There are some distributions that describe parking duration better than others, see [Richardson \(1974\)](#), [Lautso \(1981\)](#), [Cao and Menendez \(2013\)](#); although in theory any distribution can be used, e.g., negative binomial, poisson ([Cao and Menendez \(2015a\)](#)). Note that these probability distributions can be used to describe the parking durations in our model as we discretize time and split the total time

horizon into small time slices. The parking-state-based matrix, as an output of this model, estimates the proportion of cars cruising-for-parking and the cruising time, as well as the traffic conditions and parking usage over time.

Table 2.1 presents the list of all main variables and parameters used in section 2.4.

Table 2.1. List of main variables and parameters.

Notation	Definition
L	Size (length) of the network.
L_{lane}	Size (length) of the network in lane-km (used to measure traffic density).
t	Length of a time slice.
K	Set of user groups for the network's demand indexed by k . Each user group has a different value of time (VOT).
A^i	Number of available on-street parking spaces at the beginning of time slice i .
v^i	Average travel speed in time slice i , including stopped time at intersections.
v	Free flow speed, i.e., maximum speed on the network, including stopped time at intersections.
Q_{max}	Maximum traffic throughput for the network.
k_c	Optimal/critical traffic density on the network.
k_j	Jam density.
k^i	Density of vehicles in time slice i .
d^i	Maximum driven distance per vehicle in time slice i .
β^i	Proportion of new arrivals during time slice i that corresponds to traffic that is not searching for parking.
$l_{ns/}$	Average distance driven by a vehicle before it starts to search for parking.
$l_{p/}$	Average distance driven by a vehicle before it leaves the area after it has parked.
$l_{/}$	Average distance driven by a vehicle before it leaves the area without having parked.
t_d	Parking duration.

2.3 Macroscopic vs. microscopic approach

The searching time and distance depend on the current traffic conditions, and on drivers' probability of finding an available parking space (based on their own location, that of the available parking spaces and the competitors). To specify each vehicle's driving time and driving distance, one normally needs to record the location of all cars and parking spaces throughout the different time slices in the system (microscopic approach). We can avoid that by using a macroscopic approach. As the data requirements correspond to aggregate values at the network level, this has the advantage that there is no data required for individual vehicles and the location of individual parking spaces. We only consider the average number of vehicles that access parking during a time slice i , and the total/average searching distance driven during this time slice i . The number of available parking spaces and the number of parking searchers are recorded over time in the parking-state-based matrix. However, their locations are not tracked. The following two assumptions are used in this model: First, we assume the stochastically independent distribution of parking availability on the network, i.e., at the beginning of each time slice i the locations of available parking spaces are assumed as random. Second, the traffic demand is homogeneously generated and the locations of all parking searchers are uniformly distributed on the

network at the beginning of each time slice i . The second assumption is used to compute the average number of vehicles that find parking, and ultimately the average number of parking spaces being taken. These average values only stand for a situation where, more or less all searchers are uniformly distributed on the network. This, however, limits the model. In reality, searchers can focus on one street to find parking while parking spaces are easily available in other areas of the network. In this case, the model would likely overestimate the amount of parking spaces being taken. However, the model does provide indicative and realistic results regarding the effects that parking might have on traffic performance under general conditions, as we are interested in whether there is on average at least one car that takes each available parking space. For that, we do not need to know the exact location of each car or available parking space. For the validation of the original macroscopic model, including these assumptions, we refer to [Cao et al. \(2019\)](#).

2.4 Overview of the parking-state-based matrix

The parking-state-based matrix describes how vehicles transition from one parking-related state to another over time, taking into account the transition events and the traffic states as shown in Fig. 2.1 and Table 2.2. It accounts for the system dynamics of urban traffic and its interactions with the parking system over time. This section presents the traffic states and transition events as in [Cao and Menendez \(2015a\)](#), which are enhanced in the following chapters 3 to 6 by reflecting the changes for different user groups $k \in K$. Here, K represents the set of user groups for the network's demand.

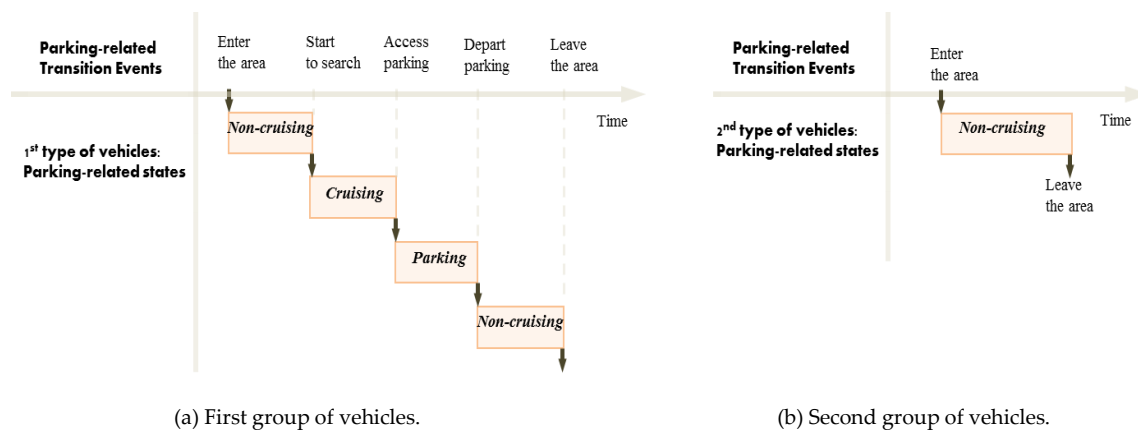


Fig. 2.1. The transition events of urban traffic in-between different parking-related states (Source: [Cao and Menendez \(2015a\)](#)).

Two types of traffic demands are considered in this network and they are generated simultaneously in each time slice. The first group of vehicles searches for parking. This portion of the traffic demand experiences five transition events in the area of interest as seen in Fig. 2.1(a). During one single time slice a vehicle may experience at most one of the transition events. The notation for the three parking-related traffic states and the five transition events is shown in detail in Table 2.2. The second group

of vehicles does not search for parking, i.e., the vehicles can be considered as through traffic and/or heading to a given private or reserved parking space. This portion of vehicles in Fig. 2.1(b) only experiences the transition events “enter the area” and “leave the area” in Table 2.2, and the decision to leave the area depends on their driven distance in the network.

Table 2.2. Relevant key variables for matrix per time slice.

	Notation	Definition
Traffic states	N_{ns}^i	Number of vehicles in the state “non-searching” at the beginning of time slice i (Non-searching).
	N_s^i	Number of vehicles in the state “searching” at the beginning of time slice i (Searching).
	N_p^i	Number of vehicles in the state “parking” at the beginning of time slice i (Parking).
Transition events	$n_{/ns}^i$	Number of vehicles that enter the area and transition to “non-searching” during time slice i (Enter the area).
	$n_{ns/s}^i$	Number of vehicles that transition from “non-searching” to “searching” during time slice i (Start to search for parking).
	$n_{s/p}^i$	Number of vehicles that transition from “searching” to “parking” during time slice i (Access parking).
	$n_{p/ns}^i$	Number of vehicles that transition from “parking” to “non-searching” during time slice i (Depart parking).
	$n_{ns/}^i$	Number of vehicles that leave the area and transition from “non-searching” during time slice i (Leave the area).

2.4.1 Traffic states

Details about the mathematical formulations of the three traffic states summarized in Table 2.2 can be found in [Cao and Menendez \(2015a\)](#), but a summary is given here for the readers’ convenience. All traffic state variables need an initial condition as an input to the model that can be measured, assumed or simulated.

The number of non-searching vehicles, N_{ns}^{i+1} , are updated at the beginning of time slice $i + 1$ in Eq. (1). Vehicles entering the area (i.e., $n_{/ns}^i$) and vehicles departing from parking (i.e., $n_{p/ns}^i$) join these states. Vehicles starting to search for parking in the area (i.e., $n_{ns/s}^i$) and vehicles leaving the area (i.e., $n_{ns/}^i$) leave these states.

$$N_{ns}^{i+1} = N_{ns}^i + n_{/ns}^i + n_{p/ns}^i - n_{ns/s}^i - n_{ns/}^i \quad (1)$$

The number of vehicles searching for parking at the beginning of time slice $i + 1$, N_s^{i+1} , is updated in Eq. (2). Vehicles starting to search for parking in the area (i.e., $n_{ns/s}^i$) join this state, and vehicles accessing parking (i.e., $n_{s/p}^i$) leave this state.

$$N_s^{i+1} = N_s^i + n_{ns/s}^i - n_{s/p}^i \quad (2)$$

The number of vehicles parked in the area at the beginning of time slice $i + 1$, N_p^{i+1} , is determined in Eq. (3). Vehicles accessing an available parking space (i.e., $n_{s/p}^i$) join this traffic state, and vehicles departing from parking (i.e., $n_{p/ns}^i$) leave this state.

$$N_p^{i+1} = N_p^i + n_{s/p}^i - n_{p/ns}^i \quad (3)$$

Note that the formulations of N_{ns}^{i+1} (Eq. (1)) and N_s^{i+1} (Eq. (2)) will change throughout the following chapters when reflecting different user groups $k \in K$. The design of N_p^{i+1} (Eq. (3)), however, remains consistent, even when differentiating between on-street and garage parking in chapter 3.

The traffic states (Eq. (1)-(2)) are then used to determine the average travel speed, v^i , during time slice i in Eq. (4a-b). v^i is formulated in Eq. (4b) based on a triangular MFD ([Haddad and Geroliminis \(2012\)](#); [Haddad et al. \(2013\)](#); [Yang et al. \(2017\)](#); [Yang et al. \(2019\)](#)), and the average traffic density k^i (Eq. (4a)) in the same time slice. This triangular approximation of the MFD, which basically discards the impact of traffic signals, is used here only for simplification purposes. More realistic MFD shapes could be easily used to estimate v^i instead, potentially changing Eq. (4b) below, but nothing else in the proposed model. k^i is determined based on the total number of vehicles on the road network (consisting of non-searching, N_{ns}^i , and searching vehicles, N_s^i), and the network length, L_{lane} , in lane-km ([Cao and Menendez \(2015a\)](#); [Cao et al. \(2019\)](#)). The vehicles travel at free flow speed v when traffic is not congested, and at a lower speed in case the traffic density exceeds the critical density, k_c . The actual speed in congestion is calculated based on the traffic density in that time slice, k^i , the critical density, k_c , the jam density, k_j , and the maximum traffic throughput, Q_{max} , for the network.

$$k^i = \frac{N_{ns}^i + N_s^i}{L_{lane}} \quad (4a)$$

$$v^i = \begin{cases} v, & \text{if } 0 \leq k^i \leq k_c \\ \frac{Q_{max}}{k_c - k_j} \cdot \left(1 - \frac{k_j}{k^i}\right), & \text{if } k_c < k^i \leq k_j \end{cases} \quad (4b)$$

Note that v^i is modelled in Eq. (4b) based on a MFD, which is replaced by a 3D-MFD ([Dakic et al. \(2020\)](#), [Loder et al. \(2017\)](#), [Paipuri and Leclercq \(2020\)](#), [Zheng et al. \(2014\)](#)) in chapter 4.

2.4.2 Transition events

Based on some initial conditions, the output of the model is the parking-state related matrix. This matrix contains the number of vehicles experiencing each transition event as well as the resulting parking and traffic conditions (e.g., parking occupancy/availability and average travel speed) for each time slice. The conditions at any given time slice affect the transition events in the next time slice, so the matrix can be updated iteratively until the whole period is analyzed, or a defined criterion is reached (e.g., all the cars leave the area).

All transition events are modelled macroscopically using a deterministic approach. However, the model is not thoroughly deterministic, as for example, the parking

location of each vehicle is not fixed, nor the travel time, nor the parking duration. The model is not thoroughly stochastic either as there are no random values involved in the computation of the transition events. Having a not thoroughly stochastic model does not necessarily make the model less valuable than one under completely stochastic conditions, because the model is meant to look for average values based on some probability distributions rather than the random values themselves. Since all variables are based on average values and not on random values, every simulation run returns the same results as long as the input variables to the model are not changed. In addition, there is no need to run the model many times in order to account for its stochasticity, as it is based on probability functions (i.e., the stochasticity is already implicit within the model formulations) (Cao and Menendez (2015a)).

The total number of vehicles entering the network, n_{ns}^i , during time slice i is a known demand input to the framework (Fig. 2.1 and Table 2.2). Depending on the proportion of through-traffic, β^i , the vehicles will directly leave the area after driving a given distance l_j , or they will go through all transition events presented below. l_j is considered as fixed or taken out of any given probability density function, and it can vary by the network size and the average trip lengths.

The number of vehicles starting to search for parking, $n_{ns/s}^i$, is determined in Eq. (5) depending on whether the vehicles' driven distance by time slice i has been long enough to cover a given distance $l_{ns/}$. $l_{ns/}$ can be fixed or taken out of any given probability density function. We capture the condition by $\gamma_{ns/}^{i'}$ in Eq. (5). d^i represents the maximum driven distance per vehicle in time slice i . It is estimated based on the speed during that interval v^i (from Eq. (4b)) and the length of a time slice, t (i.e., $d^i = v^i \cdot t$). Evidently, in reality, not all vehicles will drive the full distance before transitioning to another event on a given time slice. However, it is trivial to show that the bias of d^i becomes negligible as the length of the time interval t becomes very small (in this case, 1 min).

$$n_{ns/s}^i = \sum_{i'=1}^{i-1} (1 - \beta^{i'}) \cdot n_{ns}^{i'} \cdot \gamma_{ns/}^{i'} \quad (5)$$

where

$$\gamma_{ns/}^{i'} = \begin{cases} 1, & \text{if } l_{ns/} \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq l_{ns/} + d^{i-1} \\ 0, & \text{otherwise} \end{cases}$$

The likelihood formulations from Cao and Menendez (2015a) and Cao and Menendez (2018) are used to model the number of vehicles finding and accessing parking, $n_{s/p}^i$, in Eq. (6). Depending on the number of competing vehicles trying to find parking, N_s^i , the number of available parking spaces at the beginning of time slice i , A^i , and the proportion of the network covered by a searching vehicle during time slice i , d^i/L , the number of vehicles accessing parking can vary. Here, we differentiate between a low share of vehicles accessing parking, when $A^i < N_s^i$, i.e., the number of available parking spaces is not enough for all drivers cruising for parking; and a high share of

vehicles accessing parking, when $A^i > N_s^i$. More modelling details on $n_{s/p}^i$ are illustrated in [Cao and Menendez \(2015a\)](#) with a simplified version in [Cao and Menendez \(2018\)](#).

$$n_{s/p}^i = \begin{cases} \begin{cases} N_s^i \left[1 - \left(1 - \frac{d^i}{L} \right)^{A^i} \right], & \text{if } t \in \left[0, \frac{L}{v^i \cdot N_s^i} \right] \\ A^i + \left[A^i - N_s^i + N_s^i \cdot \left(1 - \frac{1}{N_s^i} \right)^{A^i} \right] \cdot \left(\frac{\log \frac{N_s^i}{A^i} \cdot \frac{d^i}{L}}{\log A^i} \right), & \text{if } t \in \left[\frac{L}{v^i \cdot N_s^i}, \frac{L}{v^i} \cdot \frac{A^i}{N_s^i} \right] \end{cases}, & \text{if } A^i \leq N_s^i \\ \begin{cases} A^i, & \text{if } t \in \left[\frac{L}{v^i} \cdot \frac{A^i}{N_s^i}, \infty \right) \\ N_s^i \left[1 - \left(1 - \frac{d^i}{L} \right)^{A^i} \right], & \text{if } t \in \left[0, \frac{L}{v^i \cdot N_s^i} \right] \\ N_s^i + N_s^i \cdot \left(1 - \frac{1}{N_s^i} \right)^{A^i} \cdot \left(\frac{\log \frac{d^i}{L}}{\log N_s^i} \right), & \text{if } t \in \left[\frac{L}{v^i \cdot N_s^i}, \frac{L}{v^i} \right] \end{cases}, & \text{if } A^i \geq N_s^i \\ N_s^i, & \text{if } t \in \left[\frac{L}{v^i}, \infty \right) \end{cases} \quad (6)$$

After departing from their parking spaces, the vehicles $n_{p/ns}^i$ (Eq. (7)) drive towards their destinations outside the area during time slice i . The likelihood that these vehicles depart from the parking spaces in time slice i is based on the distribution of parking durations $f(t_d)$ and the number of vehicles having accessed parking spaces, $n_{s/p}^{i'}$ in a former time slice $i' \in [1, i-1]$. The probability of their parking duration is between $(i-i') \cdot t$ and $(i+1-i') \cdot t$, i.e., $\int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_d) dt_d$.

$$n_{p/ns}^i = \sum_{i'=1}^{i-1} n_{s/p}^{i'} \cdot \int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_d) dt_d \quad (7)$$

Depending on whether the vehicles have parked or not, they leave the area, $n_{ns/l}^i$ in Eq. (8), after having driven a given distance $l_{p/l}$ or l_l , respectively. These distances are considered as fixed or taken out of any given probability density function.

$$n_{ns/l}^i = \sum_{i'=1}^{i-1} \left(\beta^{i'} \cdot n_{ns}^{i'} \cdot \gamma_{l'}^{i'} + n_{p/ns}^{i'} \cdot \gamma_{p/l}^{i'} \right) \quad (8)$$

where

$$\gamma_{l'}^{i'} = \begin{cases} 1, & \text{if } l_l \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq l_l + d^{i-1} \\ 0, & \text{otherwise} \end{cases}$$

$$\gamma_{p/}^{i'} = \begin{cases} 1, & \text{if } l_{p/} \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq l_{p/} + d^{i-1} \\ 0, & \text{otherwise} \end{cases}$$

$\gamma_{/}^{i'}$ and $\gamma_{p/}^{i'}$ indicate whether the number of vehicles $n_{/ns}^{i'}$ and $n_{p/ns}^{i'}$ have driven long enough, $l_{/}$ and $l_{p/}$, respectively, in order to leave the area in time slice i . Recall that d^i represents the maximum driven distance per vehicle in time slice i .

Note that the transition events $n_{/ns}^i$, $n_{ns/s}^i$ and $n_{s/p}^i$ are modified in the following chapters when reflecting different user groups $k \in K$. The concept to determine the likelihood of finding on-street parking in $n_{s/p}^i$, however, stays the same throughout the dissertation. The formulations of $n_{p/ns}^i$ and $n_{ns/}^i$ remain consistent within the following chapters, even when modelling them for $k \in K$.

A case study for an area within the city of Zurich, Switzerland, was carried out in [Cao et al. \(2019\)](#) using this macroscopic model. Results showed that this model can be easily applied with limited data requirements and low computational costs, yielding relevant and trustworthy indicators of the cruising-for-parking phenomenon. Moreover, the model has also been used to quantify the potential cruising time savings generated by intelligent parking services ([Cao and Menendez \(2018\)](#)). We now extend it to include

- i. on-street and garage parking (chapter 3),
- ii. the system dynamics of urban car and P+R traffic using a multimodal traffic and parking framework focusing on parking and congestion pricing (chapter 4),
- iii. a dynamic macroscopic parking pricing methodology (chapter 5), and
- iv. multiple vehicle types in the demand with different parking needs to determine the optimal parking occupancy rate (chapter 6).

The modified models use different traffic states and transition events in their outputs, i.e., an enhanced parking-state-based matrix, which is presented in the following chapters.

Part I

Parking Pricing

Abstract

As traffic congestion gets worse year by year in metropolitan areas, cities search for solutions to improve their traffic performance and reduce their environmental impacts. This first part of the dissertation focuses on parking pricing policies and their short-term effects not only on traffic congestion but also on the potential revenue for a city. We differentiate these policies by looking first at static and later at dynamic pricing strategies.

We develop a macroscopic on-street and garage parking decision model and integrate it into a traffic system with an on-street and garage parking search model over time. Here, we formulate an on-street and garage parking-state-based matrix that describes the system dynamics of urban traffic based on different parking-related states and the number of vehicles that transition through each state in a time slice. This macroscopic modeling approach is based on aggregated data at the network level over time. All parking searchers face the decision to drive to a parking garage or to search for an on-street parking space in the network. This decision is affected by several parameters including the static on-street and garage parking fees.

A further framework develops an easy to implement multimodal macroscopic traffic and parking search model for a central area allowing us to analyze how introducing parking pricing inside a network, or a congestion toll combined with a P+R scheme can affect the drivers' decision between entering the network by car (private vehicle) or using P+R instead. The decision directly influences the number of drivers using P+R, and this impacts, in turn, the traffic performance. Based on such analysis using aggregated data at the network level, a city can get valuable insights to evaluate whether congestion pricing is a necessity or if the traffic improvements resulting from implementing static parking pricing strategies are sufficient when combined with P+R facilities.

Finally, we develop a dynamic macroscopic parking pricing model in order to maximize the revenue for a city, while simultaneously minimizing the total cruising time on the network. The proposed responsive pricing scheme takes the parking search phenomenon into consideration. This means that the parking fee also changes in response to the number of searching vehicles, in addition to changes in response to the parking occupancy. Compared to most literature, this macroscopic pricing model is embedded into a dynamic macroscopic urban traffic and parking model and has rather low data requirements, mostly related to average values and probability distributions at the network level.

We illustrate all parking pricing policies in regard to the financial revenues they generate and their short-term impacts on traffic performance, congestion and environmental conditions using a case study of an area within the city of Zurich, Switzerland.

Chapter 3:

Macroscopic Modeling of On-Street and Garage Parking: Impact on Traffic Performance

This chapter is based on the results presented in:

Jakob, M., and M. Menendez. 2019. "Macroscopic Modeling of On-Street and Garage Parking: Impact on Traffic Performance". *Journal of Advanced Transportation*, Volume 2019, Article ID 5793027, 20 pages, doi: 10.1155/2019/5793027.

3.1 Introduction

As the population in urban areas is increasing, more and more cars need to find parking spaces in city centers. These vehicles normally have the choice between on-street and garage parking. Both parking possibilities follow diverse policies, which can sometimes lead to rather complex interdependencies and significant changes in the performance of a transportation network. In this research, we develop a macroscopic on-street and garage parking model such that the influence of different on-street and garage parking policies on the traffic system can be studied and illustrated. Hereafter, off-street parking is referred to as garage parking. The macroscopic model is built on a traffic system with a parking search model over time. It is incorporated into the on-street parking framework from [Cao and Menendez \(2015a\)](#).

Compared to methodologies concentrating on long-term demand management strategies, our dynamic macroscopic modeling approach focuses on the short-term effects in the traffic network, i.e., the demand entering the network is treated as exogenous, and the on-street and garage parking capacity is taken as fixed. An on-street and garage parking-state-based matrix is used to capture the system dynamics of urban traffic. It is based on multiple parking-related traffic states and transition events to update the number of vehicles per state over time ([Cao and Menendez \(2015a\)](#)). Here, our macroscopic model in chapter 2 is enhanced to include on-street and garage parking. The total traffic demand entering the network is divided into two groups; through-traffic, and vehicles searching for parking. The first group of vehicles represents the proportion of traffic that is driving through this area but does not want to park or has a destination outside. Therefore, it only experiences two transition events, as seen in Fig. 3.1(a). The second group of vehicles needs to decide between searching for on-street parking or driving towards a parking garage, as seen in Fig. 3.1(b). During one single time slice, a vehicle may experience at most one transition event.

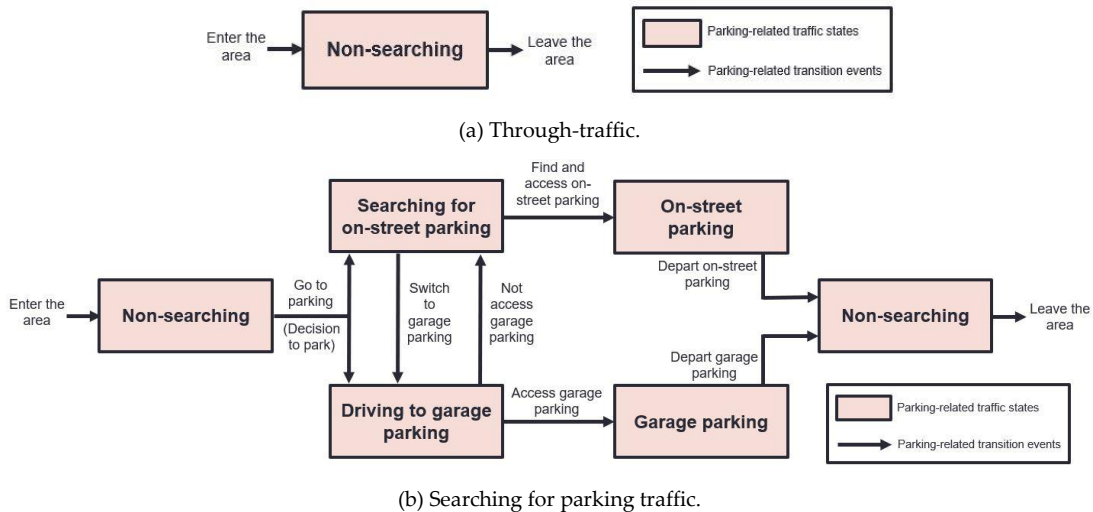


Fig. 3.1. The transition events of urban traffic focusing on on-street and garage parking in-between different parking-related states.

In case the drivers decide for on-street parking, they might need to circulate in the city to search for an available on-street parking space, which contributes to the problem of traffic congestion. In case the drivers decide for garage parking, there is no need to search-for-parking. These vehicles drive towards the closest parking garage and access it depending on its current availability. Our methodology differentiates between on-street and garage parking. Note that this differs from the macroscopic model introduced in chapter 2 as garage parking was not explicitly considered in the former framework. With limited data collection efforts, our macroscopic on-street and garage parking decision model shows the influence of different on-street and garage parking pricing ratios on the average searching time/distance. We analyze the relationship between on-street and garage parking, but also their interdependency on cruising-for-parking traffic and traffic performance with respect to different parking fees. Different pricing strategies affect the drivers' decision to park on-street or to drive towards a parking garage. Insights from this chapter will help city councils or private agencies to analyze the short-term impacts on the traffic system, for example, when changing the hourly on-street and garage parking fee rates on the network, or when converting on-street to garage parking spaces (as it has been the case in cities like Zurich, Switzerland).

In summary, the existing literature approaches on-street and garage parking models either with empirical data collection efforts or with methodologies concentrating on user equilibrium or social optimum solutions that focus on long-term demand management strategies. Our on-street and garage parking decision model follows a macroscopic approach and focuses on short-term effects. The main contributions of this study are three-fold.

- i. First, without large data collection efforts, our macroscopic decision model provides valuable insights into different on-street and garage parking fee ratios and their impacts on cruising-for-parking traffic as well as the overall traffic performance. The macroscopic model of garage parking also allows us to provide an easy to implement methodology with low computational costs based on aggregated data at the network level over time that can be easily solved with a simple numerical solver.
- ii. Second, our framework provides the tools to study the trade-off between the parking revenue and the cruising-for-parking traffic. We analyze the relationship between on-street and garage parking, but also their interdependency on traffic performance with respect to different parking fees. This study can be used for city councils or private agencies to find reasonable hourly on-street and garage parking fees such that the average vehicle time/distance is not negatively affected and additionally, acceptable financial revenues are obtained.
- iii. Third, different parking policies in city center areas, e.g., the short-term effects of converting on-street to garage parking spaces on the traffic system,

or the availability of garage usage information to all drivers can be simulated using our methodology and recommendations for city councils can be made.

The chapter is organized as follows. Section 3.2 presents the overall framework of the macroscopic on-street and garage parking decision model. Section 3.3 illustrates the concept and mathematical model of the on-street and garage parking-state-based matrix. Section 3.4 shows a case study of an area within the city of Zurich, Switzerland. Section 3.5 summarizes this chapter.

3.2 On-Street and Garage Parking Decision

Several cost factors influence the on-street/garage parking decision, as seen in Fig. 3.2. These cost variables include variables that have an impact on either the on-street parking option (e.g., the on-street parking pricing), the garage parking option (e.g., the garage parking pricing) or on both parking options (e.g., the number of parking spaces of each kind, and the desired parking duration). Drivers with desired long parking durations are more likely to choose garage parking. All drivers are assumed to be rational during their parking decision and only compare the relevant parking costs between on-street and garage parking, i.e., all drivers are treated as risk-neutral.

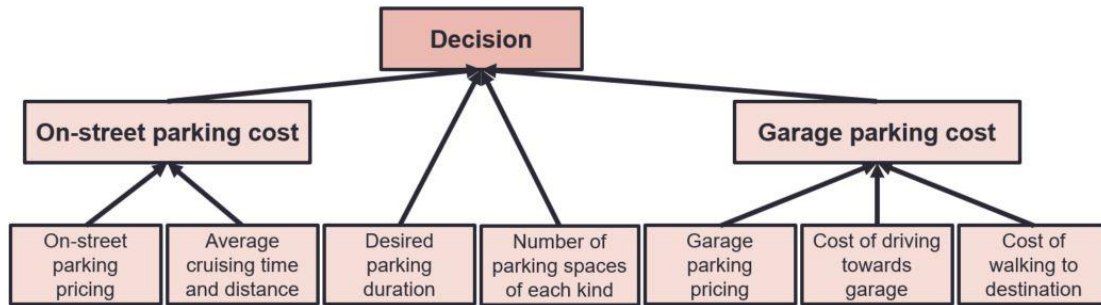


Fig. 3.2. Decision Model for on-street and garage parking based on several cost factors.

The parking decision is then modeled macroscopically using a logistic function based on the on-street and garage parking cost variables. The data inputs are presented in section 3.2.1. All mathematical details of this modeling approach are illustrated in section 3.2.2.

3.2.1 Data inputs for decision model

The decision between on-street and garage parking is dependent on the input variables shown in Table 2.1, 3.1 and 3.2. The model parameters and all variables that are required to define the traffic network are presented in Table 2.1 and 3.1. These variables can either be directly measured, or estimated based on simulation results and/or the MFD.

Recall that all data inputs are based on a compact urban area with a relatively homogeneous network. The total time horizon is divided into small time slices (e.g., 1 minute). All traffic and parking conditions can change over multiple time slices, but

they are assumed to be steady within each time slice.

Table 3.1. Independent variables for parking decision (inputs to the model): Traffic network and model parameters.

Notation	Definition
b	Average length of a block in the network.
T	Length of the simulation's time horizon.
VOT^k	VOT for user group $k \in K$.
w	Walking speed in the network.

It is assumed that all trips are exclusively made by car, i.e., the mode choice has been previously made. In addition, we assume that drivers do not cancel their trips while searching for parking. The VOT is assumed to be different for individual vehicles depending on their user group. Such user group can be dependent on the residents' location, income, careers, working states, etc.

Table 2.1 and 3.2 show all independent variables associated with on-street and garage parking. This includes parking duration and parking pricing specific input parameters. These variables can be estimated based on real measurements, historical on-street and garage parking and pricing data, or defined otherwise. All variables related to the travel demand and the distances driven can be estimated based on historical data, e.g., traffic data on main roads to enter the network, etc. The distance variables that are associated with a transition into the next state can be reasonably assumed based on the length of the network, and other data collected from drivers.

Given the homogeneous network, parking searchers are assumed to be homogeneously distributed within the overall driving traffic. This is reasonable, as we also assume that all on-street parking spaces (not only the available ones) are uniformly distributed on the network. Recall that we focus on small compact areas with standard parking policies (e.g., downtown areas or portions thereof). We do not need to record the location of individual cars and parking spaces throughout the different time slices in the system, i.e., only average numbers of vehicles during a time slice and total/average searching times and distances are tracked.

Parking garages are also assumed to be uniformly distributed within the network, and without loss of generality, all associated garage parking capacities are assumed to be equal. In other words, all parking garages have equal limited capacities. The distribution of desired parking durations is considered as an input to this model. Some distributions describe the parking duration better than others, see [Cao and Menendez \(2013\)](#), [Richardson \(1974\)](#). Remember that in theory, however, any distribution can be used, e.g., poisson, negative binomial ([Cao and Menendez \(2015a\)](#)). It is assumed that during the period of one working day drivers do not repark their car after the on-street parking time limit has expired.

Table 3.2. Independent variables for parking decision (inputs to the model): On-street and garage parking parameters.

Notation	Definition
A	Total number of existing on-street parking spaces (for public use) in the area.
G	Number of parking garages in the network.
R	Total capacity of all parking garages, i.e., total number of all garage parking spaces.
t_d	Parking duration of vehicles (independently of on-street and garage parking).
$t_{d,\xi}$	Parking duration of vehicles focusing on on-street (op) or garage parking (gp), $\xi \in \{op, gp\}$.
τ_ξ	On-street (op) or garage parking (gp) time limit, $\xi \in \{op, gp\}$.
p_ξ	Hourly on-street (op) or garage parking (gp) fee rate, $\xi \in \{op, gp\}$.
p_d	Price per kilometer driven on the network (i.e., external costs as petrol, wear and tear of vehicles).
l_{ns}^k	Average distance that must be driven by a vehicle from user group $k \in K$ before it starts to search for parking.
$l_{/}^k$	Average distance that must be driven by a vehicle from user group $k \in K$ before it leaves the area without having parked.
$l_{p/}^k$	Average distance that must be driven by a vehicle from user group $k \in K$ before it leaves the area after it has parked (on-street or in a garage).

3.2.2 Mathematical decision framework

Table 3.3 summarizes the intermediate modeling variables – in addition to Table 2.1 – that are needed to model the on-street and garage parking decision. The model outputs provide, amongst others, the results of the interactions between on-street and garage parking and their influence on the urban traffic system.

Table 3.3. Intermediate model variables.

Notation	Definition
$C_\xi^{i,k}$	Total cost of on-street (op) or garage parking (gp) in time slice i for user group $k \in K$, $\xi \in \{op, gp\}$.
$\delta_{gp}^{i,k}$	Choice of drivers for garage parking (gp) in time slice i for user group $k \in K$.
$\gamma_\xi^{i,k}$	Proportion of drivers deciding for on-street (op) or garage parking (gp) in time slice i for user group $k \in K$, $\xi \in \{op, gp\}$.
ACT^i	Average cruising time for vehicles parking on-street at the beginning of time slice i .
ADD	Average driving distance to closest garage location.
AWD_ξ	Average walking distance from on-street (op) or garage parking (gp) parking to destination, $\xi \in \{op, gp\}$.
R^i	Garage parking availability of all parking garages in time slice i .
P_{tot}	Total revenue resulting from hourly on-street and garage parking fee rates for the city.

We model the parking decision between on-street and garage parking macroscopically in Eq. (9)-(11). This will then be incorporated into the on-street and garage parking-state-based matrix in section 3.3. We assume that the on-street parking time limit τ_{op} is smaller than the garage parking time limit τ_{gp} , i.e., $\tau_{op} \leq \tau_{gp}$. All drivers with a desired parking duration of $t_d \leq \tau_{op}$ decide between on-street and garage parking, whereas drivers with $\tau_{op} < t_d \leq \tau_{gp}$ are restricted and can only park at garages. Notice that t_d is taken out of a distribution and no individual vehicles are tracked. We assume that $t_d \leq \tau_{gp}$ for all drivers, since vehicles with $t_d > \tau_{gp}$ cannot find a parking place according to their desired parking duration anywhere within this

network. The choice for garage parking over on-street parking, $\delta_{gp}^{i,k}$, is modeled in Eq. (1) using a logistic function based on R (the total capacity of all parking garages), A (the total number of existing on-street parking spaces), $C_{op}^{i,k}$ (the cost of on-street parking in section 3.2.2.1), and $C_{gp}^{i,k}$ (the cost of garage parking in section 3.2.2.2).

$$\delta_{gp}^{i,k} = \frac{\frac{\frac{R}{R+A} \cdot C_{op}^{i,k} - \frac{A}{R+A} \cdot C_{gp}^{i,k}}{e^{\min\{\frac{R}{R+A} \cdot C_{op}^{i,k}, \frac{A}{R+A} \cdot C_{gp}^{i,k}\}}}}{1 + e^{\min\{\frac{R}{R+A} \cdot C_{op}^{i,k}, \frac{A}{R+A} \cdot C_{gp}^{i,k}\}}} \quad (9)$$

Drivers base their parking choice on expected costs. These cost variables are determined macroscopically without stochastic components, using average values and probability distributions across the whole population. Therefore, $\delta_{gp}^{i,k}$ is modeled as an average corresponding to aggregated data at the network level based on the logistic probability distribution. To make sure the parking choice takes the supply into consideration we add the weight parameters $\frac{R}{R+A}$ and $\frac{A}{R+A}$ to Eq. (9). These terms are not time-dependent since there is no real-time information for on-street and garage parking availability. We assume that the drivers have only information available about the VOT for their own user group $k \in K$, about total parking capacities in the network and about the system averages required to determine the cost variables $C_{op}^{i,k}$ and $C_{gp}^{i,k}$. It is further assumed that the drivers are unsophisticated in their decision-making since they do not use their experienced vehicle speed values as additional information to update the available system average information required to determine $C_{op}^{i,k}$ and $C_{gp}^{i,k}$. In an alternative scenario in section 3.4.5 we relax this assumption by having real-time garage parking availability information accessible to the drivers when deciding to park on-street or to drive towards a parking garage. However, no real-time on-street parking information is assumed to be available in this alternative scenario, as this is less common. In future research, other scenarios can be investigated involving a forecast about future on-street and/or garage parking availability when making their decision. Notice that the decision of some drivers is restricted by τ_{op} and τ_{gp} . This is taken into account when calculating $\gamma_{gp}^{i,k}$ in Eq. (10), which described the proportion of vehicles deciding for garage parking, and $\gamma_{op}^{i,k}$ in Eq. (11) which describes the proportion of vehicles deciding to search for on-street parking.

$$\gamma_{gp}^{i,k} = \underbrace{\int_0^{\tau_{op}} f(t_d) dt_d}_{\text{term 1}} \cdot \delta_{gp}^{i,k} + \underbrace{\int_{\tau_{op}}^{\tau_{gp}} f(t_d) dt_d}_{\text{term 2}} \quad (10)$$

$$\gamma_{op}^{i,k} = 1 - \gamma_{gp}^{i,k} \quad (11)$$

Term 1 in Eq. (10) represents the portion of vehicles with a parking duration $t_d \leq \tau_{op}$ that have the option to decide for on-street or garage parking. Term 2 represents the portion of vehicles with $\tau_{op} < t_d \leq \tau_{gp}$ that has to park in a garage because of their

desired parking duration. Notice that both $\int_0^{\tau_{op}} f(t_d)dt_d$ and $\int_{\tau_{op}}^{\tau_{gp}} f(t_d)dt_d$ are assumed to be k -independent, i.e., the distribution of the parking durations is assumed to be independent of the drivers' VOT.

3.2.2.1 Cost of on-street parking

In Eq. (12), we derive the cost of on-street parking, $C_{op}^{i,k}$ for each user group $k \in K$ in time slice i .

$$C_{op}^{i,k} = \underbrace{p_{op}}_{\text{term 1}} + \underbrace{p_d \cdot v^i \cdot ACT^i}_{\text{term 2}} + \underbrace{VOT^k \cdot ACT^i}_{\text{term 3}} + \underbrace{VOT^k \cdot \frac{AWD_{op}}{w}}_{\text{term 4}} \quad (12)$$

Term 1 represents the hourly on-street parking fee rate which, in the remainder of this chapter, is assumed to be constant. In theory, however, the on-street parking fee could also be modeled as a responsive parking pricing scheme (chapter 5) that takes the parking search phenomenon into consideration. Notice that the parking decision in Eq. (9) is assumed to be based on the parking fee rates per hour independently of the parking durations. Term 2 represents the average cruising distance for on-street parking (i.e., external costs as petrol, wear and tear of vehicles) converted to price units. Term 3 represents the average cruising time based on the drivers' VOT expressed in price units for $k \in K$. The average cruising time ACT^i is determined in section 5.3.3.3, and is based on a queueing diagram showing the cumulative number of vehicles going through each transition event as a function of time. Notice that the longer the drivers search for on-street parking, the higher the average cruising time ACT^i is, and consequently also the $C_{op}^{i,k}$. Therefore, it is more likely that the drivers might decide for garage parking in congested areas. Term 4 represents the cost of walking from the on-street parking to the destination expressed in price units for $k \in K$. Even though our abstracted network was a ring, we may assume without loss of generality that the real network is a square grid, where the average length of a block b in the network is known. The total length of the ring network, L , is then equivalent to joining all blocks of length b together. As on-street parking spaces are uniformly distributed throughout the network, the walking costs can be determined using the average Manhattan distance traveled AWD_{op} (Eq. (13)) between two random points in the square grid ([Ortigosa et al. \(2019\)](#)).

$$AWD_{op} = \frac{2}{3} \cdot b \cdot \underbrace{\left(-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}} \right)}_{\text{term 1}} \quad (13)$$

Term 1 represents the side length of the square grid.

3.2.2.2 Cost of garage parking

The cost of garage parking, $C_{gp}^{i,k}$ for each user group $k \in K$ in time slice i , is based on multiple cost terms as shown in Eq. (14).

$$C_{gp}^{i,k} = \underbrace{p_{gp}}_{\text{term 1}} + \underbrace{p_d \cdot ADD}_{\text{term 2}} + \underbrace{VOT^k \cdot \frac{ADD}{v^i}}_{\text{term 3}} + \underbrace{VOT^k \cdot \frac{AWD_{gp}}{w}}_{\text{term 4}} \quad (14)$$

Term 1 represents the hourly garage parking fee rate which, in the remainder of this chapter, is assumed to be constant. Terms 2 and 3 show the cost of driving from the actual vehicle's garage parking decision location to the closest garage for $k \in K$. It contains the average distance to the closest garage parking expressed in distance price units (term 2) and the average time expressed in price units for $k \in K$ (term 3). Both terms include the associated average driving distance ADD , determined in Eq. (15).

$$ADD = \frac{L}{2 \cdot G} \quad (15)$$

Remember that the actual garage locations are assumed to be uniformly distributed on the network and that we assume that traffic on the abstracted ring moves in a single direction.

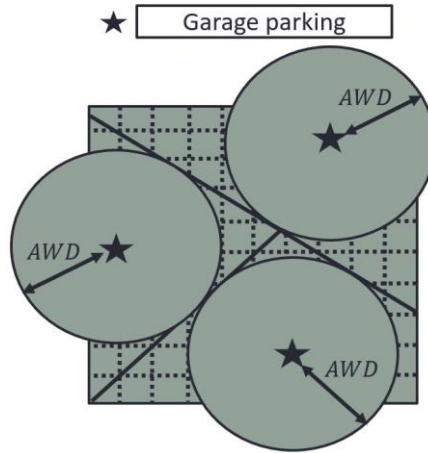


Fig. 3.3. Simple example of uniformly distributed garage parking to illustrate the average walking distance in Eq. (16).

Term 4 in Eq. (14) represents the cost of walking from the garage parking to the destination expressed in price units for $k \in K$. As the number of garages is limited, they are expected to require, on average, some walking distance. The walking speed w is assumed to be a constant input. To estimate the area served by each parking garage, we take the surface of the square grid $\left[b \cdot \left(-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}} \right) \right]^2$ and divide it by G (Fig. 3.3). Assuming destinations are uniformly distributed in the network, we can compute the average walking distance AWD_{gp} in Eq. (16) as $2/3$ of the radius of each of the areas served by a parking garage.

$$AWD_{gp} = \frac{2b}{3\sqrt{\pi \cdot G}} \left[-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}} \right] \quad (16)$$

Note that we enhance $C_{gp}^{i,k}$ in section 3.4.5 by including garage usage information to

all drivers.

3.2.2.3 Total revenue

One component of the parking decision is paying an hourly fee for on-street or garage parking. However, the drivers pay the final parking fee from on-street or garage parking depending on how long they have parked. Eq. (17) expresses the total revenue P_{tot} obtained from all user groups K for the time horizon T .

$$P_{tot} = \sum_{i=1}^T \sum_{k=1}^K \underbrace{n_{op/ns}^{i,k} \cdot p_{op} \cdot \overline{t_{d,op}}}_{\text{term 1}} + \underbrace{n_{gp/ns}^{i,k} \cdot p_{gp} \cdot \overline{t_{d,gp}}}_{\text{term 2}} \quad (17)$$

Term 1 shows the revenue from on-street parking for user group $k \in K$ during time slice i . Term 2 illustrates the revenue from garage parking for user group $k \in K$ during time slice i . $\overline{t_{d,op}}$ and $\overline{t_{d,gp}}$ illustrate the average on-street/garage parking duration obtained from all user groups K for the time horizon T . Notice that $n_{op/ns}^{i,k}$ in term 1 and $n_{gp/ns}^{i,k}$ in term 2 are both defined in section 3.3.1 (Table 3.5).

3.3 On-Street and Garage Parking-State-Based Matrix

The on-street and garage parking-state-based matrix describes the system dynamics of urban traffic based on multiple parking-related states as in chapter 2 according to [Cao and Menendez \(2015a\)](#). The matrix is used to incorporate our parking decision model into a macroscopic traffic system framework that captures the interactions over time between the on-street and garage parking systems. This section shows an overview of all on-street and garage parking-related traffic states (section 3.3.1), and the analytical formulations for the transition events between those states (section 3.3.2).

3.3.1 Parking-related traffic states

Recall that the parking-related traffic states build the foundation for the parking-state-based matrix. The matrix updates all parking-related traffic states based on the number of vehicles going through different transition events in each time slice. The matrix is then updated iteratively over time until the whole period is analyzed, or a defined criterion is reached (e.g., all the cars leave the area). Here, we enhance the basic matrix from our macroscopic model in chapter 2 to include on-street and garage parking. By integrating our on-street and garage parking decision model from section 3.2, the matrix allows us to illustrate the effects of different on-street and garage parking policies on the searching time and searching distance.

All vehicles searching for parking in Fig. 3.1(b) have the option to decide for on-street or garage parking at their current location. This decision involves the on-street and garage parking decision model from section 3.2. The vehicles that have decided to

search for on-street parking can change their mind and switch to garage parking later. As soon as the vehicles decide for garage parking, they will drive towards the closest parking garage and access it based on availability. For these drivers, the location of the parking garages is assumed to be known, or guidance to the garage location is available. Once the garage parking decision is made, we assume the drivers do not change their decision while driving to the garage location. If there are no available garage parking spaces, the vehicles cannot access the parking garage and might move to the searching-for-on-street-parking state. After the vehicles have accessed on-street or garage parking, they depart and move back to the non-searching state before they leave the area. All traffic states in Fig. 3.1 are summarized in Table 3.4. They show modifications of the traffic states presented in Table 2.2 and include the differentiation between on-street and garage parking. The initial conditions of all traffic state variables are model input variables that can be measured, assumed, or simulated.

Table 3.4. All traffic state variables for the on-street and garage parking-state-based matrix per time slice.

Notation	Name	Definition
$N_{ns}^{i,k}$	Non-searching	Number of vehicles in the state "non-searching" for user group $k \in K$ at the beginning of time slice i .
$N_s^{i,k}$	Searching for on-street parking	Number of vehicles in the state "searching for on-street parking" for user group $k \in K$ at the beginning of time slice i .
$N_{op}^{i,k}$	On-street parking	Number of vehicles in the state "on-street parking" for user group $k \in K$ at the beginning of time slice i .
$N_{dgp}^{i,k}$	Driving to garage parking	Number of vehicles in the state "driving to garage parking" for user group $k \in K$ at the beginning of time slice i .
$N_{gp}^{i,k}$	Garage parking	Number of vehicles in the state "garage parking" for user group $k \in K$ at the beginning of time slice i .

These parking-related states are determined using the information on the transition events. We introduce the transition events in Table 3.5. These transition events enhance the variables presented in Table 2.2 allowing us to model the differentiation between on-street and garage parking.

Eq. (18) to (22) update the number of "non-searching", "searching for on-street parking", "on-street parking", "driving to garage parking", and "garage parking" vehicles, respectively. Eq. (18) presents an enhancement of Eq. (1), and Eq. (19) shows a modification of Eq. (2). Eq. (20) and (22) relate to Eq. (3), differentiating between on-street and garage parking. Eq. (21) is a newly defined traffic state required to model the number of vehicles driving to garage parking and thus, it has no counterpart in the original model shown in section 2.4.1. Notice that all equations need to be determined for every user group $k \in K$, where K is the total number of user groups for the demand input of the network.

$$N_{ns}^{i+1} = \sum_{k=1}^K N_{ns}^{i+1,k}, \text{ where } N_{ns}^{i+1,k} = N_{ns}^{i,k} + n_{/ns}^{i,k} + n_{op/ns}^{i,k} + n_{gp/ns}^{i,k} - n_{ns/s}^{i,k} - n_{ns/dgp}^{i,k} - n_{ns/}^{i,k} \quad (18)$$

$$N_s^{i+1} = \sum_{k=1}^K N_s^{i+1,k}, \text{ where } N_s^{i+1,k} = N_s^{i,k} + n_{ns/s}^{i,k} + n_{dgp/s}^{i,k} - n_{s/op}^{i,k} - n_{s/dgp}^{i,k} \quad (19)$$

$$N_{op}^{i+1} = \sum_{k=1}^K N_{op}^{i+1,k}, \text{ where } N_{op}^{i+1,k} = N_{op}^{i,k} + n_{s/op}^{i,k} - n_{op/ns}^{i,k} \quad (20)$$

$$N_{dgp}^{i+1} = \sum_{k=1}^K N_{dgp}^{i+1,k}, \text{ where } N_{dgp}^{i+1,k} = N_{dgp}^{i,k} + n_{ns/dgp}^{i,k} + n_{s/dgp}^{i,k} - n_{dgp/gp}^{i,k} - n_{dgp/s}^{i,k} \quad (21)$$

$$N_{gp}^{i+1} = \sum_{k=1}^K N_{gp}^{i+1,k}, \text{ where } N_{gp}^{i+1,k} = N_{gp}^{i,k} + n_{dgp/gp}^{i,k} - n_{gp/ns}^{i,k} \quad (22)$$

Table 3.5. All transition event variables for the on-street and garage parking-state-based matrix per time slice.

Notation	Name	Definition
$n_{/ns}^{i,k}$	Enter the area	Number of vehicles that enter the area and transition to “non-searching” for user group $k \in K$ during time slice i (i.e., travel demand per VOT user group).
$n_{ns/dgp}^{i,k}$	Go to parking (Decision to park: Driving to garage parking)	Number of vehicles that transition from “non-searching” to “driving to garage parking” (depending on their parking decision) for user group $k \in K$ during time slice i .
$n_{ns/s}^{i,k}$	Go to parking (Decision to park: Searching for on-street parking)	Number of vehicles that transition from “non-searching” to “searching for on-street parking” (depending on their parking decision) for user group $k \in K$ during time slice i .
$n_{s/dgp}^{i,k}$	Switch to garage parking	Number of vehicles that transition from “searching for on-street parking” to “driving to garage parking” for user group $k \in K$ during time slice i .
$n_{s/op}^{i,k}$	Find and access on-street parking	Number of vehicles that transition from “searching for on-street parking” to “on-street parking” for user group $k \in K$ during time slice i .
$n_{dgp/gp}^{i,k}$	Access garage parking	Number of vehicles that transition from “driving to garage parking” to “garage parking” for user group $k \in K$ during time slice i .
$n_{dgp/s}^{i,k}$	Not access garage parking	Number of vehicles that transition from “driving to garage parking” to “searching for on-street parking” for user group $k \in K$ during time slice i .
$n_{op/ns}^{i,k}$	Depart on-street parking	Number of vehicles that transition from “on-street parking” to “non-searching” for user group $k \in K$ during time slice i .
$n_{gp/ns}^{i,k}$	Depart garage parking	Number of vehicles that transition from “garage parking” to “non-searching” for user group $k \in K$ during time slice i .
$n_{ns/}^{i,k}$	Leave the area	Number of vehicles that leave the area and transition from “non-searching” for user group $k \in K$ during time slice i .

Eq. (18) updates the number of “non-searching” vehicles for each $k \in K$ before aggregating them to N_{ns}^{i+1} . Vehicles entering the area (i.e., $n_{/ns}^{i,k}$), and vehicles that depart from on-street or garage parking (i.e., $n_{op/ns}^{i,k}$ and $n_{gp/ns}^{i,k}$) join this state; vehicles that start searching or drive to garage parking (i.e., $n_{ns/s}^{i,k}$ and $n_{ns/dgp}^{i,k}$), and vehicles

leaving the area (i.e., $n_{ns/}^{i,k}$) quit this state. Eq. (19) updates the number of “searching” vehicles for each $k \in K$ and aggregates them after to N_s^{i+1} . Vehicles starting to search for on-street parking (i.e., $n_{ns/s}^{i,k}$) and vehicles not able to access garage parking (i.e., $n_{dgp/s}^{i,k}$) join this state; vehicles accessing on-street parking (i.e., $n_{s/op}^{i,k}$) and vehicles driving to garage parking (i.e., $n_{s/dgp}^{i,k}$) leave this state. Eq. (20) updates the number of “on-street parking” vehicles for each $k \in K$ and then aggregates them to N_{op}^{i+1} . Vehicles accessing an on-street parking space (i.e., $n_{s/op}^{i,k}$) join this state; vehicles departing from on-street parking (i.e., $n_{op/ns}^{i,k}$) leave this state. Eq. (21) updates the number of vehicles that “drive to garage parking” for each user group $k \in K$ and then aggregates them to N_{dgp}^{i+1} . Vehicles that drive to a parking garage during time slice i (i.e., $n_{ns/dgp}^{i,k}$ and $n_{s/dgp}^{i,k}$) join this state; vehicles that actually access garage parking (i.e., $n_{dgp/gp}^{i,k}$) and vehicles that cannot access garage parking (i.e., $n_{dgp/s}^{i,k}$) quit this state. Eq. (22) updates the number of “garage parking” vehicles for each $k \in K$ before aggregating them to N_{gp}^{i+1} . Vehicles that access a garage during time slice i (i.e., $n_{dgp/gp}^{i,k}$) join this state; vehicles that depart garage parking (i.e., $n_{gp/ns}^{i,k}$) quit this state. The total number of vehicles driving in the network at the beginning of time slice i is $N_{ns}^i + N_s^i + N_{dgp}^i$. The total number of vehicles parked at the beginning of time slice i is $N_{op}^i + N_{gp}^i$.

3.3.2 Transition events

We model the transition events introduced in Table 3.5 in the sections 3.3.2.1 to 3.3.2.9 below.

3.3.2.1 Enter the area

The traffic demand $n_{/ns}^{i,k}$ is – analogously to section 2.4.2 – an input to the model. It can be based on a probability distribution or it can be extracted from an agent-based model (e.g., MATSim). However, similarly to all other transition events, $n_{/ns}^{i,k}$ is deterministic and represents average values, i.e., there are no random values involved in their computation. A portion β^i of all vehicles entering the area is considered as through-traffic, i.e., these vehicles will drive through the area without needing to park.

3.3.2.2 Go to parking (Decision to park)

We assume that the vehicles from user group $k \in K$ make their parking decision (searching for on-street parking or driving to garage parking) after driving a distance $l_{ns/}^k$ since they enter the area. $l_{ns/}^k$ can be fixed or taken out of any given probability density function. The vehicles have the option to drive to garage parking as modeled in Eq. (23), or search for an on-street parking space as shown in Eq. (24). Both $n_{ns/dgp}^{i,k}$ and $n_{ns/s}^{i,k}$ may consist of vehicles from user group $k \in K$ entering the network in any former time slice $i' \in [1, i - 1]$. Eq. (23) and Eq. (24) are modifications of Eq. (5), and include the proportions of vehicles deciding for garage parking, $\gamma_{gp}^{i,k}$, or to search for on-street parking, $\gamma_{op}^{i,k}$, for $k \in K$.

$$n_{ns/dgp}^{i,k} = \left[\sum_{i'=1}^{i-1} \underbrace{(1 - \beta^{i'}) \cdot n_{ns}^{i',k}}_{\text{term 1}} \cdot \underbrace{\gamma_{ns/}^{i',k}}_{\text{term 2}} \right] \cdot \underbrace{\gamma_{gp}^{i,k}}_{\text{term 3}} \quad (23)$$

$$n_{ns/s}^{i,k} = \left[\sum_{i'=1}^{i-1} \underbrace{(1 - \beta^{i'}) \cdot n_{ns}^{i',k}}_{\text{term 1}} \cdot \underbrace{\gamma_{ns/}^{i',k}}_{\text{term 2}} \right] \cdot \underbrace{\gamma_{op}^{i,k}}_{\text{term 4}} \quad (24)$$

where

$$\gamma_{ns/}^{i',k} = \begin{cases} 1, & \text{if } l_{ns/}^k \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq l_{ns/}^k + d^{i-1} \\ 0, & \text{otherwise} \end{cases} \quad (25)$$

Term 1 in Eq. (23) and Eq. (24) shows the portion of the total demand $n_{ns}^{i',k}$ that needs to park, i.e., all vehicles excluding through traffic. The proportion of through-traffic, $\beta^{i'}$, is assumed to be independent of the individual user group $k \in K$. Term 2 indicates whether these vehicles can decide for parking in time slice i or need to continue driving until they cover a distance $l_{ns/}^k$ (Eq. (25)). Term 3 in Eq. (23) expresses the proportion of drivers deciding to drive towards a parking garage (from Eq. (10)) in time slice i depending on user group k . Term 4 in Eq. (24) expresses the proportion of drivers deciding to search for an on-street parking space (from Eq. (11)) in time slice i depending on user group k .

3.3.2.3 Switch to garage parking

In this section, the transition event $n_{s/dgp}^{i,k}$ is modeled in Eq. (26) to determine the number of vehicles switching to garage parking after being in the searching-for-on-street-parking state for at least one time slice. This represents the drivers that change their mind regarding where to park.

$$n_{s/dgp}^{i,k} = \left[\underbrace{N_s^{i,k} - n_{s/op}^i \cdot \frac{N_s^{i,k}}{N_s^i}}_{\text{term 1}} \right] \cdot \underbrace{\delta_{gp}^{i,k}}_{\text{term 2}} \cdot \underbrace{\min\{(N_s^i)^{-\alpha}; 1\}}_{\text{term 3}} \quad (26)$$

Term 1 represents all searching vehicles of user group k that have not parked on-street in this time slice i . Further details on the computation of $n_{s/op}^i$ can be found in section 2.4.2. Here, we can refer to $n_{s/p}^i$ in Eq. (6), as we do not differentiate between on-street and garage parking in the original model (section 2.4). Term 2 shows the proportion of searching vehicles deciding to drive towards a parking garage (Eq. (9)). Notice that the same vehicles have to go over the same decision at multiple time slices in the transition events “Go to parking” and “Switch to garage parking” (potentially revising their previous decision). Term 3 represents a penalty term that prevents drivers from flipping between $n_{s/dgp}^{i,k}$ and $n_{dgp/s}^{i,k}$. It is dependent on N_s^i since the likelihood of flipping is high when there are a lot of searching vehicles on the network. The level of the penalty for the simulation is characterized by α . This parameter is defined as $\alpha > 1$ such that $(N_s^i)^{-\alpha} < 1$, if $N_s^i > 1$. We introduce a minimum function in term 3 to keep term 3 as a probability value, i.e., between 0 and

1. It can be shown in a sensitivity analysis that as long as $\alpha > 1$, changes to its value only have a marginal influence on the average searching time/distance, the average time/distance of drivers driving to garage parking, and on the revenue collected by on-street and garage parking fees in the network, but the details are omitted in this chapter for brevity. In the remainder of this study, we assume a square root dependency and set $\alpha = 2$.

3.3.2.4 Find and access on-street parking

The vehicles $n_{s/op}^{i,k}$ from user group k searching for on-street parking that find and access a parking space are determined in Eq. (27).

$$n_{s/op}^{i,k} = n_{s/op}^i \cdot \frac{N_s^{i,k}}{N_s^i} \quad (27)$$

Notice that all drivers decide to access the first available on-street parking space in the network, as all parking spaces have the same price. As previously stated, details on $n_{s/op}^i$ can be found in section 2.4.2.

3.3.2.5 Access garage parking

The transition event $n_{dgp/gp}^{i,k}$ in Eq. (28) describes the process of accessing a parking garage. After the vehicles have decided to use garage parking, they drive towards the parking garage where they realize whether it is possible for them to access it depending on the garage parking availability.

$$n_{dgp/gp}^{i,k} = \underbrace{\frac{N_{dgp}^{i,k}}{N_{dgp}^i}}_{\text{term 1}} \cdot \min \left\{ \underbrace{\sum_{k=1}^K \sum_{i'=1}^{i-1} (n_{ns/dgp}^{i',k} + n_{s/dgp}^{i',k})}_{\text{term 2}} \cdot \underbrace{\gamma_{ADD}^{i',k}}_{\text{term 3}} ; R^i \right\} \quad (28)$$

where

$$\gamma_{ADD}^{i',k} = \begin{cases} 1, & \text{if } ADD - l_{ns/}^k \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq ADD - l_{ns/}^k + d^{i-1} \\ 0, & \text{otherwise} \end{cases} \quad (29)$$

Term 1 in Eq. (28) represents the portion of vehicles trying to access garage parking that belong to user group k . Term 2 shows the sum of all vehicles (from sections 3.3.2.2 and 3.3.2.3) that have decided to use garage parking in any former time slice $i' \in [1, i - 1]$. Term 3 (computed in Eq. (29)) indicates whether these vehicles have arrived at the garage after reaching $ADD - l_{ns/}^k$ (section 3.2.2.2). Note that the vehicles driving to garage parking are assumed to drive directly towards their garage as soon as they enter the area. Thus, the distance $l_{ns/}^k$ is deducted from ADD . Two conditions must be satisfied: the vehicles have driven enough distance to arrive at a parking garage after having decided for it, and they have not accessed a garage in a former time slice. Finally, the number of vehicles that can actually access garage parking is the minimum of the available garage parking spaces and the number of vehicles that want to park.

3.3.2.6 Not access garage parking

This transition event includes all vehicles that do not access garage parking due to limited availability. In this situation, some of these vehicles $n_{dgp/s}^{i,k}$ in Eq. (30) return back to searching-for-on-street-parking state. However, depending on A and R some drivers might prefer to stay in the “drive to garage parking” state as a result of a low total number of existing on-street parking spaces compared to the total existing garage capacity.

$$n_{dgp/s}^{i,k} = \underbrace{\frac{N_{dgp}^{i,k}}{N_{dgp}^i}}_{\text{term 1}} \cdot \max \left\{ \underbrace{\sum_{k=1}^K \sum_{i'=1}^{i-1} \left(n_{ns/dgp}^{i',k} + n_{s/dgp}^{i',k} \right)}_{\text{term 2}} \cdot \underbrace{\gamma_{ADD}^{i',k}}_{\text{term 3}} - R^i; 0 \right\} \cdot \underbrace{\frac{A}{R+A}}_{\text{term 4}} \quad (30)$$

Term 1, 2, and 3 are already determined as in Eq. (28). In case the garage parking availability limit is reached and the vehicles that would like to enter a parking garage, i.e., $\sum_{k=1}^K \sum_{i'=1}^{i-1} \left(n_{ns/dgp}^{i',k} + n_{s/dgp}^{i',k} \right) \cdot \gamma_{ADD}^{i',k}$ surpass R^i , the remaining vehicles need to return to searching-for-parking state; otherwise all vehicles can successfully enter a garage. This portion of vehicles returning back to searching-for-on-street-parking state is reduced by term 4 that represents the drivers’ decision to stay in the “drive to garage parking” state due to a low A in comparison to $R + A$. This term is not time-dependent since there is no real-time usage information available. This constraint is relaxed later (section 3.4.5) when real-time information is available. Notice that for more realistic applications, the capacity of garage parking will not be an active constraint. It is included here, however, for the sake of completeness.

3.3.2.7 Depart on-street parking

The number of vehicles that depart from on-street parking is based on the distribution of on-street parking durations $f(t_{d,op})$ and on the number of vehicles having accessed on-street parking, $n_{s/op}^{i',k}$, in a former time slice $i' \in [1, i-1]$. The probability that these vehicles depart from on-street parking in time slice i equals to the probability of the on-street parking duration being between $(i-i') \cdot t$ and $(i+1-i') \cdot t$, i.e., $\int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_{d,op}) dt_{d,op}$. The transition event is formulated as $n_{op/ns}^{i,k}$ in Eq. (31), which is consistent with Eq. (7) and focuses only on on-street parking for $k \in K$.

$$n_{op/ns}^{i,k} = \sum_{i'=1}^{i-1} n_{s/op}^{i',k} \cdot \int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_{d,op}) dt_{d,op} \quad (31)$$

The on-street parking availability A^i is updated in Eq. (32) after vehicles access or depart from on-street parking. A^i cannot surpass the total number of existing on-street parking spaces, i.e., $A^i \leq A$ for all time slices i .

$$A^{i+1} = A^i + \sum_{k=1}^K n_{op/ns}^{i,k} - \sum_{k=1}^K n_{s/op}^{i,k} \quad (32)$$

3.3.2.8 Depart garage parking

The transition event $n_{gp/ns}^{i,k}$ in Eq. (33) is modeled analogously to $n_{op/ns}^{i,k}$. It is based on Eq. (7), but uses only garage parking related transition events and garage parking durations. As we know the number of vehicles having decided to use garage parking in all former time slices, we can find $n_{gp/ns}^{i,k}$ based on the distribution of garage parking durations $f(t_{d,gp})$.

$$n_{gp/ns}^{i,k} = \sum_{i'=1}^{i-1} n_{dgp/gp}^{i',k} \cdot \int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_{d,gp}) dt_{d,gp} \quad (33)$$

After vehicles access or depart from garage parking, the availability R^i is updated in Eq. (34). R^i cannot surpass the total capacity, i.e., $R^i \leq R$ for all time slices i .

$$R^{i+1} = R^i + \sum_{k=1}^K n_{gp/ns}^{i,k} - \sum_{k=1}^K n_{dgp/gp}^{i,k} \quad (34)$$

3.3.2.9 Leave the area

The vehicles leave the area after having driven for a given distance l_j^k or $l_{p/}^k$ depending on whether they have parked or not. Notice that the distances l_j^k and $l_{p/}^k$ analogously to $l_{ns/}^k$ can be fixed or taken out of any given probability density function. Vehicles leaving the area are modeled as $n_{ns/}^{i,k}$ in Eq. (35) and include through-traffic vehicles, $\beta^{i'} \cdot n_{/ns'}^{i',k}$ and vehicles from the transition events $n_{op/ns}^{i',k}$ and $n_{gp/ns}^{i',k}$. Eq. (35) is based on the formulation in Eq. (8), including a slight enhancement which allows us to take into account vehicles departing from on-street and garage parking.

$$n_{ns/}^{i,k} = \sum_{i'=1}^{i-1} \left(\beta^{i'} \cdot n_{/ns'}^{i',k} \cdot \gamma_{/}^{i',k} + (n_{op/ns}^{i',k} + n_{gp/ns}^{i',k}) \cdot \gamma_{p/}^{i',k} \right) \quad (35)$$

where

$$\gamma_{/}^{i',k} = \begin{cases} 1, & \text{if } l_j^k \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq l_j^k + d^{i-1} \\ 0, & \text{otherwise} \end{cases}$$

$$\gamma_{p/}^{i',k} = \begin{cases} 1, & \text{if } l_{p/}^k \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq l_{p/}^k + d^{i-1} \\ 0, & \text{otherwise} \end{cases}$$

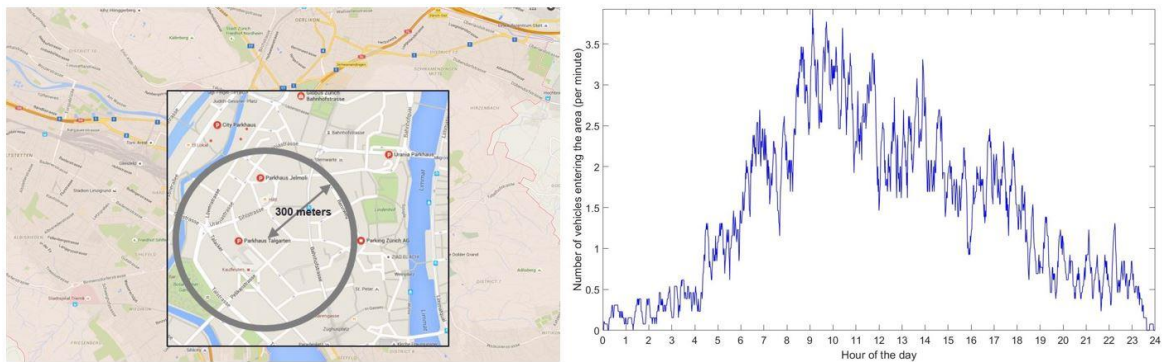
3.4 Applications

In this section, a case study of an area within the city of Zurich, Switzerland, is provided to illustrate the influences of on-street and garage parking on the traffic

system. We use real data obtained by [Cao et al. \(2019\)](#). The results are obtained with the aid of a simple numerical solver such as Matlab. We discuss the findings regarding on-street and garage parking pricing, the related parking decision, and the impacts on the average searching time/distance. We analyze the short-term effects of including garage usage information to all drivers, as well as the influences of converting on-street to garage parking spaces on the traffic system.

3.4.1 Case study of an area within the city of Zurich, Switzerland

Our study area (0.28 km^2) in Fig. 3.4(a) is located around the shopping area Jelmoli in the city center of Zurich ([Cao et al. \(2019\)](#)). There is a significant amount of retail space and offices from the financial sector in this area. This central area attracts 39 % of all trips related to shopping, 35 % related to leisure, and 26 % related to business activities (survey from May 2016 ([Cao et al. \(2019\)](#))). The total length of all roads in the area is $L = 7.7 \text{ km}$ with an associated area radius of 0.3 km and $b = 76 \text{ m}$. Most streets in this area have two lanes (one per direction or two one-way lanes).



(a) Case study area in the city center of Zurich.

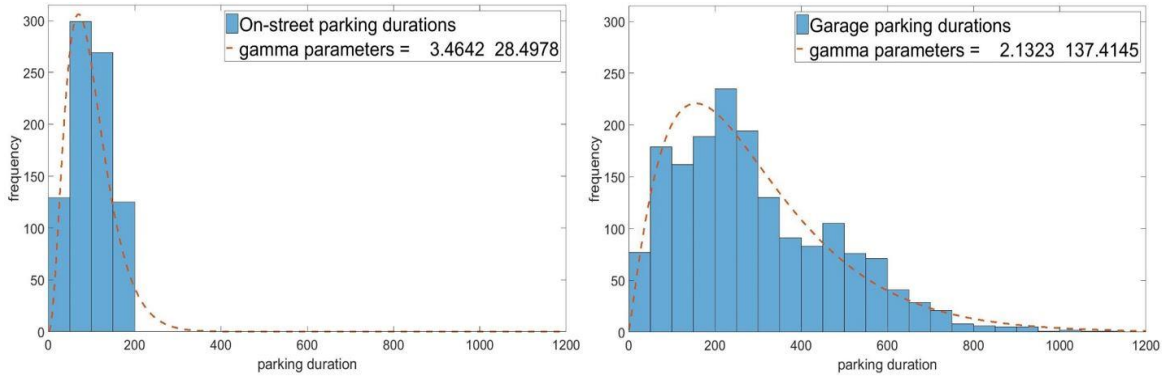
(b) Number of vehicles entering the area over one day

Fig. 3.4. Case study area and parking demand per minute computed as a moving average over 10 min (Source: [Cao et al. \(2019\)](#)).

There are $A = 207$ on-street parking spaces and $G = 2$ parking garages (Jelmoli and Talgarten garage) with a total capacity of $R = 332$ spaces. The on-street parking price is on average $p_{op} = 1.5 \text{ CHF/hour}$ and the garage parking price is on average $p_{gp} = 3 \text{ CHF/hour}$ ([Cao et al. \(2019\)](#)). We consider time slices of 1 min during a working day, i.e., $t = 1 \text{ min}$ for a time horizon of $T = 1440 \text{ min}$. The MFD of the city of Zurich was used for the traffic properties (i.e., $v = 12.5 \text{ km/h}$), based on ([Dakic and Menendez \(2018\)](#), [Loder et al. \(2017\)](#), [Ortigosa et al. \(2014\)](#)).

The parking demand (Fig. 3.4(b)), parking durations, and initial conditions are extracted from an agent-based model in MATSim that is based on previous measurements. This has been validated and proven reasonable for the city of Zurich in [Waraich and Axhausen \(2012\)](#). Note that the parking demand (Fig. 3.4(b)) is a deterministic demand that changes throughout the day. There is a total travel demand of 2687 trips spread between four different user groups (892/ 956/ 838/ 956 trips) in the network associated with different VOTs ($VOT^1 = 29.9 \text{ CHF/h}$; $VOT^2 =$

25.4 CHF/h; $VOT^3 = 25.8$ CHF/h; $VOT^4 = 17.2$ CHF/h). All VOT values are based on the estimated mean values for the VOT for car journeys in Switzerland ([Axhausen et al. \(2006\)](#)). Based on the parking demand and parking usage 23% (618 trips) of the daily demand (i.e., $\beta^i = 0.23, \forall i$) does not search for parking and can be considered as through-traffic, while 77% (2069 trips) of the daily traffic searches for parking ([Cao et al. \(2019\)](#)). At the beginning of every working day 183 vehicles are already in the area, where $N_{op}^0 = 70$ are parked on-street and $N_{gp}^0 = 113$ are in a garage. All other initial conditions are considered as zero, i.e., $N_{ns}^0 = N_s^0 = N_{dgp}^0 = 0$. Taking the network properties into account, the travel distances l_{ns}^k, l_j^k and l_p^k are all uniformly distributed between 0.1 and 0.7 km for all $k \in \{1, \dots, 4\}$.



(a) Histogram of the on-street parking durations.

(b) Histogram of the garage parking durations.

Fig. 3.5. Parking durations for on-street and garage parking.

The parking durations of vehicles are differentiated by their parking destination. Fig. 3.5(a) displays the distribution of on-street parking durations and Fig. 3.5(b) the distribution of garage parking durations. The histogram in Fig. 3.5(a) is comparable to a gamma distribution with a shape parameter of $a_1 = 3.5$ and a scale parameter of $a_2 = 28.5$. The histogram in Fig. 3.5(b) represents the two types of drivers, those that have to park in a garage because $t_d > \tau_{op}$ and those that chose to do it as $t_d \leq \tau_{op}$. It is modeled using the gamma distribution with a shape parameter of $a_1 = 2.1$ and a scale parameter of $a_2 = 137.4$. Depending on the frequency, a bi-modal gamma distribution might be suitable for other case studies. All on-street parking spaces have a parking time limit of $\tau_{op} = 180$ min and the garages have no limit within 24 hours, i.e., $\tau_{gp} = 1440$ min ([Cao et al. \(2019\)](#)). The price per distance driven is assumed as $p_d = 0.3$ CHF/km and the walking speed is set to $w = 5$ km/h ([Browning et al. \(2006\)](#)).

3.4.2 Validation

Given that the original framework ([Cao and Menendez \(2015a\)](#)) focusing only on on-street parking has already been validated – in terms of parking usage and cruising time – in former studies ([Cao et al. \(2019\)](#)) and has been used in [Cao and Menendez \(2018\)](#), here we focus on the validation of the garage parking usage. We validate the garage parking occupancy rate using empirical data collected by the city of Zurich. The real garage occupancy data in Fig. 3.6 is generated through a local monitoring system (PLS Zurich) based on 15-minute intervals between the 1st and the 22nd of

April, 2016. Only data from Tuesdays, Wednesday, and Thursdays from the Jelmoli and Talgarten garages are included in the study to represent a working day demand. Compared to [Cao et al. \(2019\)](#) the garage parking occupancy obtained in this chapter is already close to 100% after the 9.5th hour. This happens because the garage parking duration used here (gamma distribution with mean $\mu = 293$ min in Fig. 3.5(b)) is on average longer than that used in [Cao et al. \(2019\)](#) (gamma distribution with mean $\mu = 230.2$ min) due to our differentiation of parking durations based on parking destinations. Hence, the turnover-rate of the garage parking spaces is reduced, and the 100% garage occupancy is reached at an earlier hour of the day.

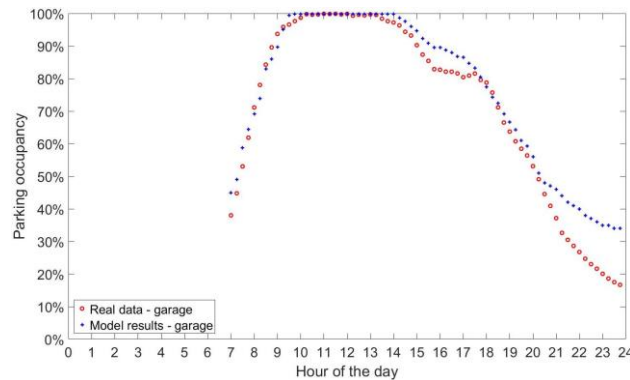


Fig. 3.6. Comparison between the empirical garage and the estimated garage parking occupancy (empirical data were collected and averaged over 12 working days from three weeks during 1st – 22nd April, 2016).

The curve reflecting the estimated garage parking occupancy rate shows a rather similar pattern to that of the real data. The approximation is more accurate compared to the validation in [Cao et al. \(2019\)](#), where no differentiation between on-street and garage parking is modeled. The mean absolute error (MAE) of our estimation is 0.046, less than in [Cao et al. \(2019\)](#).

3.4.3 Model results

In this section, we present some valuable insights with respect to on-street and garage parking. Table 3.6 illustrates the average/total time and driven distance for the vehicles in the states “Searching for on-street parking”, “Drive to garage parking” and “Non-searching” during a typical working day.

On average, each vehicle spends 9.7 minutes in the network (excluding the time spent parked). Not surprisingly, vehicles spend on average longer in the “Searching for on-street parking”-state (3.7 minutes) than in the “Drive to garage parking”-state (3 minutes). A similar behavior can be detected when looking at the average driven distance in the network (Table 3.6). What is interesting, however, is that the absolute difference in average travel time between the two parking options is less than a minute. This happens because of two reasons. First, the area itself is rather small. Second, based on our decision framework in Eq. (10) on average, only 48.8% of the parking vehicles are able to make a decision between on-street and garage parking. The remaining 51.2% must drive towards a parking garage, given that the on-street

parking duration limit is set to $\tau_{op} = 180$ min.

Table 3.6. Average/Total time and driven distance in the network during a typical working day.

State	Average time per vehicle (min/veh)	Total time (min)	Average driven distance (km/veh)	Total driven distance (km)
Searching for on-street parking state	3.72	4323	0.77	901
Driving to garage parking state	2.96	7458	0.69	1554
Non-searching state	4.46	10047	0.93	2093
Total	9.69	21827	2.02	4547

Following the parking demand (Fig. 3.4(b)), the number of vehicles searching for on-street parking increases drastically between the 9th and the 13th hour, and the number of available on-street parking spaces goes down (Fig. 3.7(a)). After the 9.5th hour, the number of available garage parking spaces gets close to zero (Fig. 3.7(b)). The vehicles that cannot access garage parking then return back to the searching-for-on-street-parking state. This leads to more searching vehicles and less available on-street parking spaces at an earlier hour compared to [Cao et al. \(2019\)](#) (Fig. 3.7(a)). The number of vehicles driving to garage parking behaves analogously to the parking demand (Fig. 3.4(b)) and increases between the 5th and the 20th hour (Fig. 3.7(b)). Given the distribution of garage parking durations and the resulting turnover, the number of available garage parking spaces decreases drastically between the 9.5th and the 14th hour (see also Fig. 3.6):

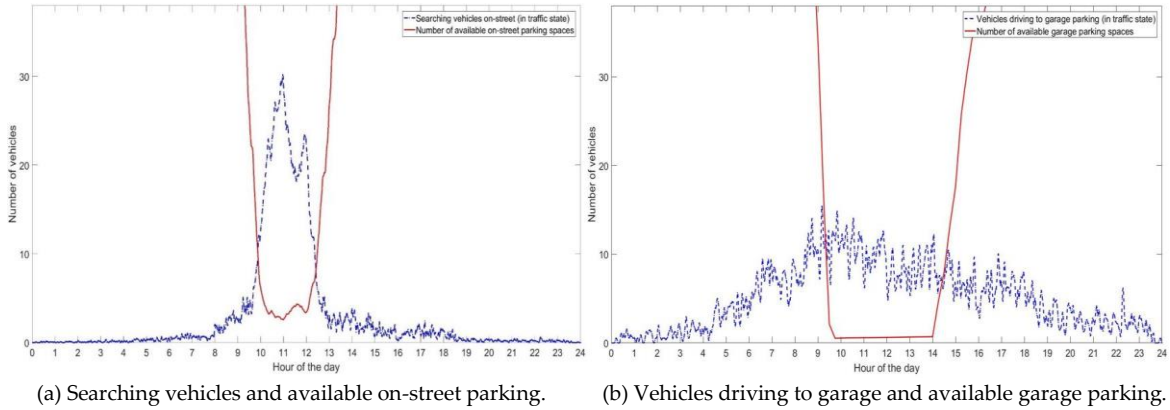


Fig. 3.7. On-street and garage parking demand and supply over a typical working day.

Once there are no available on-street parking spaces anymore (Fig. 3.7(a)), the average cruising time increases (Fig. 3.8). This leads to an increase in the costs associated with cruising-for-on-street-parking.

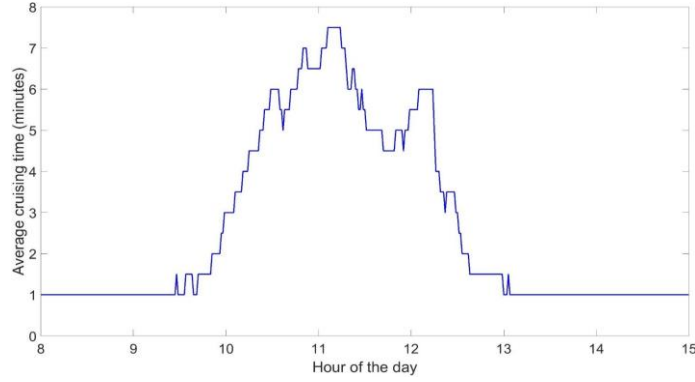
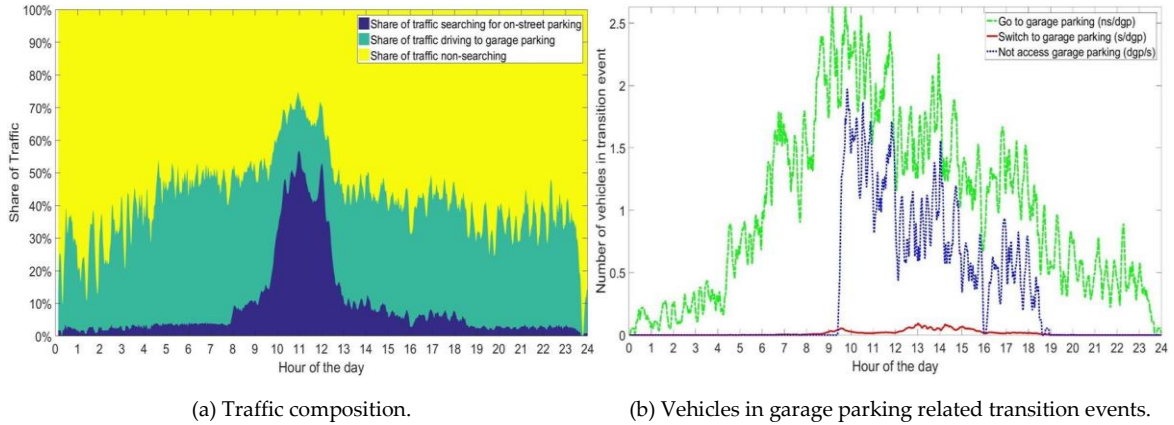


Fig. 3.8. Average cruising time for on-street parking over a typical working day.



(a) Traffic composition.

(b) Vehicles in garage parking related transition events.

Fig. 3.9. Traffic composition and garage parking related transition events as a moving average over 10 min.

Fig. 3.9(a) shows the share of vehicles searching for on-street parking, driving to garage parking, or non-searching over time. This traffic composition is related only to the vehicles circulating on the network, and not those that are parked. Between the 10th and the 13th hour, the network has the highest percentage of vehicles searching for on-street parking. Fig. 3.9(b) shows the number of vehicles $n_{ns/dgp}^{i,k}$, $n_{s/dgp}^{i,k}$ and $n_{dgp/s}^{i,k}$ summed over all user groups $k \in K$ over a typical working day. $n_{ns/dgp}^{i,k}$ behaves analogously to the parking demand (Fig. 3.4(b)). It increases between the 5th and the 20th hour. $n_{s/dgp}^{i,k}$ is negligibly small. $n_{dgp/s}^{i,k}$ increases from approximately the 9.5th hour since the garage parking occupancy rate is close to 100% (Fig. 3.6). Thus, not enough available garage parking spaces are left (Fig. 3.7(b)) and vehicles are not able to access the parking garages.

3.4.4 Impacts of on-street and garage parking pricing

We now use our model to capitalize on the interactions between on-street and garage parking pricing to improve traffic performance in the short-term (i.e., minimize the average searching time and distance). This might be accomplished by increasing the attractiveness of garage parking such that fewer vehicles insist on searching for an on-street parking space, or vice versa, once the garages become full. Remember that this is only possible for drivers who actually have a choice and not for drivers who can only use a garage (Eq. (10)) due to the on-street parking time limit restrictions.

What is the ideal ratio between on-street and garage parking fees to attract drivers such that they avoid cruising for on-street parking? We study the impacts of a limited on-street and garage capacity in combination with different on-street and garage parking pricing parameters, i.e., due to the limited number of garage parking spaces and different related pricing schemes congestion might occur and affect the traffic performance in the network.

Remember that both the hourly on-street and garage parking fee rates, p_{op} and p_{gp} , are part of the decision related cost variables for on-street and garage parking. Based on these cost variables, the drivers decide for on-street or garage parking, affecting the average travel time in each parking-related state as illustrated in Fig. 3.10. Increasing the ratio $\frac{p_{op}}{p_{gp}}$ leads to a higher cost variable $C_{op}^{i,k}$ (section 3.2.2.1) and the drivers are more likely to drive to garage parking. Thus, the average time for vehicles driving to garage parking increases, while the average searching time decreases (Fig. 3.10). Both times are equal for $\frac{p_{op}}{p_{gp}} = 1.75$. At the same time, the average vehicle time for both searching and driving to garage parking vehicles increases in the network after some initial drop (green dotted line in Fig. 3.10). The results for the average distance driven follow a similar pattern as Fig. 3.10, but the details are omitted in this chapter for brevity.



Fig. 3.10. The impact of on-street and garage parking pricing schemas on average time searching/driving to garage parking.

Table 3.7 highlights these findings by comparing the reference scenario in section 3.4.3 with an average $p_{op} = 1.5$ CHF/hour and an average $p_{gp} = 3$ CHF/hour, i.e., $\frac{p_{op}}{p_{gp}} = \frac{1}{2}$, with the following scenarios:

- $p_{op} = 0.75$ CHF/hour and $p_{gp} = 3$ CHF/hour, i.e., $\frac{p_{op}}{p_{gp}} = \frac{1}{4}$
- $p_{op} = 3$ CHF/hour and $p_{gp} = 3$ CHF/hour, i.e., $\frac{p_{op}}{p_{gp}} = 1$
- $p_{op} = 6$ CHF/hour and $p_{gp} = 3$ CHF/hour, i.e., $\frac{p_{op}}{p_{gp}} = 2$.

As one would expect, the short-term financial benefits for the city, i.e., the total revenue from both on-street and garage parking pricing, increase as either p_{op} and p_{gp} increase.

Table 3.7. Comparison of different policies presented in section 3.4.4 (Different on-street and garage parking fees), section 3.4.5 (Availability of garage usage information) and section 3.4.6 (Converting on-street to garage parking) to the reference scenario in section 3.4.3. Value within parenthesis represents the percentage change with respect to the reference scenario.

Policies	Section 3.4.3: Reference scenario	Section 3.4.4: Different on-street and garage parking pricing			Section 3.4.5: Garage usage information available	Section 3.4.6: Conversion rate from on-street to garage parking		
	$\frac{p_{op}}{p_{gp}} = \frac{1}{2}$	$\frac{p_{op}}{p_{gp}} = \frac{1}{4}$	$\frac{p_{op}}{p_{gp}} = 1$	$\frac{p_{op}}{p_{gp}} = 2$	Known to all drivers	10 %	30 %	50 %
Average time for vehicles searching for on-street parking (min/veh)	3.72	4.32 (+16.1 %)	3.61 (-3 %)	3.53 (-5.1 %)	2.93 (-21.2 %)	2.61 (-29.8 %)	0.89 (-76.1 %)	0.18 (-95.2 %)
Average time for vehicles driving to garage parking (min/veh)	2.96	2.29 (-22.6 %)	3.31 (+11.8 %)	3.83 (+29.4 %)	2.14 (-27.7 %)	4.04 (+36.5 %)	5.38 (+81.8 %)	5.93 (+100 %)
Average time for vehicles searching for on-street parking and driving to garage parking (min/veh)	6.68	6.61 (-1.1 %)	6.92 (+3.6 %)	7.36 (+10.2 %)	5.07 (-24.1 %)	6.65 (-0.4 %)	6.27 (-6.1 %)	6.11 (-8.5 %)
Average time for vehicles non-searching (min/veh)	4.46	4.46 (+0 %)	4.45 (-0.2 %)	4.44 (-0.5 %)	4.48 (+0.5 %)	4.41 (-1.1 %)	4.4 (-1.3 %)	4.4 (-1.3 %)
Average driven distance for vehicles searching for on-street parking (km/veh)	0.77	0.9 (+16.9 %)	0.75 (-2.6 %)	0.73 (-5.2 %)	0.61 (-20.8 %)	0.53 (-31.1 %)	0.18 (-76.6 %)	0.1 (-87 %)
Average driven distance for vehicles driving to garage parking (km/veh)	0.69	0.54 (-21.7 %)	0.77 (+11.6 %)	0.89 (+29 %)	0.5 (-27.5 %)	0.92 (+33.3 %)	1.19 (+72.5 %)	1.23 (+78.3 %)
Average driven distance for vehicles searching for on-street parking and driving to garage parking (km/veh)	1.46	1.44 (-1.4 %)	1.52 (+4.1 %)	1.62 (+11 %)	1.11 (-24 %)	1.45 (-0.7 %)	1.37 (-6.2 %)	1.33 (-8.9 %)
Average driven distance for vehicles non-searching (km/veh)	0.93	0.93 (+0 %)	0.93 (+0 %)	0.93 (+0 %)	0.93 (+0 %)	0.93 (+0 %)	0.92 (-1.1 %)	0.92 (-1.1 %)
Total on-street parking revenue	3968	2040 (-48.6 %)	7764 (+95.7 %)	13845 (+248.9 %)	3974 (+0.2 %)	3720 (-6.3 %)	3192 (-19.6 %)	2634 (-33.6 %)
Total garage parking revenue	13163	12714 (-3.4 %)	13443 (+2.1 %)	13634 (+3.6 %)	13131 (-0.2 %)	14314 (+8.7 %)	16606 (+26.2 %)	19008 (+44.4 %)
Total revenue created by both on-street and garage parking	17131	14754 (-13.9 %)	21207 (+23.8 %)	27479 (+60.4 %)	17105 (-0.2 %)	18034 (+5.3 %)	19798 (+15.6 %)	21642 (+26.3 %)

As a matter of fact, increasing only the price of on-street parking (e.g., to 3 CHF or 6 CHF) increases the revenues for both the on-street and the garage parking. The

former is intuitive, the latter comes from the fact that more vehicles move into garage parking in order to avoid the expensive on-street parking fees. Only doubling p_{op} compared to the reference scenario (scenario $\frac{p_{op}}{p_{gp}} = 1$) leads to 23.8% more parking revenue. The total revenue would increase slightly faster if p_{gp} were to increase, since more than 60% of the parking spaces in the network are garage parking spaces. Every city can estimate their best on-street and garage parking fees according to its plans on improving the traffic performance, the congestion and the environmental conditions and on collecting parking fee revenue (see the different on-street and garage parking pricing ratios in Table 3.7).

It is also possible to use more advanced sensitivity analysis techniques (e.g., as in [Ge et al. \(2015\)](#) and [Ge and Menendez \(2017\)](#)) to further understand the impact of different inputs (dependent or independent) on these metrics.

Different on-street and garage parking fee rates can lead not only to more vehicle time/distance on the network, worse traffic performance, and worse environmental conditions, but also to various financial revenue outputs. Based on these results cities can find reasonable hourly on-street and garage parking fees such that the average time driving to garage parking and searching for on-street parking are not negatively affected and additionally, acceptable financial revenues are obtained. Our methodology provides the tools to do a cost-benefit analysis and to study the trade-off between revenues and the average travel time of vehicles trying to park.

3.4.5 Availability of garage usage information to all drivers

In reality, the actual garage parking availability also influences the drivers' decision to park on-street or to drive towards a parking garage. This garage usage information can be made available to the drivers by providing real-time smartphone applications or garage information signs in the traffic network.

In this section, we include full real-time information of garage parking availability into our on-street and garage parking model, i.e., the drivers have access to real-time usage information but no forecast of future garage availability. Since this garage parking availability influences the driver's parking decision, we replace all R by R^i in Eq. (9) and Eq. (30). Table 3.7 illustrates the average time and driven distance for the scenario with garage availability information given to all drivers in the network during a typical working day. This additional information helps to reduce the average searching time by 21.2 % and the average time driving to garage parking by 27.7 % compared to the scenario without garage information available (section 3.4.3). The average driven distance in the network reduces similarly and the revenue from on-street and garage parking fees stays constant (Table 3.7). Allowing drivers to make their on-street or garage parking decision based on real-time occupancy data leads to a better traffic performance on the network, and on average, a faster journey for drivers searching for parking, without affecting much the parking revenues.

The parking choice for garage over on-street parking decreases drastically for drivers with available garage usage information between the 9.5th and the 14th hour

compared to drivers who have no garage information available (Fig. 3.11). Since the increase in the average cruising time (Fig. 3.8) has an impact on the drivers' decision, more drivers without any available garage usage information drive to garage parking between the 9.5th and the 13th hour. Due to the lack of garage information, this parking choice is made even if the garage occupancy rate is low. Note that this parking choice only affects the portion of the parking demand that can make a decision between on-street and garage parking due to the on-street parking duration limit. By including the garage usage information into the decision framework, the drivers react towards the garage occupancy rate. The garage occupancy rate (Fig. 3.6) is then reflected in Fig. 3.11 and the parking choice for garage parking increases from the 14th hour analogously to the decrease of the garage occupancy rate in Fig. 3.6.

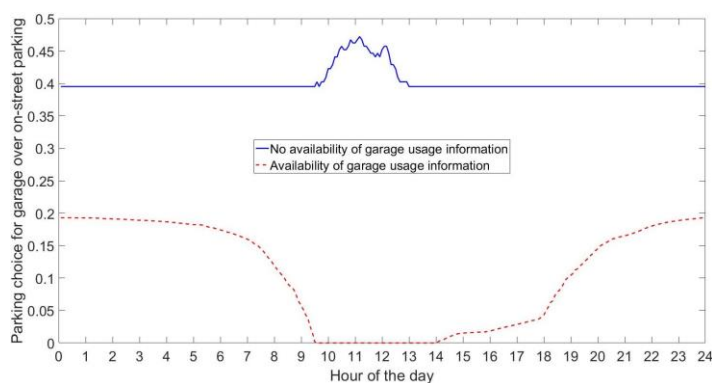


Fig. 3.11. Parking choice for garage over on-street parking over a typical working day. The parking choice is illustrated for the scenarios without (section 3.4.3) and with (section 3.4.5) available garage usage information for all drivers. This choice is only possible for drivers with desired parking duration $t_d \leq \tau_{op}$.

3.4.6 Impacts of converting on-street parking to garage parking spaces

It has been one of the policies in Zurich, Switzerland to convert on-street to garage parking spaces. In this section, we evaluate the effects of this policy on traffic performance and the city's revenue. Converting on-street to garage parking spaces is not a trivial task, since real estate in downtown areas is normally expensive to be dedicated to parking garages. However, many cities around the world have indeed done it in order to remove on-street parking spaces without necessarily downsizing the overall parking supply. For example, since the 1990's Zurich has introduced a parking supply cap system in the inner-city ([Fellmann et al. \(2009\)](#)), i.e., in case a new parking space is created in a parking garage, an existing on-street parking space must be removed such that the parking supply is kept the same ([Kodransky and Hermann \(2011\)](#)). Since the introduction of this policy a few parking garages (e.g., City Parkhaus Zurich and Globus Parkhaus Zurich) and office parking lots have been built, and as a result, on-street parking space has been recovered for other activities. In this chapter, we assume a new parking garage is built and the number of parking garages increases to $G = 3$. At the same time, valuable on-street parking space becomes available. We assume that the recovered road space while converting on-street parking to garage parking spaces has no influence on the traffic flow, and can be used

for other activities as in the case of Zurich (e.g., to create pedestrian zones or bicycle lanes). It is further assumed that the conversion of on-street parking does not influence the on-street and garage parking accessibility in the network. The total garage capacity starts at $R = 332$ (as in section 3.4.3) and increases dependent on the number of converted on-street parking spaces. Note that the initial conditions for N_{op}^0 and N_{gp}^0 are adapted accordingly.

The outputs in Fig. 3.12(a)-(b) show the impacts of the on-street parking conversion on the average time searching/driving to garage parking and the parking fee revenue. The impacts on the average/total driven distance follow a similar pattern, but the details are omitted in this chapter for brevity.

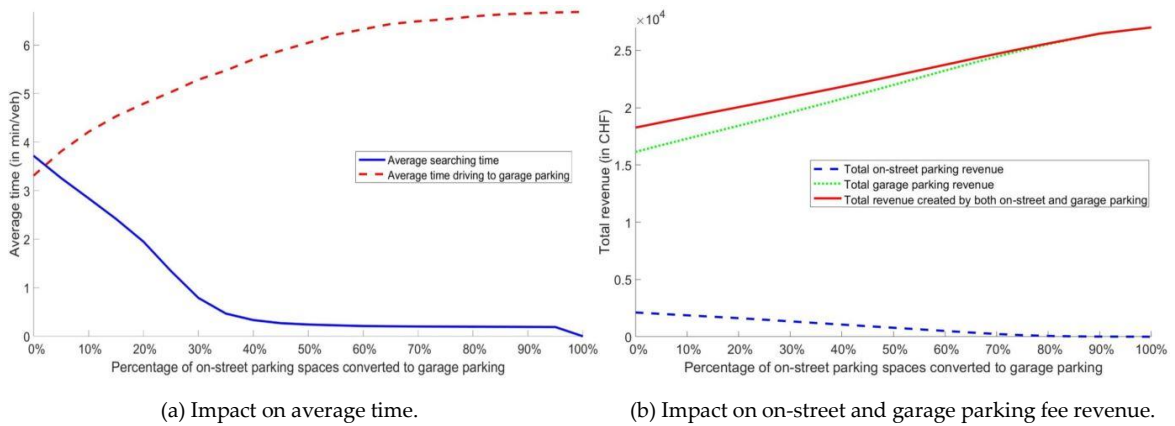


Fig. 3.12. The influence of converting on-street to garage parking on the average/total time searching and driving to garage parking, and on the parking fee revenue in the network.

The more on-street parking spaces that are converted to garage parking spaces, the less drivers chose to go to on-street parking in the first place. This leads to a decreasing average searching time and an increasing average time driving to garage parking in the short-term (Fig. 3.12(a)). Table 3.7 highlights these findings by comparing the reference scenario in section 3.4.3 with the scenarios of having a 10%, 30%, and 50% conversion rate from on-street to garage parking spaces. The average time/distance for vehicles that wish to park decreases as more on-street parking spaces are converted to garage parking. When converting on-street parking, for simplicity, we assume that the distribution for the garage parking durations becomes the same for all levels (based on the combination of Fig. 3.5(a) and Fig. 3.5(b)) as in [Cao et al. \(2019\)](#). Fig. 3.12(b) and Table 3.7 show the impact of the on-street parking conversion on the total revenue created by on-street/garage parking. While a decreasing number of on-street parking spaces leads to a decreasing total on-street parking revenue, it leads to an increasing total revenue from both on-street and garage parking fees. A conversion of on-street parking to garage parking spaces leads to a reduced travel time and distance for vehicles wishing to park and an increase in the total parking revenue for the city.

3.5 Summary of the chapter

In this study, we develop a dynamic macroscopic on-street and garage parking model such that the short-term influences of different on-street and garage parking policies on the traffic system can be studied and illustrated. The macroscopic model is built on a traffic system with a parking search model over time. It is incorporated into the on-street parking framework from [Cao and Menendez \(2015a\)](#) (chapter 2). We validate this model based on real data for a case study of an area within the city of Zurich, Switzerland.

The main contributions of this chapter are three-fold.

First, we model garage parking macroscopically, including the parking searchers' decision between driving to a parking garage or searching for an on-street parking space in the network. This includes the influences on the searching-for-parking traffic (cruising), the congestion in the network (traffic performance), the total driven distance (environmental impact), and the revenue created by on-street and garage parking fees for the city.

Second, we analyze not only the relationship between on-street and garage parking, but also their interdependency on cruising-for-parking traffic and traffic performance with respect to different parking fees. Different hourly on-street and garage parking fee ratios can lead not only to more vehicle time/distance in the network, but also to various financial revenue outputs. Thus, this analysis can be used for city councils or private agencies to find reasonable hourly on-street and garage parking fee ratios such that the average vehicle time/distance is not negatively affected and additionally, acceptable financial revenues are obtained. Our methodology provides the tools to do a cost-benefit analysis and to study the trade-off between the revenue and the average travel time. In the long-term, drivers might avoid paying high on-street or garage parking fees and quit their journeys. This could affect the demand, but long-term effects are out-of-scope of this research.

Third, our model allows us to analyze parking policies in city center areas, e.g., the short-term effects of converting on-street to garage parking spaces on the traffic system can be simulated, and recommendations for city councils can be made. In the city of Zurich, a conversion of on-street parking to garage parking spaces might lead to a higher average time driving to garage parking and a lower average searching time in the short-term with an increase in the total parking revenue. Additionally, the impact of the availability of garage usage information on all drivers can be analyzed. This might lead to a better traffic performance on the network and an on average faster and shorter journey for each driver searching for parking.

The general framework provides an easy to implement methodology to macroscopically model on-street and garage parking. All methods are based on very limited data inputs, including travel demand, VOT, number of garages with their capacity, the traffic network, and initial parking specifications. Only aggregated data at the network level over time are required such that there is no need for individual

on-street and garage parking data. This macroscopic approach saves on data collection efforts and reduces the computational costs significantly compared to existing literature. Additionally, there is no requirement of complex simulation software, and the model can be easily solved with a simple numerical solver.

So far, the model only accounts for cars, so any changes in the demand and how those could affect other transportation modes have not been studied. However, recent advances in the MFD and its multimodal extension, the 3D-MFD ([Dakic et al. \(2020\)](#), [Geroliminis et al. \(2014\)](#), [Loder et al. \(2017\)](#)), could open new opportunities to enhance the model by including public transport. If public transport was introduced, the effect of using parking revenue to improve or subsidize mass transit and increase service frequency could potentially be analyzed. Also, here we assume that double parking is not an issue, and we do not account explicitly for delivery parking. Notice, however, that there are already some studies on the development of dynamic delivery parking spaces [Roca-Riu et al. \(2017\)](#) which could also be integrated into the proposed framework in the future.

Overall, the usage of the model is far beyond the illustration in the case study presented here. Here we have assumed that the driving time/distance within the parking garages is negligible. We have done so because that travel does not affect traffic performance at the city level. However, it would be relatively easy to integrate the cost of travel within the parking garages into our decision model, and account for the fact that drivers prefer to park on lower floors close to the exits. A further consideration is tiered parking pricing, which could also be included into the model. Certain cities have tiered pricing for both on-street and garage parking such that the driver may pay a low rate for the first hours, and then the rate jumps up significantly to increase turnover and promote higher parking availability. The model could then be extended to study responsive parking pricing schemes. Time-dependent parking fees can be used to move the parking demand away from the daily peak. Future research can investigate parking fees that are not only dependent on the parking demand of each user group over time, but also on the available parking supply in the network. Additionally, this could include a traffic demand split with a fixed (low subsidized) parking fee for all on-street and/or garage parking spaces. All remaining portions of demand could be treated responsively, reflecting the external costs for parking. This approach can be motivated by, e.g., the subsidy by a company or a city for their residents.

In summary, the model can be used to efficiently analyze the influence of different on-street and garage parking policies on the traffic system for a smaller geographic scale network, despite its simplicity in data requirements. Based on scarce aggregated data, this model can be used to analyze how on-street and garage parking policies can affect the traffic performance; and how the traffic performance can affect the decision to use on-street or garage parking.

Chapter 4:

Parking Pricing vs. Congestion Pricing: A Macroscopic Analysis of their Impact on Traffic

This chapter is based on the results presented in:

Jakob, M., and M. Menendez. 2020. "Parking pricing vs. congestion pricing: a macroscopic analysis of their impact on traffic". *Transportmetrica A: Transport Science*, doi: 10.1080/23249935.2020.1797924.

4.1 Introduction

Traffic congestion is a growing challenge for cities worldwide. Therefore, many city councils have considered introducing a congestion charge to improve speeds and reduce congestion in downtown areas. The first cities to introduce an electronic road pricing system with a combination of cordon and corridor pricing schemes were Singapore ([Goh \(2002\)](#), [Olszewski and Xie \(2005\)](#)) and London ([Leape \(2006\)](#), [Santos \(2005\)](#), [Santos and Shaffer \(2004\)](#)). Other cities such as Stockholm, Bergen, Oslo and Milan ([Eliasson \(2009\)](#), [Hess and Börjesson \(2019\)](#)) also implemented similar schemes. However, the introduction of congestion pricing has not been successful so far in other areas such as Hong Kong ([Ison and Rye \(2005\)](#)). New York City rejected its congestion pricing proposal in 2008, but new efforts in 2019 will lead New York to become the first city in the U.S. to implement a traffic congestion fee by 2021 ([Gu et al. \(2018a\)](#), [Griswold \(2019\)](#), [Schaller \(2010\)](#)). Overall, the actual implementation of congestion pricing schemes is rather limited due to the controversial issues regarding the high initial costs, problems of discrimination, and where to start the border. There are also many debates in relation to the disposition of the revenues raised, undesirable distribution effects, and the social and political acceptability of the congestion charge ([Button \(1993\)](#), [Cervero \(1998\)](#), [Small et al. \(2007\)](#)). In this research, we analyze the differences in traffic performance driven by parking pricing policies as a comparable option to congestion pricing. Parking pricing strategies can be easily installed and maintained by a city, and they normally face much less political opposition ([Arnott et al. \(1991\)](#)). In addition, their introduction can lead to remarkable traffic performance improvements ([Arnott et al. \(1991\)](#), [Cao et al. \(2019\)](#), [Shoup \(2019\)](#)). However, parking pricing policies only affect drivers using public parking in the area compared to congestion pricing policies affecting a larger group of drivers in the network (e.g., drivers using private parking, drivers passing through the central area, drivers picking up and/or dropping off passengers). That being said, when the share of drivers searching for public parking is large enough, parking pricing could indeed be considered as a viable alternative to congestion pricing. In this chapter, we take these trade-offs into account, so cities can use our methodology to evaluate the parking and congestion pricing policies especially in areas with a high parking demand for public parking spaces. We propose a macroscopic framework to evaluate the short-term performance of an urban network under the implementation of parking pricing policies as an alternative to a congestion pricing scheme.

The contributions of this chapter are fourfold. First, we evaluate how parking and congestion pricing affect the traffic and parking system (i.e., traffic performance, parking availability, revenue for the city, etc.) and how the traffic and parking system (i.e., traffic congestion, parking pricing, etc.) affect the drivers' decision between entering the network by car or using P+R instead. Second, we propose a decision model and integrate it into a multimodal macroscopic traffic and parking framework focusing on parking and congestion pricing. This decision is faced by multiple user

groups with respect to their VOT. This allows us to evaluate the distributional effects of different VOTs on the drivers' decision between entering the area by car or switching to P+R instead. Third, we not only provide a framework to compare parking and congestion pricing scenarios, but also to find the best relation between the parking fee and the congestion charge in order to improve the traffic performance in the network or the total revenue for the city (which could be used to improve the P+R facilities). Fourth, we illustrate our parking and congestion pricing methodology in a central area with a high parking demand for public parking spaces within the city of Zurich, Switzerland, and show that parking pricing is indeed a viable option compared to congestion pricing, potentially leading to traffic performance improvements inside the protected network.

The chapter is organized as follows. Section 4.2 shows the overall decision model associated with the introduction of parking and congestion pricing to a central area. Section 4.3 illustrates the multimodal macroscopic traffic and parking framework including our decision model. Section 4.4 presents a case study of an area within the city of Zurich. Section 4.5 summarizes this chapter.

4.2 Introducing parking pricing vs. congestion pricing policies for a central area

In this section, we build the framework to compare the traffic performance impacts of different parking and/or congestion pricing policies. When introducing/increasing parking pricing within an area with no congestion pricing combined with P+R facilities, the drivers face a new choice between entering the network and leaving their car outside the area, potentially using the available P+R facilities and PT (i.e., bus, tram and/or train) to reach the center. A similar decision happens for drivers when congestion pricing gets introduced to a central area. Please note that we assume P+R facilities exist in both policies.

In this research, we analyze the influencing factors (section 4.2.1) and the mathematical decision model (section 4.2.2) for two policies: parking pricing (policy 1) and congestion pricing (policy 2).

4.2.1 Factors affecting the decision framework

The main variables and parameters for our framework, and basic model assumptions are briefly described below.

Main variables and parameters:

All policies are modeled macroscopically using a logistic function based on the cost of entering the network by car and the cost of using the P+R facility outside the network. Some factors including the congestion or parking charges have only an impact on the cost of entering the network, some factors including the P+R pricing only affect the cost of not entering the network, and others (i.e., the number of parking

spaces for P+R and spaces inside the network) impact both cost variables by directly influencing the decision. Table 4.1 introduces the main variables and parameters used in our methodology, in addition to some variables from Table 2.1, 3.1, 3.2 and 3.3 which are also used in this chapter.

Recall that our traffic model analyzes a homogeneous, compact urban network of length L (in link-km) and L_{lane} (in lane-km) representing a central area with standard parking policies (e.g., downtown areas or portions thereof) and a high parking demand for public parking spaces. The network's average block size is represented as b . It is simulated over a total time horizon T (e.g., a day). This time period is divided into time slices t (e.g., 1 minutes) such that the traffic and parking conditions are steady within each time slice, but they can change over multiple time slices. Drivers have different VOTs, VOT^k , according to their individual user group $k \in K$, with the total number of user groups denoted as K . This can be dependent on the drivers' residence location, income, career, working state, etc. Due to our macroscopic modelling approach it is not necessary to record the individual location of each car and parking space throughout time. Instead, our multimodal macroscopic traffic model (section 4.3.1) tracks the average number of cars during every time slice and the average searching times and traveled distances in the area.

Assumptions about homogeneity:

For simplicity, the area contains A identical parking spaces inside, and P P+R spaces outside the parking and congestion pricing area. A differentiation between on-street and garage parking can be added using the macroscopic modelling approach in chapter 3, but here, for simplicity, we obviate that. All drivers searching for parking are assumed to be homogeneously distributed within the overall traffic, and all parking spaces (not necessarily the available ones) are assumed to be uniformly distributed on the network.

Assumptions about PT and mode choice:

The PT route is assumed to be unidirectional (i.e., it goes on a loop around the network). The total number of PT stops is assumed to be uniformly distributed across the network and the actual travel distance of each PT passenger is on average uniformly distributed over time. Once the drivers have entered the network by car, it is assumed that they continue their trip with their car and do not change towards PT within the network. This is reasonable since the drivers already paid the congestion toll. We also assume that drivers do not cancel their trip.

Assumptions about walking:

After parking in or riding a bus into the area, the drivers require some walking distance to reach their final destination. The drivers' walking speed, w , is assumed to be constant. At an earlier stage, the drivers switching to P+R already require some walking distance between the parking space and the PT stop near the P+R facility which is assumed to be negligible for our decision framework.

Assumptions about pricing and toll delays:

The hourly parking fee p_p , the congestion toll rate p_t , the P+R fee p_{pr} , and the round-trip PT fare p_{PT} are assumed to be constant over time. There is no traffic delay

assumed while paying the congestion toll.

Table 4.1. List of main variables and parameters.

Notation	Definition
P	Total number of existing P+R spaces outside the area.
P^i	Number of available P+R spaces outside the area at the beginning of time slice i .
p_p	Hourly parking fee in the area.
p_t	Congestion toll rate to enter the area by car.
p_{pr}	P+R fee outside the area. It is considered as a fixed fee over the time horizon T .
p_{PT}	Round-trip PT fare paid to enter the area from the P+R facility by PT.
u^i	Average PT speed in time slice i , i.e., average speed of buses, trams and/or trains, including PT dwell time.
μ_{car}	Coefficient capturing the aspect that PT vehicles typically move slower than cars due to frequent stops.
μ_{PT}	Coefficient capturing the aspect that PT speeds might exceed car speeds during congested times due to dedicated lanes.
ϑ_{car}	Coefficient capturing the marginal effects of car density on car speeds in the area.
ϑ_{PT}	Coefficient capturing the marginal effects of PT vehicle density on car speeds in the area.
k_{car}^i	Density of cars in time slice i .
k_{PT}^i	Density of PT vehicles in time slice i .
l_{PT}	Average distance driven by using PT from the P+R facility to the area.
$t_{d,\xi}$	Parking duration of cars parking inside the area (p) or using P+R (pr), $\xi \in \{p, pr\}$.
h	Average headway of PT from the P+R facility to PT stops.
S	Total number of PT stops in the area.
$C_{\xi}^{i,k}$	Total cost of entering the area by car (car) or by using P+R (pr) in time slice i for user group $k \in K$, $\xi \in \{car, pr\}$.
$\delta_{car}^{i,k}$	Share of drivers that enter the area by car in time slice i for user group $k \in K$.
ADD_{PT}	Average distance travelled using PT from P+R space to PT stop in the network.
AWD_{ξ}	Average walking distance from on-street parking space (op) or PT stop (PT) to destination, $\xi \in \{p, PT\}$.
t_s	Average searching time per car to find an available parking space for all user groups K over T .
I_{tot}	Total revenue resulting from parking fees, P+R and congestion pricing (tolls) for all user groups K over T .

4.2.2 Mathematical model for the parking and congestion pricing decision framework

This section illustrates the mathematical decision framework for drivers entering the network by car or choosing to use P+R instead. The model can be used for both policies explained before, so that we can compare and analyze the traffic performance under different scenarios.

Drivers' choice, $\delta_{car}^{i,k}$, for entering the area by car is modelled in Eq. (36a-b) using a logistic function based on A and P (the total number of existing parking and P+R spaces, respectively), $C_{car}^{i,k}$ (the total cost of entering the area by car, modelled in section 4.2.2.1), and $C_{pr}^{i,k}$ (the total cost of using P+R, modelled in section 4.2.2.2) in time slice i for user group $k \in K$.

$$\delta_{car}^{i,k} = \frac{e^{\eta^{i,k}}}{1 + e^{\eta^{i,k}}} \quad (36a)$$

where

$$\eta^{i,k} = \frac{\frac{A}{A+P} \cdot C_{pr}^{i,k} - \frac{P}{A+P} \cdot C_{car}^{i,k}}{\min\left\{\frac{A}{A+P} \cdot C_{pr}^{i,k}, \frac{P}{A+P} \cdot C_{car}^{i,k}\right\}} \quad (36b)$$

The drivers' choice between entering the area by car or by using P+R is based on the comparison between the weighted cost variables $\frac{A}{A+P} \cdot C_{pr}^{i,k}$ and $\frac{P}{A+P} \cdot C_{car}^{i,k}$ in Eq. (36b). Their difference is set in relation to $\min\left\{\frac{A}{A+P} \cdot C_{pr}^{i,k}, \frac{P}{A+P} \cdot C_{car}^{i,k}\right\}$ as the drivers' choice is based on a relative weighted cost difference. Using the minimum here is necessary to set a reference to the lowest cost value. The weight parameters $\frac{A}{A+P}$ and $\frac{P}{A+P}$ in Eq. (36b) illustrate the parking supply dependency incorporated into the parking choice. An underlying assumption for Eq. (36a-b) is that all drivers have access to information about A , P and the basic data to estimate $C_{car}^{i,k}$ and $C_{pr}^{i,k}$. However, drivers have, for simplicity, no access to real-time parking usage information, i.e., we only consider the total number of existing parking and P+R spaces, A and P , respectively; and we do not use the time-dependent parking availabilities in Eq. (36b). This information could, however, be added to this model as per the methodology proposed in section 3.4.5 to account for the value of real-time parking information.

4.2.2.1 Cost of entering the network by car

Eq. (37) describes the cost of entering the network by car, $C_{car}^{i,k}$, for each user group $k \in K$ in time slice i .

$$C_{car}^{i,k} = \underbrace{p_t}_{\text{term 1}} + \underbrace{p_p \cdot E(f(t_{d,p}))}_{\text{term 2}} + \underbrace{p_d \cdot v^i \cdot ACT^i}_{\text{term 3}} + \underbrace{VOT^k \cdot \left(\frac{l_{ns}^k}{v^i} + ACT^i + \frac{2 \cdot AWD_{op}}{w} + \frac{l_p^k}{v^i}\right)}_{\text{term 4}} \quad (37)$$

Term 1 represents the congestion toll rate (policy 2), p_t . Term 2 represents the total parking charge (policy 1), which is dependent on the hourly parking fee, p_p , and the expected parking duration, $E(f(t_{d,p}))$. While this fee will be fixed here, it is also possible to make it variable using a responsive parking pricing scheme (chapter 5). Term 3 represents the average cost associated with the cruising distance for parking (i.e., external costs as petrol, wear and tear of cars) converted to price units (chapter 3). The average cruising time ACT^i is determined as in section 5.3.3.3 using a queueing diagram. The price per kilometer driven is denoted as p_d and the average travel speed in time slice i is represented as v^i . Here, for simplicity, we assume that v^i is representative of the average network speed during the future search process. Term 4 represents the time-related costs based on the drivers' VOT expressed in price units for $k \in K$. It includes the costs associated with the average distance before starting to search for parking l_{ns}^k , the average cruising time ACT^i , the average walking distance AWD_{op} from the parking space to the final destination, and the average distance to

leave the area after parking $l_{p/}^k$. We multiply AWD_{op} by 2 to account for the return trip to the car as well. Notice that the longer the drivers search for parking, the higher ACT^i is, and consequently also $C_{car}^{i,k}$. In this case, it is more likely that the drivers might decide to use P+R instead of entering the area by car. Using the abstraction of the network as a square grid, its total length, L , is equivalent to joining all blocks of average known length b together. Recall that AWD_{op} is determined in Eq. (13), as parking spaces are uniformly distributed throughout the area.

4.2.2.2 Cost of using P+R

Eq. (38) describes the cost of not entering the area by car and using P+R instead, $C_{pr}^{i,k}$, for each user group $k \in K$ in time slice i . Notice that for a case where there are different areas with large variations in P+R and PT properties (e.g., in PT stops, P+R fees, PT fares, or dwell times), one can use different adjacent subnetworks, each modeled as the network presented here.

$$C_{pr}^{i,k} = \underbrace{p_{pr} + p_{PT}}_{\text{term 1}} + \underbrace{VOT^k \cdot \left(h + \frac{2 \cdot ADD_{PT}}{u^i} + \frac{2 \cdot AWD_{PT}}{w} \right)}_{\text{term 2}} \quad (38)$$

Term 1 represents the total fee, including the P+R fee, p_{pr} , and the round-trip PT fare, p_{PT} , for buses, trams and/or trains from the P+R facility. Note that the P+R fee is fixed over the time horizon T . This is often the case, for example in cities like Zurich, Switzerland. However, this is not necessary for our model, as we can adapt term 1 according to, e.g., an hourly P+R pricing rate. In some instances, p_{pr} could also be zero. Term 2 represents all the time-related costs expressed in price units to reach the driver's destination within the network and to return back to the parked car at the P+R facility. Once the driver has parked the car at the P+R space, he/she has to wait until the next PT vehicle arrives. This average waiting time is reflected by $h/2$ for the one-way trip (h for the two-way trip), where h is the average headway of the PT line connecting the P+R facility to the area. The average round-trip travel time for the PT ride is modelled by $2 \cdot ADD_{PT}/u^i$, where ADD_{PT} represents the average distance travelled using PT and u^i describes the average PT speed in the network (including dwell times). We model u^i in Eq. (39) as a function of the car speed v^i using the statistical model for the vehicle based 3D-MFD in [Loder et al. \(2017\)](#). The coefficients μ_{car} and μ_{PT} are to be estimated and calibrated depending on the network of interest. μ_{car} captures the reduction of speed for PT vehicles compared to cars due to frequent stops. μ_{PT} adjusts the PT vehicle speed based on network topology and PT network design (e.g., whether the PT vehicles use dedicated lanes and exceed car speeds during congested times or not).

$$u^i = \mu_{car} \cdot v^i + \mu_{PT} \quad (39)$$

ADD_{PT} is computed in Eq. (40) by using the mean based on the round-trip PT travel distance in Fig. 4.1. Given that the total length of the network is L and the average

block size is b , the network side is $b \cdot \left(-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}}\right)$. S is the total number of PT stops with an average distance of $\frac{b \cdot \left(-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}}\right)}{\sqrt{S}}$ between any consecutive stops along the unidirectional PT route. The round-trip PT travel distance in Fig. 4.1 is computed according to [Daganzo \(2010\)](#) as the surface of the square grid $\left[b \cdot \left(-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}}\right) \right]^2$ divided by $\frac{b \cdot \left(-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}}\right)}{\sqrt{S}}$. Term 1 (Eq. (40)) is then determined as half of this result representing the average PT passenger's journey. Term 2 shows the average driven distance, l_{PT} , by using PT from the P+R facilities to the area (Fig. 4.1), which is a function of the network size.

$$ADD_{PT} = \underbrace{b \cdot \frac{\sqrt{S}}{2} \cdot \left(-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}}\right)}_{\text{term 1}} + \underbrace{l_{PT}}_{\text{term 2}} \quad (40)$$

As S is limited, people are expected to require, on average, some walking time. The average round-trip walking time from the PT stop until the destination is modelled by $2 \cdot AWD_{PT}/w$ in term 2 (Eq. (38)), where the average walking distance, AWD_{PT} , is determined in Eq. (41). Note that AWD_{PT} is modelled analogously to AWD_{gp} , replacing G by S in Eq. (16).

$$AWD_{PT} = \frac{2b}{3\sqrt{\pi \cdot S}} \left[-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}} \right] \quad (41)$$

To obtain Eq. (41), the surface $\left[b \cdot \left(-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}}\right) \right]^2$ is divided by the number of PT stops, S , to estimate the area served by each PT stop. Assuming the drivers' destinations are uniformly distributed in the area we determine the average walking distance as $2/3$ of the radius (average distance from the center of a circle) of each of the areas surrounding one PT stop.

It is possible to add a discomfort term to Eq. (38) for drivers using PT instead of using their more comfortable car to enter the area according to [Zheng and Geroliminis \(2013\)](#). However, we omit such term in this chapter for brevity.

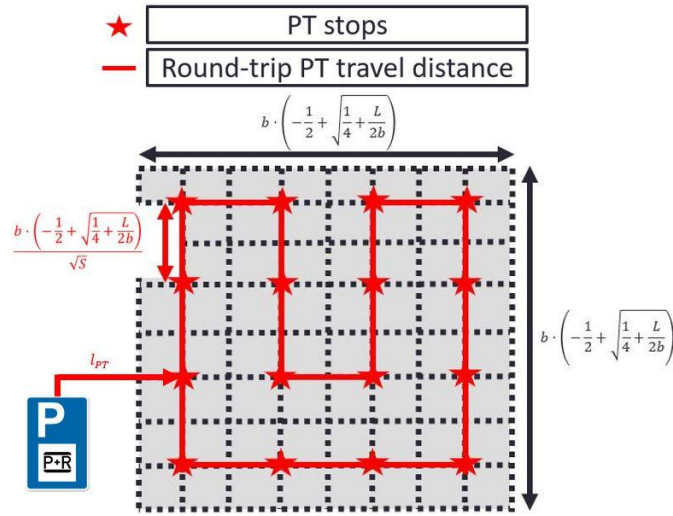


Fig. 4.1. Simple example of an abstracted square grid with uniformly distributed PT stops to illustrate ADD_{PT} .

4.3 Parking and congestion pricing

Introducing parking and congestion pricing can lead to traffic performance and/or revenue changes for an area. To compare and analyze these impacts both policies are integrated into a modification of the macroscopic urban traffic and parking framework from chapter 2.

In section 4.3.1, we propose a multimodal macroscopic traffic and parking model including the option of using P+R instead of entering the network by car. In sections 4.3.2 and 4.3.3, we determine the traffic performance in the area and the total revenue for the city, respectively.

4.3.1 A multimodal macroscopic traffic and parking framework focusing on parking and congestion pricing

Increasing the parking fees or introducing a congestion toll might lead to less traffic within the area of interest. Our multimodal macroscopic traffic and parking model uses the 3D-MFD framework from [Loder et al. \(2017\)](#) and [Zheng and Geroliminis \(2016\)](#) as a foundation to analyze that. We combine this 3D-MFD model with insights from the parking-state-based matrix framework (chapter 2), and the methodology to determine the likelihood of finding parking from section 2.4.2. The matrix is used to capture the system dynamics of urban car and P+R traffic, i.e., it allows us to evaluate, for example, how the cars searching for parking or the drivers deciding to enter the area using P+R affect the traffic performance and the congestion in the network.

Our model uses the five traffic states summarized in Table 4.2. They show modifications of the traffic states presented in Table 2.2, differentiating between non-searching cars with external and internal destinations, and presenting a traffic state for P+R. Updating the traffic states is an iterative process until the end of the time

horizon, or until a defined criterion is reached (e.g., all the cars leave the network). Notice that all state variables need an initial condition as an input to the model. That value can be measured, assumed or simulated.

Table 4.2. Traffic states for our multimodal macroscopic traffic and parking framework in an area of interest.

Notation	Name	Definition
$N_{nse}^{i,k}$	Non-searching (external destination)	Number of cars not searching for parking with external destination (i.e., outside the area) for user group $k \in K$ at the beginning of time slice i .
$N_{nsi}^{i,k}$	Non-searching (internal destination)	Number of cars not searching for parking with internal destination (i.e., within the area) for user group $k \in K$ at the beginning of time slice i .
$N_s^{i,k}$	Searching for parking	Number of cars searching for parking within the area for user group $k \in K$ at the beginning of time slice i .
$N_p^{i,k}$	Parking	Number of cars parking within the area for user group $k \in K$ at the beginning of time slice i .
$N_{pr}^{i,k}$	Park + Ride (P+R)	Number of cars using P+R for user group $k \in K$ at the beginning of time slice i .

The traffic states are determined based on the transition events depicted in Fig. 4.2 and defined in Table 4.3. Note that these transition events enhance the variables presented in Table 2.2 by modelling drivers entering the area by car, or by PT. The latter portion of drivers uses the P+R facilities outside the area.

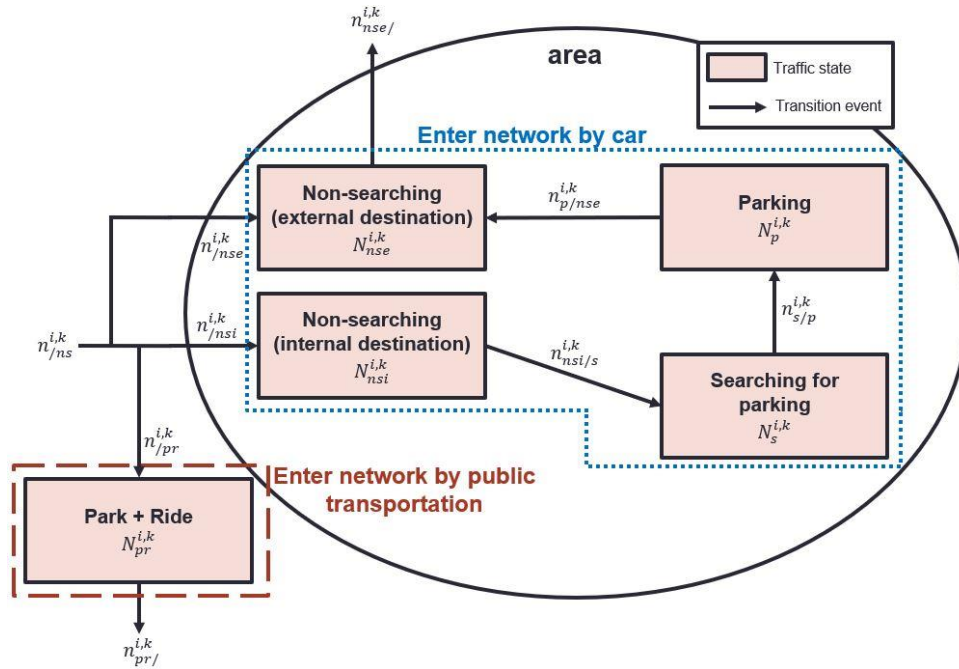


Fig. 4.2. The transition events in-between different traffic states in an area.

Fig. 4.2 illustrates two groups of drivers. The first group shows the drivers using a car to enter the network, with an internal or an external destination. The latter represents the through-traffic. For each user group $k \in K$, the through-traffic enters the area and drives some distance l_j^k ("non-searching (external destination)") before leaving the area. Once the cars focusing on internal destinations enter the area, they drive some

distance $l_{ns/}^k$ towards their destination (“non-searching (internal destination)”) before they search for an available parking space (“searching for parking”). After having parked for a given duration (“parking”), they travel some distance $l_{p/}^k$ to leave the area (“non-searching (external destination)”). The second group of drivers decides to use PT to reach their destination inside the area from the P+R facility (“Park + Ride”). They leave the P+R spaces after having returned by PT from the area.

Table 4.3. Transition events for our multimodal macroscopic traffic and parking framework in an area of interest.

Notation	Name	Definition
$n_{/ns}^{i,k}$	Enter the area	Number of cars entering the area by car and by P+R for user group $k \in K$ during time slice i .
$n_{/nse}^{i,k}$	Enter the area by car (external destination)	Number of cars entering and having their destination outside the area for user group $k \in K$ during time slice i .
$n_{/nsi}^{i,k}$	Enter the area by car (internal destination)	Number of cars entering and having their destination inside the area for user group $k \in K$ during time slice i .
$n_{/pr}^{i,k}$	Enter the area by P+R	Number of cars using P+R to enter the area for user group $k \in K$ during time slice i .
$n_{nsi/s}^{i,k}$	Start to search for parking	Number of cars starting to search for parking within the area for user group $k \in K$ during time slice i .
$n_{s/p}^{i,k}$	Access parking	Number of cars accessing parking within the area for user group $k \in K$ during time slice i .
$n_{p/nse}^{i,k}$	Depart parking	Number of cars departing from parking and moving towards a destination outside the area for user group $k \in K$ during time slice i .
$n_{nse/}^{i,k}$	Leave the area by car	Number of cars leaving the area by car for user group $k \in K$ during time slice i .
$n_{pr/}^{i,k}$	Leave the area by P+R	Number of cars leaving the area by P+R for user group $k \in K$ during time slice i .

The traffic states (Table 4.2) are modelled in Eq. (42a-e) using the transition events (Table 4.3) according to Fig. 4.2. Note that Eq. (42a-b) enhance Eq. (1) by differentiating between non-searching cars with external and internal destinations. Eq. (42c-d) are consistent with Eq. (2) and Eq. (3), showing the cars searching and parking for each user group $k \in K$. Eq. (42e) is a newly defined traffic state modelling the cars using the P+R facilities outside the area, which is not available in the original model shown in section 2.4.1.

$$N_{nse}^{i+1} = \sum_{k=1}^K N_{nse}^{i+1,k}, \text{ where } N_{nse}^{i+1,k} = N_{nse}^{i,k} + n_{/nse}^{i,k} + n_{p/nse}^{i,k} - n_{nse/}^{i,k} \quad (42a)$$

$$N_{nsi}^{i+1} = \sum_{k=1}^K N_{nsi}^{i+1,k}, \text{ where } N_{nsi}^{i+1,k} = N_{nsi}^{i,k} + n_{/nsi}^{i,k} - n_{nsi/s}^{i,k} \quad (42b)$$

$$N_s^{i+1} = \sum_{k=1}^K N_s^{i+1,k}, \text{ where } N_s^{i+1,k} = N_s^{i,k} + n_{nsi/s}^{i,k} - n_{s/p}^{i,k} \quad (42c)$$

$$N_p^{i+1} = \sum_{k=1}^K N_p^{i+1,k}, \text{ where } N_p^{i+1,k} = N_p^{i,k} + n_{s/p}^{i,k} - n_{p/nse}^{i,k} \quad (42d)$$

$$N_{pr}^{i+1} = \sum_{k=1}^K N_{pr}^{i+1,k}, \text{ where } N_{pr}^{i+1,k} = N_{pr}^{i,k} + n_{/pr}^{i,k} - n_{pr/}^{i,k} \quad (42e)$$

All traffic states are determined for each user group $k \in K$ before aggregating them. The total number of cars parked for all user groups at the beginning of time slice i is $N_p^i + N_{pr}^i$ (Eq. (42d-e)), whereas the total number of cars driving in the area at the beginning of time slice i is $N_{nse}^i + N_{nsi}^i + N_s^i$ (Eq. (42a-c)). The calculation of the traffic states in Eq. (42a-e) could be advanced by using an MFD simulator model approximating the dynamic user equilibrium conditions in large scale networks ([Yildirimoglu and Geroliminis \(2014\)](#)). These improvements, however, are considered out-of-scope for this chapter. The traffic composition change (i.e., the change of the number of cars in each parking-related state) between two consecutive time slices can be illustrated in queuing diagrams for cars entering the area (Fig. 4.3(a)) and cars switching to P+R (Fig. 4.3(b)).

The average travel speed of cars, v^i , during time slice i is formulated in Eq. (43a) based on the statistical model for the vehicle based 3D-MFD in [Loder et al. \(2017\)](#). It uses the free flow speed of cars, v , when traffic is not congested, and includes the marginal effects of each mode (ϑ_{car} and ϑ_{PT} for cars and PT vehicles, respectively) on car speeds when traffic starts to be congested. The density of cars, k_{car}^i , is determined in Eq. (43b) based on the total number of cars on the road network (consisting of non-searching, $N_{nse}^i + N_{nsi}^i$, and searching cars, N_s^i), and the network length, L_{lane} , in lane-km ([Cao and Menendez \(2015a\)](#), [Cao et al. \(2019\)](#), [Loder et al. \(2017\)](#)). The density of PT vehicles, k_{PT}^i , is computed in Eq. (43c) using the number of PT vehicles in the area divided by L_{lane} . The number of PT vehicles can be obtained as the cycle for one PT run, $2 \cdot ADD_{PT}/u^i$, divided by the average headway, h .

$$v^i = v + \vartheta_{car} \cdot k_{car}^i + \vartheta_{PT} \cdot k_{PT}^i \quad (43a)$$

$$k_{car}^i = \frac{N_{nse}^i + N_{nsi}^i + N_s^i}{L_{lane}} \quad (43b)$$

$$k_{PT}^i = \frac{2 \cdot ADD_{PT}}{u^i \cdot h \cdot L_{lane}} \quad (43c)$$

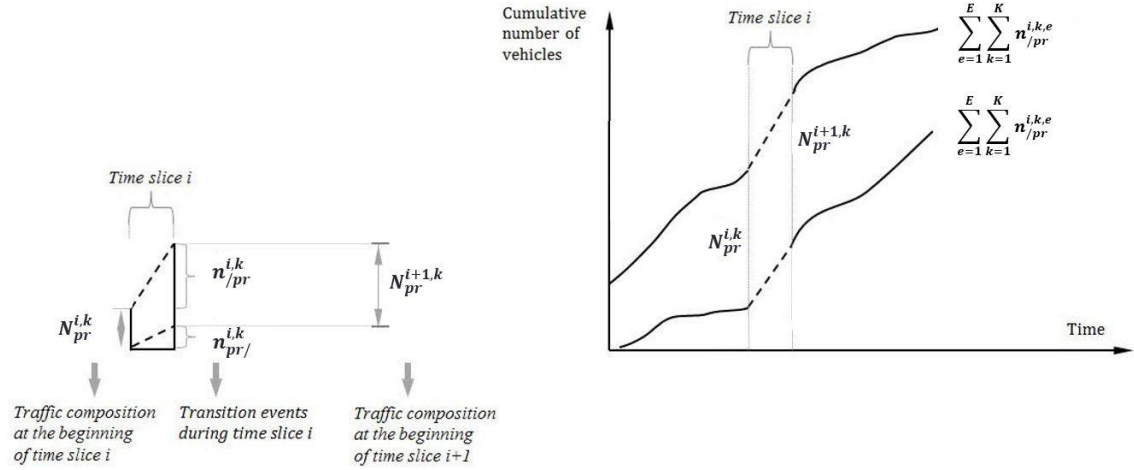
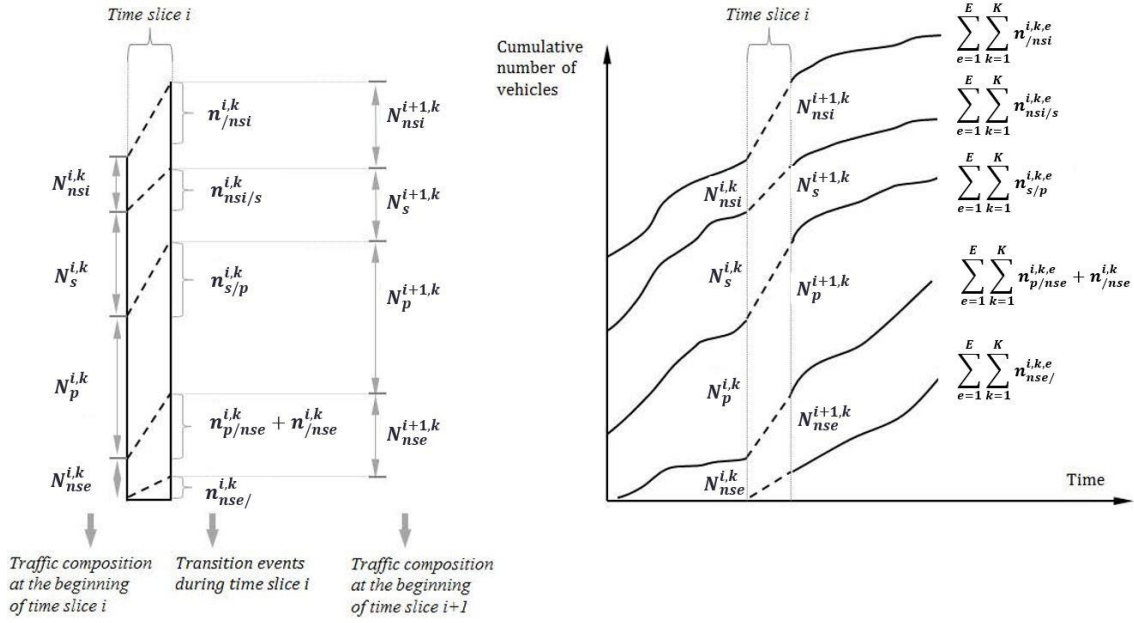


Fig. 4.3. Traffic composition between consecutive time slices and queuing diagrams for cars entering the area or switching to P+R.

Below, we model each of the transition events. The total number of cars, $n_{/ns}^{i,k}$, entering the network for user group $k \in K$ during time slice i is considered as the known input demand to the model. Based on the proportion of through-traffic (input to the model), β^i , and the choice of drivers entering the area by car or PT, $\delta_{car}^{i,k}$, the demand $n_{/ns}^{i,k}$ is split based on three transition events (Fig. 4.4), Eq. (44a-c). The transition events in Eq. (44a-c) are newly modelled in this chapter and do not exist in the original framework presented in section 2.4.2.

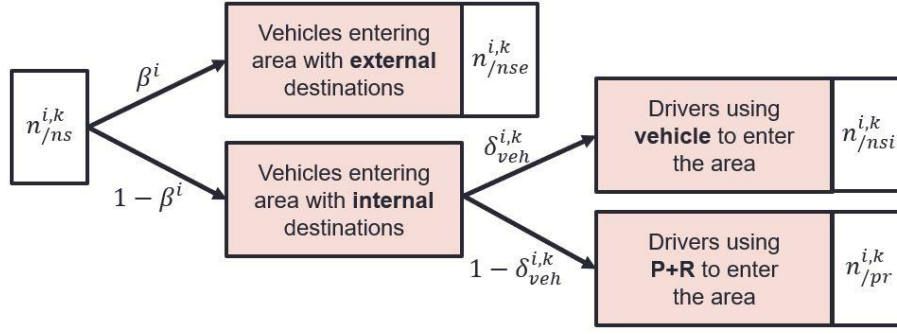


Fig. 4.4. The transition events with internal/external destinations using cars or P+R to enter the area.

$$n_{/nse}^{i,k} = \beta^i \cdot n_{/ns}^{i,k} \quad (44a)$$

$$n_{/nsi}^{i,k} = \begin{cases} (1 - \beta^i) \cdot n_{/ns}^{i,k} \cdot \delta_{car}^{i,k}, & \text{if } (1 - \beta^i) \cdot n_{/ns}^{i,k} \cdot (1 - \delta_{car}^{i,k}) \leq P^i \\ (1 - \beta^i) \cdot n_{/ns}^{i,k} - P^i, & \text{if } (1 - \beta^i) \cdot n_{/ns}^{i,k} \cdot (1 - \delta_{car}^{i,k}) > P^i \end{cases} \quad (44b)$$

$$n_{/pr}^{i,k} = \begin{cases} (1 - \beta^i) \cdot n_{/ns}^{i,k} \cdot (1 - \delta_{car}^{i,k}), & \text{if } (1 - \beta^i) \cdot n_{/ns}^{i,k} \cdot (1 - \delta_{car}^{i,k}) \leq P^i \\ P^i, & \text{if } (1 - \beta^i) \cdot n_{/ns}^{i,k} \cdot (1 - \delta_{car}^{i,k}) > P^i \end{cases} \quad (44c)$$

In Eq. (44b-c) we differentiate between enough (i.e., $(1 - \beta^i) \cdot n_{/ns}^{i,k} \cdot (1 - \delta_{car}^{i,k}) \leq P^i$) and not enough (i.e., $(1 - \beta^i) \cdot n_{/ns}^{i,k} \cdot (1 - \delta_{car}^{i,k}) > P^i$) available parking spaces, P^i , at the P+R facility. The proportion of through-traffic, β^i , is assumed to be independent of the individual user group $k \in K$. For cars entering the area we assume that they start searching for parking after driving a distance $l_{ns/}^k$, which is a function of the network size. $l_{ns/}^k$ can be fixed or follow any given probability density function. The number of cars starting to search for parking, $n_{/nsi/s}^{i,k}$, for user group $k \in K$ are modelled in Eq. (45). Note that Eq. (45) is consistent with Eq. (5) as $n_{/nsi}^{i,k}$ already includes the proportion of cars entering the area, $1 - \beta^i$, for each $k \in K$.

$$n_{/nsi/s}^{i,k} = \sum_{i'=1}^{i-1} n_{/nsi}^{i',k} \cdot \gamma_{ns/}^{i',k} \quad (45)$$

The $\gamma_{ns/}^{i',k}$ in Eq. (45) indicates whether the cars $n_{/nsi}^{i',k}$ have driven long enough, i.e., they cover a distance $l_{ns/}^k$, such that they start searching for parking in time slice i . Please refer to Eq. (25) for the formulation of $\gamma_{ns/}^{i',k}$.

The number of cars finding, accessing and paying for parking, $n_{/s/p}^{i,k}$, is modelled in Eq. (46) as in section 2.4.2 using the finding parking likelihood formulations from [Cao and Menendez \(2015a\)](#), [Cao and Menendez \(2018\)](#) and [Cao et al. \(2019\)](#). Note that we show Eq. (46) below for the sake of completeness as it is consistent with Eq. (6) with $d^i = v^i \cdot t$, and modelled for each user group $k \in K$. It is a function of the number of available parking spaces A^i , the number of competing cars searching for parking $N_s^{i,k}$,

and the distance an average searcher can drive in a single time slice in reference to the network length $v^i \cdot t/L$.

$$n_{s/p}^{i,k} = \begin{cases} \begin{cases} N_s^{i,k} \left[1 - \left(1 - \frac{v^i \cdot t}{L} \right)^{A^i} \right], & \text{if } t \in \left[0, \frac{L}{v^i \cdot N_s^{i,k}} \right] \\ A^i + \left[A^i - N_s^{i,k} + N_s^{i,k} \cdot \left(1 - \frac{1}{N_s^{i,k}} \right)^{A^i} \right] \cdot \left(\frac{\log \frac{N_s^{i,k}}{A^i} \cdot \frac{v^i \cdot t}{L}}{\log A^i} \right), & \text{if } t \in \left[\frac{L}{v^i \cdot N_s^{i,k}}, \frac{L}{v^i} \cdot \frac{A^i}{N_s^{i,k}} \right] \\ A^i, & \text{if } t \in \left[\frac{L}{v^i} \cdot \frac{A^i}{N_s^{i,k}}, \infty \right) \end{cases}, & \text{if } A^i \leq N_s^{i,k} \\ \begin{cases} N_s^{i,k} \left[1 - \left(1 - \frac{v^i \cdot t}{L} \right)^{A^i} \right], & \text{if } t \in \left[0, \frac{L}{v^i \cdot N_s^{i,k}} \right] \\ N_s^{i,k} + N_s^{i,k} \cdot \left(1 - \frac{1}{N_s^{i,k}} \right)^{A^i} \cdot \left(\frac{\log \frac{v^i \cdot t}{L}}{\log N_s^{i,k}} \right), & \text{if } t \in \left[\frac{L}{v^i \cdot N_s^{i,k}}, \frac{L}{v^i} \right] \\ N_s^{i,k}, & \text{if } t \in \left[\frac{L}{v^i}, \infty \right) \end{cases}, & \text{if } A^i \geq N_s^{i,k} \end{cases} \quad (46)$$

When $A^i < N_s^{i,k}$, the number of cars accessing parking is low as there are not enough available parking spaces for all drivers searching for parking. When $A^i > N_s^{i,k}$, the number of cars accessing parking can potentially be high depending on the drivers' distance driven in one time slice. The number of cars accessing parking might, however, be low in the latter case, if the length of a time slice, t , is very short. Notice that all drivers decide to access the first available parking space they find, as all parking spaces have the same price. More details on $n_{s/p}^{i,k}$ can be found in [Cao and Menendez \(2015a\)](#) with its simplified version in [Cao and Menendez \(2018\)](#).

Once the cars depart from parking they move towards an external destination ($n_{p/nse}^{i,k}$ modelled in Eq. (47) for user group $k \in K$ during time slice i). Note that Eq. (47) is consistent with Eq. (7), as all cars for each $k \in K$ depart from parking towards an external destination outside the area.

$$n_{p/nse}^{i,k} = \sum_{i'=1}^{i-1} n_{s/p}^{i',k} \cdot \int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_{d,p}) dt_{d,p} \quad (47)$$

$n_{p/nse}^{i,k}$ is based on the distribution of parking durations $f(t_{d,p})$ and on the number of cars having accessed parking spaces, $n_{s/p}^{i',k}$, in a former time slice $i' \in [1, i-1]$. The likelihood that these cars depart from the parking spaces in time slice i equals the probability of the parking duration being between $(i-i') \cdot t$ and $(i+1-i') \cdot t$, i.e., $\int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_{d,p}) dt_{d,p}$.

The transition event $n_{pr}^{i,k}$ in Eq. (48) describes the number of cars departing from the P+R spaces. It is modelled analogously to Eq. (47) depending on $n_{pr}^{i',k}$ and the distribution of P+R durations $f(t_{d,pr})$.

$$n_{prj}^{i,k} = \sum_{i'=1}^{i-1} n_{pr}^{i',k} \cdot \int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_{d,pr}) dt_{d,pr} \quad (48)$$

After cars access or depart the parking spaces in the area and the P+R facilities, the number of available parking spaces, A^i , and the number of available P+R spaces, P^i , are updated in Eq. (49a-b). Neither A^i nor P^i can surpass the total number of existing parking/P+R spaces, i.e., $A^i \leq A$ and $P^i \leq P$ for any time slice i .

$$A^i = A - N_p^i \quad (49a)$$

$$P^i = P - N_{pr}^i \quad (49b)$$

The cars heading towards external destinations, $n_{nsej}^{i,k}$, leave the area after having driven a given distance l_j^k or $l_{p_j}^k$ depending on whether they have parked or not. The distances l_j^k and $l_{p_j}^k$ are – analogously to $l_{ns_j}^k$ – considered as fixed or taken out of any given probability density function. They both depend on the network size and average trip lengths. $n_{nsej}^{i,k}$ is modelled in Eq. (50) for user group $k \in K$ based on $n_{nse}^{i',k}$ and $n_{p/nse}^{i',k}$. Note that Eq. (50) is consistent with Eq. (8), as $n_{nse}^{i',k}$ includes the proportion of through-traffic, β^i , for each user group $k \in K$.

$$n_{nsej}^{i,k} = \sum_{i'=1}^{i-1} \left(n_{nse}^{i',k} \cdot \gamma_j^{i',k} + n_{p/nse}^{i',k} \cdot \gamma_{p_j}^{i',k} \right) \quad (50)$$

$\gamma_j^{i',k}$ and $\gamma_{p_j}^{i',k}$ in Eq. (50) indicate whether the cars $n_{nse}^{i',k}$ and $n_{p/nse}^{i',k}$ have driven l_j^k and $l_{p_j}^k$, respectively, to leave the area in time slice i . Please refer to Eq. (35) for the formulations of $\gamma_j^{i',k}$ and $\gamma_{p_j}^{i',k}$.

4.3.2 Traffic performance in the area

The average searching time per car, t_s , in Eq. (51) reflects the traffic performance in the area and shows whether the network is congested or not. A high average searching time, for example, might occur due to a small number of available parking spaces in the area. This will lead to traffic congestion in the network.

$$t_s = \frac{\sum_{i=1}^T \sum_{k=1}^K t \cdot N_s^{i,k}}{\sum_{i=1}^T \sum_{k=1}^K n_{s/p}^{i,k}} \quad (51)$$

t_s is determined by computing the total searching time for all user groups $k \in K$ in the network, $\sum_{i=1}^T \sum_{k=1}^K t \cdot N_s^{i,k}$, and dividing it by the total number of cars having searched for parking in the area, $\sum_{i=1}^T \sum_{k=1}^K n_{s/p}^{i,k}$, over the time horizon T .

4.3.3 Total revenue for the city

Introducing parking and congestion pricing schemes are options for generating revenue I_{tot} (Eq. (52)).

$$I_{tot} = \underbrace{\sum_{i=1}^T \sum_{k=1}^K (n_{/nse}^{i,k} + n_{/nsi}^{i,k}) \cdot p_t}_{\text{term 1}} + \underbrace{\sum_{i=1}^T \sum_{k=1}^K n_{pr/}^{i,k} \cdot (p_{pr} + p_{PT})}_{\text{term 2}} + \underbrace{\sum_{i=1}^T \sum_{k=1}^K n_{p/nse}^{i,k} \cdot p_p \cdot \overline{t_{d,p}}}_{\text{term 3}} \quad (52)$$

Term 1 represents the revenue from the congestion toll for all $k \in K$ during all time slices i . Term 2 shows the revenue from the P+R and the round-trip PT fees for all user groups $k \in K$ during all time slices i . Term 3 illustrates the revenue from parking in the area for all user groups $k \in K$ during all time slices i , depending on the average parking duration $\overline{t_{d,p}}$.

4.4 Applications

In this section, we illustrate the use of the proposed methodology by comparing different parking and congestion pricing scenarios for a central area with a high parking demand for public parking spaces within the city of Zurich, Switzerland. Our results help answering the question whether introducing congestion pricing is a necessity or implementing parking pricing strategies are sufficient to improve the area's traffic performance. Our case study uses real traffic and parking data obtained and validated in [Cao et al. \(2019\)](#), which is based on historical data collections and an agent-based model in MATSim ([Waraich and Axhausen \(2012\)](#)). It was proven reasonable and validated in [Cao et al. \(2019\)](#) using the parking occupancy data over a working day based on a local monitoring system (PLS Zurich), and the cruising time based on survey results that were conducted during May 2016. Note that we use MATSim to estimate the demand, i.e., daily traffic data arriving to the network and the distribution of parking durations, and we do not use it for traffic modelling purposes. The framework is implemented with the aid of a simple numerical solver such as Matlab.

4.4.1 Case study of an area within the city of Zurich, Switzerland

We concentrate on the same study area as in section 3.4.1. Recall that the total length of all roads is $L = 7.7$ km, and $b = 76$ m. As most of the streets have two lanes (either one lane per direction or two lanes in a one-way street), the total network length is $L_{lane} = 15.4$ lane-km.

There are 539 public parking spaces in the area. As the policy of removing on-street parking spaces without necessarily downsizing the overall parking supply has been evaluated in the inner-city of Zurich since the 1990's (Zurich parking supply cap system in [Fellmann et al. \(2009\)](#)), we assume that 200 on-street parking spaces can be

moved out of our network and turned into P+R spaces, i.e., $P = 200$. The remaining $A = 339$ parking spaces stay in the area. It is assumed that the recovered road space while removing on-street parking spaces in the inner-city area has no influence on the traffic flow, and can be used for other activities (e.g., to create pedestrian zones or bicycle lanes). The P+R fee outside the area is a fixed lump-sum for parking up to $T = 1440$ min. The average P+Rail fee around the city of Zurich including the round-trip PT fee paid to enter the area from the P+R facility by PT equals $p_{pr} + p_{PT} = 10$ CHF (SBB (2020), VBZ (2002)). Both P+R outside and parking spaces inside the area have no parking time limit, i.e., drivers can park there for the whole time horizon of 24 hours. The working day is divided into time slices of 1 min, i.e., $t = 1$ min. To model the traffic, we use traffic properties (i.e., $v = 27.93$ km/h) and model parameters ϑ_{car} , ϑ_{PT} , μ_{car} , and μ_{PT} are based on the 3D-MFD of the city of Zurich (Ambühl et al. (2017), Dakic and Menendez (2018), Loder et al. (2017, 2019)). We assume the price per distance driven as $p_d = 0.3$ CHF/km, the average distance driven from the P+R facility to the area as $l_{PT} = 5b = 380$ m, and the walking speed as $w = 5$ km/h (Browning et al. (2006)). The average headway of PT lines from the P+R facility to the PT stops is $h = 7.5$ min and the total number of PT stops in the area is $S = 2$. Here we use bus line 31 and tram lines 2, 7, 9, 10 and 13 in Zurich as a reference for h and S (Carrasco (2012)).

Recall that the parking demand (Fig. 3.4(b) in section 3.4.1), the distribution of parking durations in Fig. 4.5, and the initial conditions are based on an agent-based model in MATSim, which is in turn, based on previous measurements. This has been validated for the city of Zurich in Waraich and Axhausen (2012). The parking demand of 2687 trips is split into $K = 4$ different user groups (892/ 956/ 838/ 956 trips) associated with different VOTs ($VOT^1 = 29.9$ CHF/h; $VOT^2 = 25.4$ CHF/h; $VOT^3 = 25.8$ CHF/h; $VOT^4 = 17.2$ CHF/h) which are based on the estimated VOT mean values for car journeys in Switzerland (Axhausen et al. (2006)). 23% (618 trips) of the daily traffic (i.e., $\beta^i = 0.23, \forall i$) does not search for parking (through-traffic), and the remaining 77% (2069 trips) searches for parking. The parking durations (Fig. 4.5) are described by a probability density function following a gamma distribution with a shape parameter of 1.6 and a scale parameter of 142.

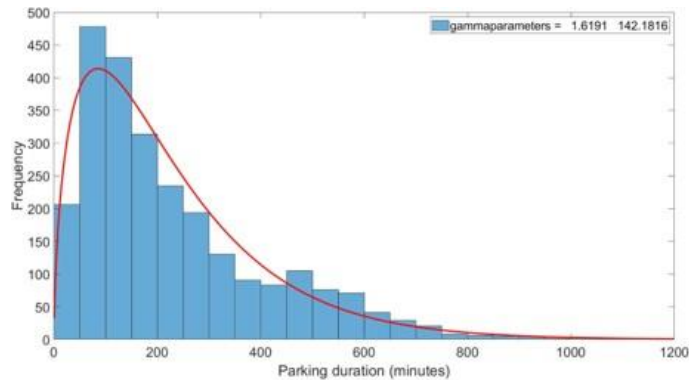


Fig. 4.5. Distribution of parking durations.

The average parking duration is 227 min (Cao et al. (2019)). We assume that parking durations at P+R spaces are longer than parking durations in the area as they

additionally account for the drivers' PT time, i.e., we add the average round-trip PT waiting and travel time to the parking durations in the area in order to determine the parking durations at P+R spaces.

The initial conditions include $N_p^0 = 113$ cars already parked in the area and $N_{pr}^0 = 70$ cars parked at P+R facilities at the beginning of the working day. All further initial conditions are considered as zero, i.e., $N_{nse}^0 = N_{nsi}^0 = N_s^0 = 0$. The travel distances l_{ns}^k , l_j^k and $l_{p_j}^k$ follow a uniform distribution between 0.1 and 0.7 km for all $k \in \{1, \dots, 4\}$.

4.4.2 Impact of parking and congestion pricing

This section focuses on the traffic impacts from different parking and congestion pricing scenarios. First, we explain the status quo in the city of Zurich (scenario (a) in Table 4.4). Currently, there are no P+R facilities (besides the ones at rail stations around Zurich) and there is no congestion toll around this case study area. The hourly parking pricing fee of 2.25 CHF approximates the average value in the city center of Zurich (Cao et al. (2019)). We compare this reference scenario to the assumed scenarios (b)-(e) in Table 4.4 in terms of traffic performance (average time spent) in the network and total revenue for the city.

Table 4.4. Scenarios and their pricing strategy.

Scenarios	Pricing strategy
Scenario (a): Reference scenario: No P+R facilities	No P+R facilities, no PT and no congestion toll are considered. Hourly parking pricing is set to 2.25 CHF in the area for all time slices.
Scenario (b): Free P+R and free PT	P+R facilities and PT are introduced, i.e., 200 on-street parking spaces are moved outside the area as P+R spaces. P+R and PT fees are set to 0 CHF. No congestion toll is considered. Hourly parking pricing is set to 2.25 CHF in the area for all time slices.
Scenario (c): Parking pricing (policy 1)	P+R facilities and PT are introduced, i.e., 200 on-street parking spaces are moved outside the area as P+R spaces. P+R fees including round-trip PT fees are set to 10 CHF for up to 24 hours. Congestion pricing is set to 0 CHF in the area for all time slices. Hourly parking pricing is doubled and set to 4.5 CHF in the area for all time slices.
Scenario (d): Congestion pricing (policy 2)	P+R facilities and PT are introduced, i.e., 200 on-street parking spaces are moved outside the area as P+R spaces. P+R fees including round-trip PT fees are set to 10 CHF for up to 24 hours. Congestion pricing is set to 12 CHF in the area for all time slices. Hourly parking pricing is set to 0 CHF in the area for all time slices.
Scenario (e): Parking and congestion pricing (combined policies 1 and 2)	P+R facilities and PT are introduced, i.e., 200 on-street parking spaces are moved outside the area as P+R spaces. P+R fees including round-trip PT fees are set to 10 CHF for up to 24 hours. Congestion pricing is set to 12 CHF in the area for all time slices. Hourly parking pricing is set to 4.5 CHF in the area for all time slices.

Table 4.5 shows the results for the traffic criteria including traffic performance (i.e., average/total searching and non-searching time), congestion (i.e., average/total delay, and queue reflected as the average number of cars searching for parking), traffic state volumes, and total revenue for the different scenarios in Table 4.4. The delay is determined as the difference between the actual and ideal travel time in the area. The latter is the time the cars spend under free-flow conditions in the network. Recall that the parking and P+R revenues come only from the cars that park in the area or at the P+R facilities, but the revenue from congestion pricing includes every single car that comes into the network, whether they park or not.

The reference scenario (a) requires the longest average/total searching and non-searching time, and the longest average/total delay compared to all other scenarios since there are no P+R facilities outside the area, i.e., all assumed scenarios (b)-(e) improve the traffic performance in the area. However, different policies lead to different results (Table 4.5). Scenario (b) analyzes the policy of moving 200 on-street parking spaces outside the area as free P+R spaces with free PT, while the hourly parking pricing in the area is kept at 2.25 CHF. The results show a lower boundary for the average time values in Table 4.5, i.e., how much we can reduce the average searching and non-searching time by encouraging drivers to use the available free P+R facilities (32.1 % and 43.8 %, respectively). The average delay decreases significantly by 56 %, as on average at any given time we have 164 cars using the P+R facility instead of parking in the area. This brings down the usage of parking spaces in the central area from an average of 338 to 172 at any given minute. Note that the average delay refers only to the traffic within the area, which explains this significant reduction compared to the reference scenario. Scenario (c) considers the parking pricing policy (policy 1 in section 4.2) with an increased hourly parking fee of 4.5 CHF in the area. The P+R fees including round-trip PT fees are set to 10 CHF for 24 hours. This decreases the average searching time by 27.2 % compared to scenario (a) as on average 141 drivers decide to use P+R instead of entering the area by car. In addition, the average non-searching time and the average delay significantly decrease by 37 % and 46.7 %, respectively. Compared to scenario (b) (free P+R facilities and free PT) more cars enter the area due to higher costs using P+R including round-trip PT fees (10 CHF for 24 hours), which results in an increased searching time and delay in the area. The P+R and PT fees, as well as the higher parking fees lead to an increased revenue of 28,999 CHF. Scenario (d) describes the congestion pricing policy (policy 2 in section 4.2) with a congestion toll set to 12 CHF (comparable to London, U.K. ([TFL \(2020\)](#))) and free parking in the area for all time slices. It considers the same P+R conditions as in scenario (c). As the congestion toll (scenario (d)) is cheaper than the parking fee for the drivers' expected parking durations (scenario (c)), more drivers would like to enter the area by car. This leads to a higher searching and non-searching time, and a higher delay/queue in scenario (d) compared to scenario (c). When comparing both scenarios (policy 1 and 2), then introducing parking pricing not only leads to better traffic performance and congestion results, but also to a similar increase in revenue for the city council. In addition, parking pricing (policy 1) might be the preferred scenario as it is not only easier to implement, but also socially and politically more accepted than congestion pricing. The significant traffic performance improvements of policy 1 compared to scenario (a) also support a decision towards a parking pricing implementation. Notice that this is in part possible because in this case the majority of the traffic coming into the area is searching for parking (i.e., $1 - \beta^i = 0.77$ for all time slices i). Even if the total revenue in scenario (c) is slightly less than in scenario (d), we would like to highlight that this revenue is mainly dependent on the hourly parking fee rate. It can increase with a higher parking fee, but this in turn, might raise social acceptability issues in the city. Scenario (e) combines the parking and congestion pricing policies 1 and 2. The traffic performance improves compared to both scenarios (c) and (d) and it comes close to the best performance in

scenario (b). The resulting daily revenue of 49,043 CHF is the highest compared to all other scenarios in Table 4.5.

Table 4.5. Comparison of different policies in terms of traffic performance, congestion, traffic state volumes, and total revenue for the city. Value within parenthesis represents the percentage change with respect to the reference scenario.

Scenarios	Scenario (a): Reference scenario: No P+R facilities	Scenario (b): Free P+R and free PT	Scenario (c): Parking pricing (policy 1)	Scenario (d): Congestion pricing (policy 2)	Scenario (e): Parking and congestion pricing (combined policies 1 and 2)
Average time for cars searching for parking (min/veh)	2.68	1.82 (-32.1 %)	1.95 (-27.2 %)	2.09 (-22 %)	1.89 (-29.5 %)
Total time for cars searching for parking (min)	6,036	4,099 (-32.1 %)	4,395 (-27.2 %)	4,710 (-22 %)	4,244 (-29.7 %)
Average travel time for cars non-searching (min/veh)	2.97	1.67 (-43.8 %)	1.87 (-37 %)	1.97 (-33.7 %)	1.78 (-40.1 %)
Total travel time for cars non-searching (min)	6,679	3,751 (-43.8 %)	4,205 (-37 %)	4,434 (-33.6 %)	4,006 (-40 %)
Average delay (min)	2.91	1.28 (-56 %)	1.55 (-46.7 %)	1.75 (-39.9 %)	1.43 (-50.9 %)
Total delay (min)	8,628	3,764 (-56.4 %)	4,513 (-47.7 %)	5,057 (-41.4 %)	4,164 (-51.7 %)
Average number of cars non-searching (external destination) (veh/min)	2.62	1.64 (-37.4 %)	1.77 (-32.4 %)	1.84 (-29.8 %)	1.71 (-34.7 %)
Average number of cars non-searching (internal destination) (veh/min)	2.02	0.97 (-52 %)	1.15 (-43.1 %)	1.24 (-38.6 %)	1.07 (-47 %)
Average number of cars searching for parking (veh/min)	4.19	2.85 (-32 %)	3.05 (-27.2 %)	3.27 (-22 %)	2.95 (-29.6 %)
Average number of cars parking in the area (veh/min)	337.99	172.27 (-49 %)	195.47 (-42.2 %)	207.85 (-38.5 %)	185.1 (-45.2 %)
Average number of cars using P+R (veh/min)	0	164.16	141.05	128.76	151.36
Revenue from P+R facilities and PT (CHF)	0	0	8,886	7,989	9,693
Revenue from congestion tolls (CHF)	0	0	0	22,657	20,612
Revenue from parking pricing (CHF)	17,628	8,438	20,113	0	18,738
Total revenue created by P+R facilities, PT, parking pricing and congestion tolls (CHF)	17,628	8,438 (-52.1 %)	28,999 (+64.5 %)	30,646 (+73.9 %)	49,043 (+178.2 %)

Nevertheless, this high revenue comes along with all the negative aspects of introducing congestion pricing to an area. The relative difference between the cost of using P+R and the cost of entering the area explains the changes in traffic performance and congestion between the scenarios (b)-(e). Our parking and congestion pricing

decision framework is based on a logistic function (Eq. (36a-b)) which results in more drivers entering the network in case of a higher gap between these relative cost variables.

In the following, we present more details about policy 1 (scenario (c)) in comparison with the status quo (reference scenario (a)). Most drivers are searching for parking between the 11th and 16th hour due to a low number of available parking spaces, i.e., there are more searching cars in the area than available parking spaces (Fig. 4.6(b), scenario (c)). 66 % of the cruising-for-parking traffic occurs in this time period due to shopping, leisure and/or business activities (Cao et al. (2019)). This leads to a high average searching time (Fig. 4.6(a)). Applying policy 1 reduces the average searching time during the peaks at the 12th and the 14th hour by more than 2.5 min compared to the reference scenario (a). The highest peak happens at the 12th hour, when 28 cars are cruising for parking while at the same time only 2 parking spaces are available (Fig. 4.6(b)). The parking system in the area remains full between the 11th and the 15th hour. After the 15th hour, parking spaces become available again as cars gradually leave the area. Note that the number of available parking spaces before the 10th and after the 16th hour exceeds 30 and is not visible in Fig. 4.6(b).

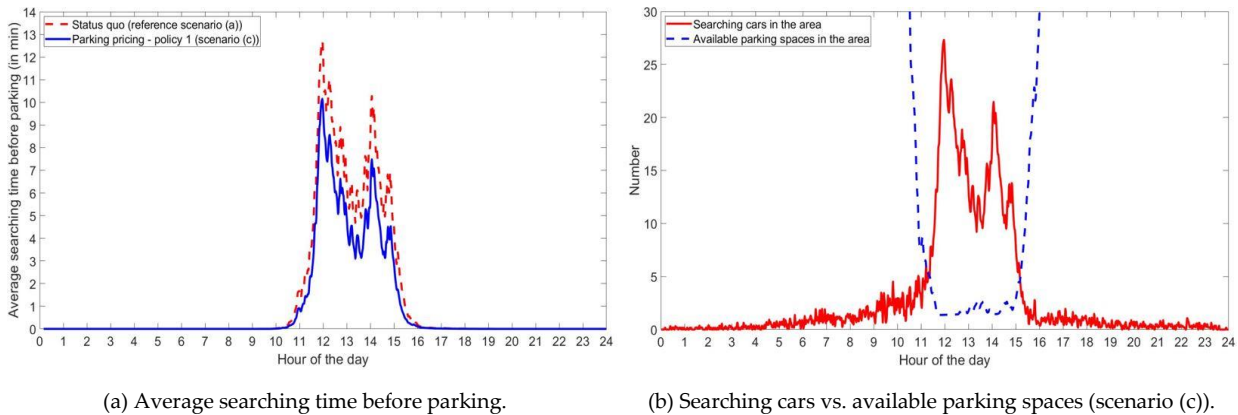


Fig. 4.6. Cars searching for an available parking space in the area over a typical working day.

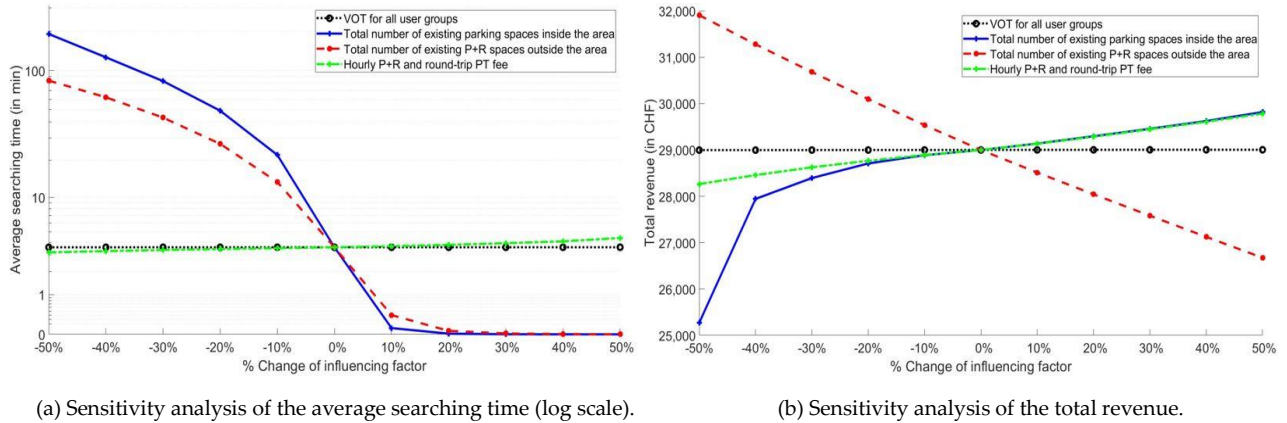
4.4.3 Sensitivity analysis

In this section, we conduct a sensitivity analysis for policy 1 (scenario (c)) in section 4.4.2) to quantitatively evaluate the effects of some influencing factors (Table 4.6) on the traffic and parking model outputs.

Fig. 4.7 shows how the average searching time (Fig. 4.7(a)) and the total revenue (Fig. 4.7(b)) change as a function of each of these four factors (each shown with a different line).

Table 4.6. Influencing factors and their reference values for this sensitivity analysis.

Influencing factors	Reference values
VOTs, VOT^k , for all user groups $k \in K$	$VOT^1 = 29.9$ CHF/h; $VOT^2 = 25.4$ CHF/h; $VOT^3 = 25.8$ CHF/h; $VOT^4 = 17.2$ CHF/h
Total number of existing parking spaces inside the area, A	$A = 339$
Total number of existing P+R spaces outside the area, P	$P = 200$
P+R fee, p_{pr} , and round-trip PT fee, p_{PT}	$p_{pr} + p_{PT} = 10$ CHF



(a) Sensitivity analysis of the average searching time (log scale).

(b) Sensitivity analysis of the total revenue.

Fig. 4.7. Sensitivity analysis of the traffic performance over the peak period between the 10th and the 16th hour of one working day and the total revenue over one full working day (for an independent A and P).

Fig. 4.7(a) shows that VOT^k for all $k \in K$, and $p_{pr} + p_{PT}$ have no influence on the average searching time over the peak period between the 10th and the 16th hour of one working day. However, there is a clear dependency between the number of parking and P+R spaces, A and P , and the traffic performance. Decreasing A or P significantly increases the average time searching for parking. It decreases faster for A , as our case study considers 69.5 % more parking spaces in the area than P+R spaces outside the area. On the other hand, increasing A or P leads to a small decrease in the average searching time. This indicates an asymmetric relation between changes to A or P and the resulting changes in searching times.

Fig. 4.7(b) illustrates the sensitivity analysis of the total revenue from one working day. The VOT^k for all $k \in K$, p_{pr} and p_{PT} have only a marginal influence on the total revenue collected – compared to both A and P . Interestingly, the revenue increases when the number of P+R spaces, P , decreases and it decreases when P increases. In case of fewer P+R spaces, more drivers have to decide for a parking space in the area. The higher hourly parking fees in the area in comparison to P+R explain this gain in revenue. Additionally, less parking spaces, A , inside the area lead to a decline in revenue, and a higher A lead to a small raise in revenue.

Evidently, changes to A and P have a significant impact on the traffic performance and the total revenue for the city. In Fig. 4.7 we treated both A and P independently from each other. However, Zurich introduced a parking supply cap system in the inner-city in 1990 (Fellmann et al. (2009)): for every newly introduced parking space an existing on-street parking space must be removed such that the parking supply is kept the same (Kodransky and Hermann (2011)). Thus, we assume now A and P are

dependent on each other, i.e., $A + P = 539$, and conduct a sensitivity analysis of the average searching time over the peak period between the 10th and the 16th hour of one working day and the total revenue from one full working day (Fig. 4.8).

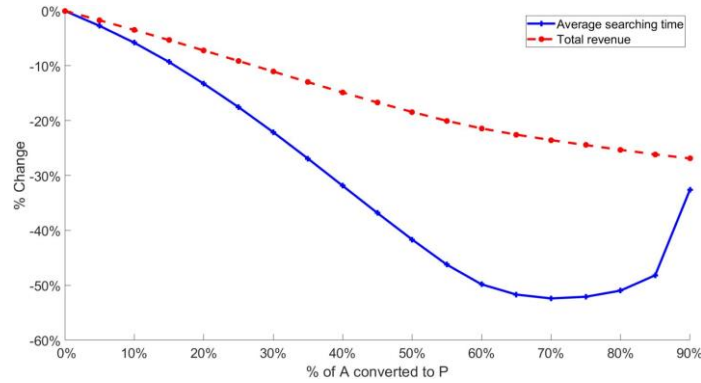


Fig. 4.8. Sensitivity analysis of the traffic performance over the peak period between the 10th and the 16th hour of one working day and the total revenue over one full working day (for a dependent A and P , i.e., $A + P = 539$).

Fig. 4.8 shows that converting up to 80 % of the parking spaces inside the area, A , into P+R spaces, P , leads to less drivers entering the network and significantly lowers the searching times. Interestingly, this reflects an opposite relation between reductions of A and the resulting changes in searching times than that shown in Fig. 4.7(a). The reason is the increases in P+R facilities, which create opportunities for people to park outside the area and avoid the whole searching for parking phenomenon. Notice, also, that the relation between the conversion rate and the reduction in searching times is not monotonically decreasing. Beyond a certain point, ~ 80 %, the average searching time in the area increases with further conversions. In other words, we can always expect that some people would prefer to park inside the area, and reducing the parking supply too much will just increase the searching times. The higher P+R capacity affects the drivers' decision between entering the area by car or switching to P+R instead. This leads to more drivers switching to P+R, such that the P+R occupancy increases faster. The very low availability of P+R spaces leads, in turn, to some drivers entering the area by car. Due to the low capacity of parking spaces in the area (caused by a high conversion rate), the drivers face a longer time searching for an available parking space. From the revenue perspective, the relation is quite intuitive. Less parking spaces inside the area lead to a decline in revenue. Such a decline is lower than the one shown in Fig. 4.7(b) as it is partially compensated by an increase in the revenues from P+R.

In [Cao \(2016\)](#), an in-depth sensitivity analysis ([Ge and Menendez \(2014\)](#)) was conducted to analyze the effects of l_{ns}^k , l_j^k and l_p^k on the model outputs. The outcomes show that the model results are not sensitive to these distance variables as long as they are within a reasonable range. It is also possible to use more advanced sensitivity analysis methods ([Ge et al. \(2014, 2015\)](#), [Ge and Menendez \(2017\)](#)) in future research to have a deeper understanding of the relations between the different influencing factors.

4.4.4 Trade-offs between parking fee and congestion toll

When introducing congestion pricing, it is often a challenge for city councils to find the best relation between parking pricing and the congestion toll. Since all variables in our framework are based on average values and not on random values, every simulation run returns the same results as long as the input variables to the model are not changed. This means that the number of cars of all transition events and the number of available parking spaces on the network are deterministic at the beginning of each time slice. We run a simulation-based search algorithm based on multiple simulation runs to understand the effects of all possible relations $\frac{p_t}{p_p}$ on the average searching time (Fig. 4.9(a)) and revenue (Fig. 4.9(b)).

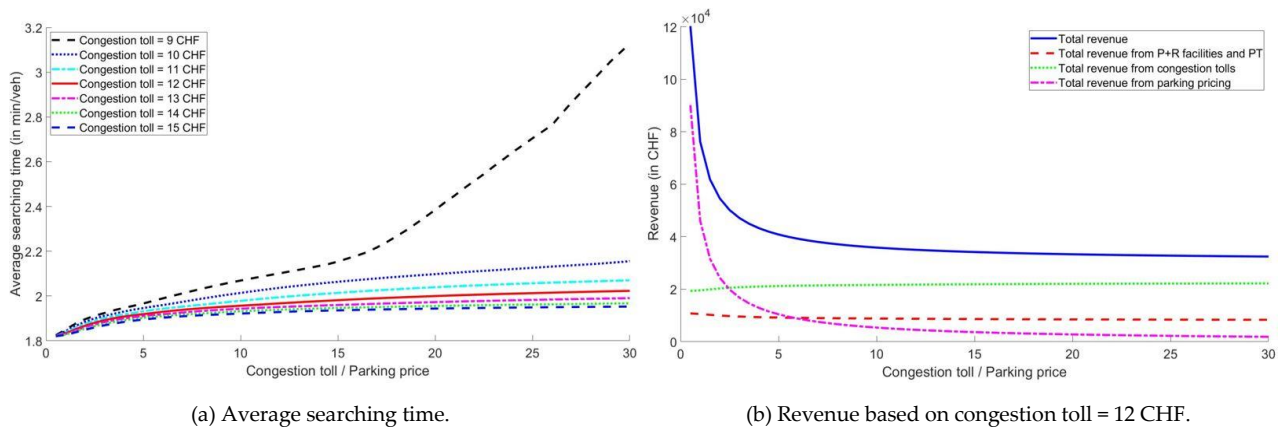


Fig. 4.9. Relation between congestion toll and parking price vs. traffic performance and revenue over a typical working day.

Increasing the relation $\frac{p_t}{p_p}$ leads to an increasing average searching time. The higher $\frac{p_t}{p_p}$, the lower is p_p for a fixed congestion toll, and the higher the number of drivers that decide not to use P+R and drive into the area. The traffic performance impacts are more severe for low congestion tolls as drivers face less costs entering the network by car. Interestingly, the average searching time for low congestion tolls stays low up to a certain $\frac{p_t}{p_p}$ value. For example, the average searching time for $p_t = 9$ CHF in Fig. 4.9(a) equals about 1.8 – 2.1 min per car up to $\frac{p_t}{p_p} = 12$ before it jumps up to 3.1 min per car ($\frac{p_t}{p_p} = 30$). Lower relations of $\frac{p_t}{p_p}$ and consequently, higher p_p values lead to the highest revenue values (Fig. 4.9(b)). The total revenue results are mainly driven by the parking pricing revenue as the parking fees are charged hourly.

In summary, low relations between the congestion toll and parking pricing, $\frac{p_t}{p_p}$, might not only lead to the best traffic performance in the network, but also to the highest revenue for the city. With a higher congestion toll, p_t , the parking price, p_p , turns out to be less important for the drivers' decisions and thus, the traffic performance becomes more and more independent of the relation $\frac{p_t}{p_p}$. However, this might evoke social and political acceptability problems and changes to the drivers' behavior in the long-term. As our research focuses on short-term effects, demand changes are

considered out-of-scope in this dissertation.

4.4.5 Distributional effects of our heterogeneous VOT model

This section investigates the capabilities of our multi-VOT framework considering several user groups associated with different VOTs. Compared to other single-VOT models, our methodology can analyze the impacts of different VOTs on the drivers' decision between entering the area by car or switching to P+R instead. The VOT is used in our decision framework (section 4.2.2) to convert time-related costs into price units. In reality, the drivers' VOTs also affect their willingness to pay for parking, congestion tolls, P+R and/or PT fees. However, here we focus on the decisions related to travel times. Thus, we relax all pricing (i.e., $p_p = p_t = p_{pr} = p_{PT} = 0$ CHF) and explore a scenario focusing on the time-related VOT impacts for different user groups.

Fig. 4.10 presents the percentage of drivers switching to P+R compared to those entering the area by car.

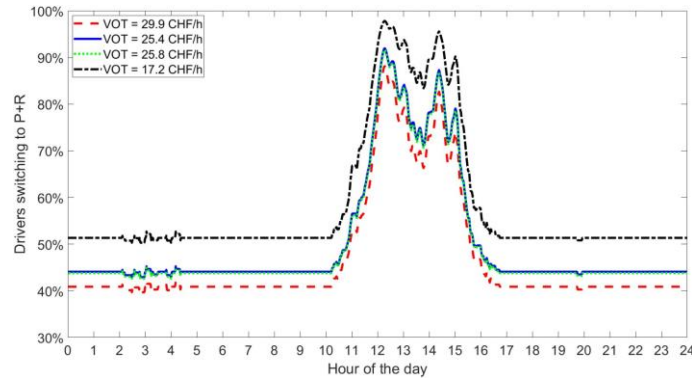


Fig. 4.10. Distributional effects of different VOTs on the drivers' decision between entering the area by car or switching to P+R as a moving average over 10 min.

Lower VOT user groups are more likely to switch to P+R. The user group associated with the lowest VOT, $VOT^4 = 17.2$ CHF/h, reaches the highest rate, with up to 98 % of the drivers switching to P+R during the 12.5 hour (peak of the day). This rate decreases for the drivers with a higher VOT. However, these reductions do not seem to be too drastic. This is due to significant increase in searching times during this peak hour, even after the lowest VOT user groups here switched to P+R.

4.5 Summary of the chapter

In this chapter, we develop a multimodal macroscopic traffic and parking search model that allows us to evaluate whether parking pricing can be considered as an alternative to the more controversial congestion pricing schemes, especially in areas with a high parking demand for public parking spaces. Our easy to implement methodology is based on aggregated data at the network level over time. Based on small data collection efforts and low computational costs, model outputs can be generated with a simple numerical solver and without complex simulation software.

Our general framework only uses very limited data inputs, including travel demand, VOT, the traffic network, parking and P+R capacities, and initial traffic and parking specifications. We illustrate our methodology using real data from an area within the city of Zurich, Switzerland. Below, we summarize the main contributions of this study.

- Our framework not only evaluates the short-term impacts on the traffic and parking system (i.e., traffic performance, parking availability, revenue for the city, etc.) resulting from implementing parking pricing and/or congestion pricing strategies, but also the impacts of the traffic and parking system (i.e., traffic congestion, parking pricing, etc.) on the drivers' decision between entering the area by car or using P+R instead.
- We propose a decision model based on multiple user groups with respect to their VOT and integrate it into a multimodal macroscopic traffic and parking framework that allows us to assess different parking and congestion pricing policies. This framework allows us to analyze the impacts of different VOTs on the drivers' decision between entering the area by car or switching to P+R instead.
- Besides comparing parking and congestion pricing scenarios, our study uses a simulation-based search algorithm to find the best relation between the parking fee and the congestion toll in order to improve the traffic performance in the network or the total revenue for the city (which could, in turn, be used to improve the P+R facilities). Low relations between the congestion toll and parking pricing (i.e., a high enough parking fee in comparison to the congestion toll) might not only lead to the best traffic performance in the network, but also to the highest revenue for the city. However, due to the high costs for drivers actually entering the area by car, a lot of drivers might prefer staying at a P+R facility outside the area. The traffic performance impacts might be more severe for low congestion tolls as drivers face less costs entering the network by car.
- Our results for Zurich show that parking pricing policies are indeed a viable option compared to congestion pricing, potentially leading to traffic performance improvements even if parking pricing policies only affect drivers using public parking in the area. Furthermore, parking pricing strategies are socially and politically more accepted and easier to implement than introducing a congestion toll in a metropolitan area.

Overall, the usage and contributions of the framework are far beyond the illustration in the presented case study. The framework could be extended to include tiered parking/P+R and congestion pricing. This scheme allows drivers to pay a low parking/P+R rate for the first hours, and then the rate jumps up significantly to promote higher parking availability and to increase turnover. Alternatively, the congestion toll might be low when you enter the area for only a limited amount of time. This ensures that cars do not stay forever in the area and congest the central streets. As some cities are developing parking policies aiming to maintain certain

occupancy rates throughout the day, we could also investigate the impacts of parking and congestion pricing decisions on the optimal parking occupancy rates (chapter 6). A further consideration is to enhance the parking fees and the congestion toll using responsive pricing schemes. The purpose of these time-dependent fees is to move the traffic demand for the central area away from the daily peak. Congestion pricing might be more expensive during the peak hours of the day compared to off-peak hours, and it might be free on Sundays as the example in London shows ([Leape \(2006\)](#), [Santos \(2005\)](#), [Santos and Shaffer \(2004\)](#)). In future research, parking fees might not only be dependent on the parking demand of each user group over time, but also on the available parking supply in the network (chapter 5). This could only affect a portion of the traffic demand, i.e., the parking fee for all parking spaces could follow a lower fixed (subsidized) charge for a portion of the demand and the remaining demand could be treated responsively, reflecting the external costs for parking. Similarly, future studies can investigate the impacts of only a portion of the demand being obliged to pay the congestion toll when entering the area. These differentiations within the traffic demand can be motivated by, e.g., the subsidy by a company or a city for their residents. In reality, drivers might prefer some parking spaces or PT stops in a central street or area of the network. Future research could investigate non-homogeneous environments (e.g., where parking spaces or PT stops are inhomogeneously distributed) by developing different subnetworks connected to each other. Each subnetwork could have, for example, a different distribution of parking spaces and PT stops.

In summary, our model helps cities to investigate the short-term influences of both parking and congestion pricing policies on the traffic performance, and how the traffic performance in the area impacts the number of cars deciding between entering the network by car or using P+R instead. Our framework offers quick evaluation possibilities for cities in terms of introducing new policies (e.g., P+R, parking pricing, and congestion charge) in an area and their impacts on the traffic and parking system, and the potential revenue over a defined time horizon.

Chapter 5:

A Dynamic Macroscopic Parking Pricing and Decision Model

This chapter is based on the results presented in:

Jakob, M., M. Menendez, J. Cao. 2018. "A dynamic macroscopic parking pricing and parking decision model". *Transportmetrica B: Transport Dynamics*, Vol. 8 (2020), Issue 1, pp. 307–331, doi: 10.1080/21680566.2018.1488226.

5.1 Introduction

In nearly all major cities, parking pricing policies can lead to significant changes on the performance of a transportation network. Short-term pricing strategies, for example, can have an influence on the performance of both the urban parking and traffic systems, e.g., parking pricing can affect the parking availability, the congestion and traffic performance, or the traffic composition in the network. In this chapter, we propose a dynamic macroscopic parking pricing model which analyzes the interdependency between responsive parking pricing and searching-for-parking traffic, while maximizing the parking pricing revenue and simultaneously minimizing the total cruising time on the network. It includes several cost variables (e.g., predicted parking cost at a future time, penalty cost for the past cruising time) in order to better replicate realistic conditions and determine the influence of parking pricing on cruising vehicles. This parking pricing scheme can then be compared to existing pricing methodologies.

In this research, we formulate a new parking pricing scheme and integrate it into the macroscopic traffic and parking model from chapter 2 proposed by [Cao and Menendez \(2015a\)](#) in order to develop a parking pricing model and estimate its influence on the searching-for-parking traffic. The original methodology, validated already in [Cao et al. \(2019\)](#), uses a parking-state-based matrix to model the interactions between urban parking and traffic macroscopically over time. With such matrix, the model provides an approximation of the proportion of cars searching for parking, as well as an approximation of the time cars spent searching for parking, or traveling through the system. The original model, however, cannot account for pricing nor different values of time. Thus, in this chapter we propose a parking pricing and decision model to fill this gap. Then, we compute all the variables associated with cruising for parking under the influence of our responsive parking pricing fee over time. The macroscopic responsive pricing scheme, taking the parking search phenomenon into consideration, is modeled as an optimization problem to maximize revenue while minimizing the cruising time on the network. In contrast with previous studies that only take the parking occupancy into account, here the parking fee changes in response to both, the parking occupancy, and the number of searching vehicles. The optimization model is formulated to maximize the parking pricing revenue to the highest level such that the cost of paying the current parking fee remains smaller than the cost of keep on searching to obtain a lower parking fee (i.e., so the total cruising time on the network is minimized). In general, in the parking pricing model, when a searcher finds an available parking space, he makes the decision to stay or to keep on searching based on several cost factors:

- the drivers' VOT;
- the current parking fee; and
- the expected cost of keep on searching (which include the predicted future

parking fee, the costs associated with traveling to the next parking possibility, and a penalty for past cruising time).

The average number of drivers that decide to park in a given time interval is computed then based on these costs, and the traffic and parking conditions can be found over time. Based on that, we analyze the efficiency of the proposed parking pricing scheme and its short-term influence on the urban traffic and parking systems. These short-term effects include:

- the searching-for-parking traffic (cruising);
- the congestion in the network (traffic performance);
- the total driven distance (environmental conditions); and
- the revenue created by parking fees for the city.

The maximal parking fee will evidently increase the revenue for the city in the short-term. It could also, in the long-term, deter drivers from driving into the city, potentially changing the demand. These long-term effects, however, are considered out-of-scope for this chapter. Instead, we concentrate on modeling the short-term effects, including not only the financial benefits of the parking pricing scheme, but also the benefits (or disbenefits) that this might bring to the area's traffic system. The responsive parking pricing model is illustrated in a case study of an area within the city of Zurich, Switzerland. In addition, it is compared to other three alternative parking pricing scenarios, including a free, a constant, and an occupancy-responsive parking pricing scheme where the fee only changes in response to the parking occupancy.

Most of the existing studies model travelers' parking preferences and decisions microscopically. Such studies tend to require huge amounts of data, and high levels of detail both on the demand and the supply side. In this research, we focus only on average values and probability distributions across the network, i.e., we look at the problem macroscopically. Thus, there is no data requirement for individual drivers or parking spaces, as all data requirements correspond to aggregated values at the network level. Compared to microscopic approaches, this not only saves on data collection efforts (e.g., drivers' parking fee preferences, individual driving routes, individual parking spaces turnovers) but also reduces the computational costs significantly. This is especially useful for real-time control algorithms or when the data is scarce.

The chapter is organized as follows. Section 5.2 presents the overall methodology of the macroscopic parking pricing model. It is integrated into the matrix that describes the system dynamics of urban traffic based on its parking-related states and transition events. Section 5.3 introduces the analytical framework for the dynamic macroscopic responsive parking pricing. It includes a cost analysis for the cost of staying at the current parking space and the cost of keep on searching with the detailed description of all the relevant cost variables. Section 5.4 shows a case study of an area within the city of Zurich, Switzerland, to explore the use of the concept and the proposed methodology. Section 5.5 summarizes the findings of this chapter.

5.2 Framework

In this section, the methodology of the dynamic macroscopic parking pricing and parking decision model is developed. It builds on the parking-state-based matrix in chapter 2 proposed by [Cao and Menendez \(2015a\)](#). We now extend it to include a dynamic macroscopic parking pricing methodology. An overview of the assumptions, inputs and outputs is shown below.

5.2.1 Basic information for analytical model

Basic model assumptions (section 5.2.1.1), inputs (section 5.2.1.2), and expected outputs (section 5.2.1.3) are briefly described below.

5.2.1.1 Assumptions

In addition to the assumptions in section 2.2, we need to add some parking pricing specific assumptions to the macroscopic model. We assume that the VOT is different for individual vehicles depending on their user group. A user group can be dependent on the residents' location, income, careers, working states, etc. This VOT affects the parking decision of the cruising vehicles. All drivers are assumed to be risk-neutral, i.e., drivers are rational during their parking decision and only compare the relevant parking costs between deciding to park or keep on searching to find a better parking price. In reality, drivers with a low VOT might not keep on searching when the parking price increases and they might quit their journeys. Thus, we compute the best possible parking price such that only a small percentage of the population is affected by this "keep on searching" decision. In addition, we assume that drivers do not cancel their trips while searching for parking. The proportion of new arrivals that corresponds to traffic that is not searching for parking (i.e., through-traffic) is assumed to be independent of vehicles' VOT. The total traffic demand for all time slices, including the actual parking demand can be obtained based on simulations, demand models, city statistics, or other sources. The percentage of the demand that does not search for parking represents the proportion of traffic that is driving through this area but has a destination outside or is going to reserved parking spaces. The distance that must be driven by a vehicle before it starts to search for parking is also assumed to be independent of vehicles' VOT. As stated before, vehicles that use private parking spaces or have parking permit reservations do not typically search for parking. Thus, they are considered as part of the through traffic. As soon as the vehicles enter the parking-state, the parking fee needs to be paid at the rate of the arrival time, i.e., the unit parking pricing is assumed to be independent of the vehicle's parking duration.

5.2.1.2 Inputs

In chapters 2 and 3, we have already introduced some relevant independent variables corresponding to the travel demand, the parking system, the traffic network, and model parameters (Table 2.1, 3.1, and 3.2). These variables can be estimated based on some historical data, e.g., traffic data on main roads to enter the network; parking data from one day's data collection, etc. Other variables can be estimated based on real measurements, the MFD, and/or simulation results. Additional input parameters are the initial conditions of the parking-related states, which can be measured, assumed or simulated.

Corresponding to the assumptions described above, Table 5.1 shows all the model's independent variables, which are newly introduced in this chapter.

Table 5.1. Independent variables (inputs to the model).

Notation	Definition
p^0	Initial parking pricing for all available parking spaces.
Δ_{max}	Maximum increase/decrease in pricing per time slice.
η_{pred}	Fixed number of time interval slices to include for approximation of predicted parking pricing.

These variables correspond to parking pricing specific input parameters. These variables can be estimated based on historical parking pricing data, or defined otherwise.

5.2.1.3 Outputs

The model provides, amongst others, the results of the interactions between the dynamic responsive parking pricing system, the urban parking system, and the urban traffic system. The responsive pricing output over time and its interdependency with cruising vehicles can be studied. The short-term effects of parking pricing on traffic conditions can be investigated, i.e., the distance driven and the time spent by both, vehicles searching and vehicles not searching. Besides these environmental, cruising-for-parking, and traffic performance effects, we also analyze the revenue created by parking fees for the city.

In addition to Table 2.1 and 2.2, Table 5.2 shows a list of new variables we define and use in our methodology. The variables in Table 2.1 and 2.2 are used to quantify the number of vehicles that experience each transition event in a time slice. The first set of variables in Table 5.2 corresponds to the parking pricing model and the cost variables that are used to compute the vehicles deciding to park. The second set is used to compute these cost variables.

Table 5.2. Intermediate model variables.

	Notation	Definition
First set	p^i	Responsive parking fee for all available parking spaces during time slice i .
	$C_{tot}^{i,k}$	Total costs of keep on searching to a next available parking possibility for each user group $k \in K$ at time slice i .
	C_{pay}^i	Costs for the predicted parking fee at all available parking spaces for the next future time slices, predicted at the beginning of time slice i .
	ΔC_{pay}^i	Change of costs for the predicted parking fee at the beginning of time slice i .
	$C_{dist}^{i,k}$	Costs of driving from a given available parking space to the next parking possibility (i.e., external costs as petrol, wear and tear of vehicles) for each user group $k \in K$ at time slice i .
	$C_{pen}^{i,k}$	Costs for penalty term with respect to past cruising time (i.e., driving costs in past iterations) for each user group $k \in K$ at time slice i .
Second set	r^i	Expected average road travel distance from a given available parking space to the next parking possibility.
	$\delta_{park}^{i,k}$	A binary indicator of vehicles' decision to park (or not) for each user group $k \in K$ in time slice i . Its value is either 1 or 0.
	ACT^i	Average cruising time per vehicle at the beginning of time slice i .
	CT_{max}^i	Maximum cruising time per vehicle at the beginning of time slice i .

5.2.2 Transition events

Below we introduce the modification of the transition events “Enter the area”, “Start to search for parking”, “Access parking”, “Depart parking”, and “Leave the area” as presented in section 2.4. The transition events are now adapted to include vehicles from different VOT user groups in the network, and the decision to park or not with respect to parking pricing.

5.2.2.1 Enter the area

Recall that the number of vehicles entering the area and transitioning to “non-searching-state” for user group $k \in K$ during time slice i , $n_{ns}^i = \sum_{k=1}^K n_{ns}^{i,k}$, is an input to the model. Please refer to section 3.3.2.1 for more information.

Remember that a number of $\beta^i \cdot n_{ns}^{i,k}$ vehicles from each user group $k \in K$ do not search for parking and will directly leave the area after driving a distance l_j^k . The remaining percentage, $1 - \beta^i$, will go through all transition events.

5.2.2.2 Start to search for parking

We assume that the vehicles from user group $k \in K$ start to search after driving a distance $l_{ns/j}^k$ since they enter the area. $l_{ns/j}^k$ and l_j^k can be assumed as a fixed value or to follow any given probability density function. In [Cao \(2016\)](#), an in-depth sensitivity analysis ([Ge and Menendez \(2014\)](#)) was conducted to quantitatively evaluate the effects of this variable on the model output. The outcomes show that the model results are not very sensitive to the values of $l_{ns/j}^k$ and l_j^k as long as they are within a reasonable range. Eq. (53) shows the number of vehicles $n_{ns/s}^{i,k}$ starting to search for parking during time slice i . Note that Eq. (53) is consistent with Eq. (5) and modelled

for each $k \in K$.

$$n_{ns/s}^{i,k} = \sum_{i'=1}^{i-1} \underbrace{(1 - \beta^{i'})}_{\text{term 1}} \cdot \underbrace{n_{ns}^{i',k}}_{\text{term 2}} \cdot \underbrace{\gamma_{ns/s}^{i',k}}_{\text{term 2}} \quad (53)$$

The number of vehicles $n_{ns/s}^{i,k}$ in Eq. (53) consists of vehicles from user group $k \in K$ that have entered the network area in any slice between 1 and $i - 1$. Here we use $i' \in [1, i - 1]$ to denote such a time slice. Term 1 in Eq. (53) shows all the vehicles that have entered the area before time slice i and need to park. Term 2 is a binary variable indicating whether these vehicles will start to search for parking in time slice i or not. Please refer to Eq. (25) for the formulation of $\gamma_{ns/s}^{i',k}$.

5.2.2.3 Find and access parking: Parking pricing and parking decision

One of the goals of this chapter is to propose a dynamic macroscopic parking pricing model with its interdependency with searching-for-parking traffic. It is included into a traffic system with a parking search model over time to replicate reality.

In the transition event “Find and access parking” when drivers find an available parking space, they make the decision to park or to keep on searching for the next parking possibility.

- **Vehicles finding parking:** We compute the portion of vehicles finding parking as those in the transition event $n_{s/p}^i$ (“Access parking”) in [Cao and Menendez \(2015a\)](#). More details can be found in section 2.4.2, referring to Eq. (6). The formulation is based on probability theory, and it depends on the number of available parking spaces A^i , the number of vehicles searching for parking N_s^i , and the maximum driven distance per vehicle in a given time slice, d^i .

The specific set of vehicles finding an available parking space is based on the vehicles’ locations, that of the available parking spaces and of the competitors. Here, however, we are only interested in the average number of drivers that find parking and the average searching time and distance driven during a time slice. Hence, we do not need to track any specific vehicle or parking space.

- **Vehicles deciding to park:** The number of vehicles that do access parking (i.e., transition from “searching” to “parking”-state) is adapted depending on the vehicles deciding to park based on the parking price as illustrated in Fig. 5.1.

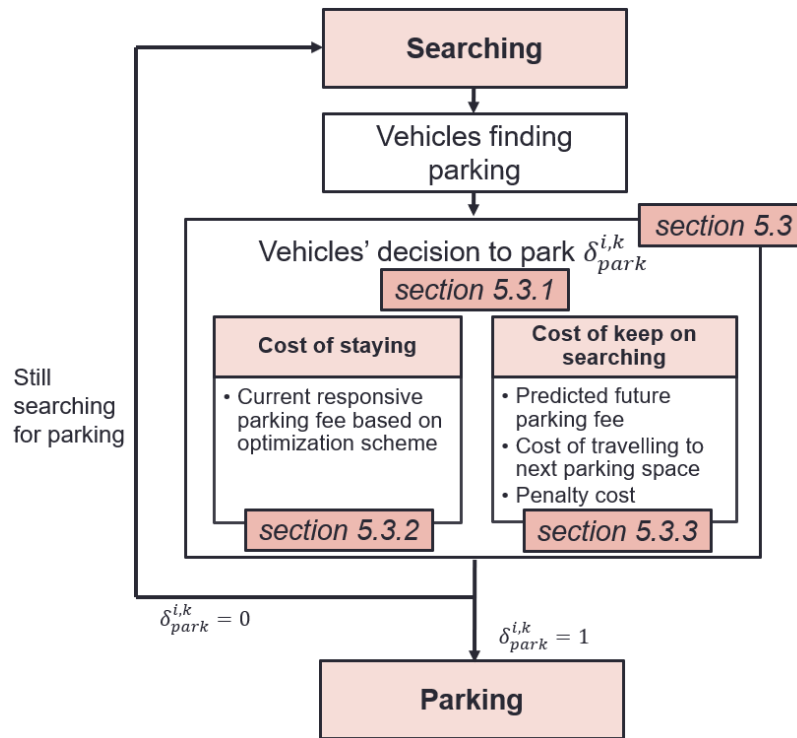


Fig. 5.1. Modelling of parking pricing and its effect on the transition between the “searching” and “parking”-state.

Fig. 5.1 shows an overview of our dynamic responsive parking pricing model within the structure of this chapter, that includes the vehicles finding parking (section 2.4.2 based on [Cao and Menendez \(2015a\)](#)) and the vehicles deciding to park (section 5.3). This last section explains the main model to determine the vehicles deciding to park (section 5.3.1), depending on the cost of staying (section 5.3.2), and the cost of keep on searching (section 5.3.3). All costs are determined macroscopically without stochastic components, using average values and probability distributions across the whole population. In section 5.3.1, the vehicles’ decision to park $\delta_{park}^{i,k}$ is determined for each user group $k \in K$. This models the decision process to park or to keep on searching dynamically. Incorporating the cost of staying and the cost of keep on searching, $\delta_{park}^{i,k}$ refers to the vehicles’ decision to park at the current parking space for each user group k .

The decision to stay (i.e., park) or keep on searching is modelled mathematically and depends on various influence factors. Below we provide an overview of those influence factors. More details are given in section 5.3.

- **Cost of staying:** The cost of staying in section 5.3.2 represents the current parking price. The dynamic responsive parking fee over time is computed macroscopically as the outcome of an optimization model. By maximizing the revenue for a city while simultaneously minimizing the cruising time for every time slice the parking fee is determined depending on the number of vehicles N_s^i in the searching-state and the number of available parking spaces A^i .
- **Cost of keep on searching:** The cost of keep on searching in section 5.3.3 is

computed based on the predicted parking fee in a future time slice (section 5.3.3.1), the costs associated with traveling to the next parking possibility (section 5.3.3.2), and some penalty for the past cruising time (section 5.3.3.3) in order to avoid an ever searching vehicle.

For the next time slice $i + 1$, the number of vehicles N_s^{i+1} in the searching-state is computed according to Eq. (54a) and (54b), which are a modification of the searching-state formulation in Eq. (2). First, $N_s^{i+1,k}$ is determined in Eq. (54a) for each user group $k \in K$. Then, we compute N_s^{i+1} in Eq. (54b) as the sum over all user groups k .

$$N_s^{i+1,k} = N_s^{i,k} + n_{ns/s}^{i,k} - \underbrace{n_{s/p}^i \cdot \frac{N_s^{i,k}}{N_s^i}}_{\text{term 1}} \cdot \underbrace{\delta_{park}^{i,k}}_{\text{term 2}} \quad (54a)$$

$$N_s^{i+1} = \sum_{k=1}^K N_s^{i+1,k} \quad (54b)$$

For any given time slice, term 1 in Eq. (54a) represents the number of vehicles that have found parking. The vehicles will then decide whether to access parking or not, depending on the parking decision variable $\delta_{park}^{i,k}$ in term 2 for user group k . The vehicles will access parking when $\delta_{park}^{i,k} = 1$, and they will keep on searching for a next parking possibility when $\delta_{park}^{i,k} = 0$. Note that we assume that the ratio of the vehicles in the searching-state from user group k is the same as the ratio of the vehicles finding parking from user group k . Thus, the portion of vehicles having found parking that belong to user group k is represented by the ratio $\frac{N_s^{i,k}}{N_s^i}$ in term 1.

5.2.2.4 Depart parking and leave the area

The number of vehicles that depart parking and the number of vehicles that leave the area are computed as in Eq. (7) and (8) in section 2.4.2. The former is a function of the distribution of parking durations. The latter is a function of some minimum driven distance.

5.3 Macroscopic parking pricing and parking decision model

In this section, the modelling parts and the analytical formulations for the dynamic macroscopic responsive parking pricing and parking decision methodology are shown. Here we propose the dynamic algorithms for the vehicles deciding to park (or not), including a cost analysis for the corresponding cost of staying and the cost of keep on searching for the next parking possibility, with the detailed description of all relevant cost variables.

5.3.1 Main model

Recall that p^i is the actual parking fee for all available parking spaces at time slice i , i.e., all parking spaces are assumed to have the same parking fee at any given time slice but the value changes over time. Thus, this leads to uniform price changes over the network. Notice that for a case where there are different areas each with a different distribution of parking spaces and parking prices, for example, one can use different subnetworks connected to each other, each modeled as the network presented here.

For all parking searchers to decide to park, we check the following condition

$$p^i \leq C_{tot}^{i,k}, \quad (55)$$

i.e., we check whether the parking price at the current parking space p^i is smaller than the cost of keep on searching to the next possible parking space (i.e., $C_{tot}^{i,k}$ for each user group $k \in K$). Since we do not track individual parking spaces, the average travel distance between available parking spaces is used as an indicator for the next possible parking space on the network. If Eq. (55) is fulfilled, the drivers decide to park at their current parking locations in time slice i . Otherwise the drivers will keep on searching hoping to find a better parking price, and as soon as they arrive at their next parking possibility, Eq. (55) will be checked again. Recall that we assume that all drivers are risk neutral and completely rational.

Now the vehicles' decision to park (or not) is indicated as $\delta_{park}^{i,k}$ in Eq. (56). Its value equals 1 if Eq. (55) is fulfilled for user group k ; otherwise the value equals 0, illustrating the decision to keep on searching for the next parking possibility. The decision is the same for all drivers belonging to the same user group, but it might be different across different user groups.

$$\delta_{park}^{i,k} = \text{Prob}(p^i \leq C_{tot}^{i,k}) = \begin{cases} 1, & \text{if } p^i \leq C_{tot}^{i,k} \\ 0, & \text{otherwise} \end{cases} \quad (56)$$

To obtain $\delta_{park}^{i,k}$ in Eq. (56), p^i and $C_{tot}^{i,k}$ will be further modelled. Note that $\delta_{park}^{i,k}$ has the same value for all parking spaces in a small compact area.

We now show the computation of p^i by using an optimization model in section 5.3.2 and then estimate $C_{tot}^{i,k}$ in section 5.3.3.

5.3.2 Cost of staying

The cost of staying, i.e., the parking fee over time is now presented as the outcome of an optimization model. This parking price changes in response to both, the parking occupancy, A^i , and the number of searching vehicles, N_s^i . In reality, N_s^i might be obtained with the help of connected vehicles and we assume this information will become available in the future. For cases where exact information regarding the

number of searchers is not available, simple estimations based on the overall demand pattern could be used. For this algorithm A^i and N_s^i at the beginning of each time slice are found based on the parking-state-based matrix over time. The ratio between the number of searchers N_s^i and the number of available parking spaces A^i changes from one time slice to the next. This change is formulated as written in Eq. (57).

$$\Delta \frac{N_s^i}{A^i} = \frac{N_s^i}{A^i} - \frac{N_s^{i-1}}{A^{i-1}} \quad (57)$$

By maximizing the revenue for a city while simultaneously minimizing the cruising time for each time slice, the parking fee p^i is determined as a multi-objective optimization problem in Eq. (58a-c). The resulting parking price, p^i , is then known at the beginning of each time slice i .

$$\max_{p^i} \left(\underbrace{p^i \cdot \frac{n_{s/p}^i}{N_s^i} \cdot \sum_{k=1}^K N_s^{i,k} \cdot \delta_{park}^{i,k}}_{\text{term 1}}, \underbrace{\sum_{k=1}^K (C_{tot}^{i,k} - p^i)}_{\text{term 2}} \right) \quad (58a)$$

$$\text{s. t. } |p^i - p^{i-1}| \leq \begin{cases} 0, & \text{if } \Delta \frac{N_s^i}{A^i} = 0 \\ \Delta_{max}, & \text{otherwise} \end{cases} \quad (58b)$$

$$p^i \geq p^0 \quad (58c)$$

The revenue maximization is stated as the objective function term 1 in Eq. (58a) where all vehicles from all user groups $k \in K$ having decided to park (as seen in Eq. (54a)) pay the parking fee p^i . The cruising time minimization is expressed by having Eq. (55) for each user group k as a soft constraint in the objective function term 2 in Eq. (58a) where $C_{tot}^{i,k}$ is dependent on the number of vehicles N_s^i in the searching-state and the number of available parking spaces A^i . This means that in case Eq. (55) is violated for user group k , i.e., $p^i > C_{tot}^{i,k}$, the optimization problem will be solved, although it will lead to additional cruising ($\delta_{park}^{i,k} = 0$) for user group k in time slice i . However, this optimization problem tries to satisfy Eq. (55) and to guarantee the same traffic performance on the network compared to a free parking scenario without parking pricing, i.e., it tries to implement a parking pricing scheme with a maximal revenue, while keeping the same travel time and distance as in a case without parking pricing (see more details in section 5.4.2). Evidently, we cannot do better than the scenario without parking pricing, but we can reach the same (or similar) traffic performance results, while collecting revenue for the city. We would like to find the maximal parking price p^i for any given time slice such that $\delta_{park}^{i,k} = 1$ for each user group k . In other words, what is the maximal price we could choose such that the drivers still decide to park and not keep on cruising for a better parking price in the future. At the end of the simulation ($i = T$) this concept will lead to a maximal revenue for a city while simultaneously minimizing the total cruising time on the network. As shown

in Eq. (58b), the absolute price difference between p^i and p^{i-1} should not exceed the maximum pricing change input parameter Δ_{max} to reduce the oscillations of the optimal parking pricing output (i.e., avoid drastic price fluctuations). Additionally, if the ratio between N_s^i and A^i in Eq. (57) is equal to zero, then we determine the parking fee as $p^i = p^{i-1}$, a constant price compared to the parking price p^{i-1} in the last time slice $i - 1$. Last but not least, as shown in Eq. (58c), the parking fees should not go below the initial parking prices.

This convex optimization problem can be solved with a simple numerical solver. It is also possible to include scale parameters within $C_{tot}^{i,k}$ to weight each decision cost from section 5.3.3 in the optimization model.

In the next section, we present the formulations for the cost of keep on searching for another parking possibility $C_{tot}^{i,k}$.

5.3.3 Cost of keep on searching

The total cost of keep on searching $C_{tot}^{i,k}$ is computed for each user group $k \in K$ based on multiple cost terms as shown in Eq. (59) which are derived in the following sections.

$$C_{tot}^{i,k} = C_{pay}^i + C_{dist}^{i,k} + C_{pen}^{i,k} \quad (59)$$

This includes:

- the cost C_{pay}^i for the predicted parking fee at all available parking spaces for the next future time slices, predicted at the beginning of time slice i (section 5.3.3.1),
- the predicted cost $C_{dist}^{i,k}$ of traveling from a given available parking space to the next parking possibility (section 5.3.3.2),
- the penalty cost $C_{pen}^{i,k}$, i.e., the driving cost associated with past iterations (section 5.3.3.3).

Note that only $C_{dist}^{i,k}$ and $C_{pen}^{i,k}$ are affected by the user group k since these are the only cost variables including a time component that is associated with the drivers' VOT.

5.3.3.1 Predicted future parking fee, C_{pay}^i

The term C_{pay}^i is the parking fee at all available parking spaces for the next future time slices, predicted at the beginning of time slice i . We assume the parking fee in the next future time slice $i + 1$ dictates the parking pricing we would pay in all next future time slices. We assume the driver predicts this future price with some information he/she has about the system (based on his/her own observations). The parking prices should be a function not only of the available supply, but also of the demand (i.e. larger demand should lead to higher prices even for the same available supply). Given that the parking price in this model is dependent on the number of searching

vehicles N_s^i and the number of available parking spaces A^i from past iterations, we use both variables to predict future pricing, i.e., we assume the driver has some very recent historical information available about the traffic and parking systems. Such assumption is not unreasonable as traffic information is nowadays generated by a number of sources ([Ambühl and Menendez \(2016\)](#)), the same as parking information ([Cao and Menendez \(2018\)](#)). Thus, in this predicted parking pricing scheme the future parking price C_{pay}^i changes in response to N_s^i and A^i from past iterations, i.e., this pricing scheme not only focuses on the parking occupancy, but also takes the parking search phenomenon and competition into account.

The predicted change of the parking fee ΔC_{pay}^i is formulated in Eq. (60) as the pricing difference between the current and consecutive future time slices. The predicted forecasting strategy uses historical information about the ratios in Eq. (57) and the current parking price p^i .

$$\Delta C_{pay}^i = \underbrace{p^i}_{\text{term 1}} \cdot \underbrace{\left(\left| \Delta \frac{N_s^{i+1}}{A^{i+1}} \right| \right)^{\frac{1}{y}}}_{\text{term 2}} \approx p^i \cdot \underbrace{\left(\left| \Delta \frac{N_s^i}{A^i} \right| \right)^{\frac{1}{y}}}_{\text{term 3}} \cdot \underbrace{\left[\frac{1}{\eta_{pred}} \cdot \sum_{j=i-\eta_{pred}+1}^i \frac{\Delta \frac{N_s^j}{A^j}}{\Delta \frac{N_s^{j-1}}{A^{j-1}}} \right]}_{\text{term 4}}, \quad (60)$$

where $\Delta \frac{N_s^{j-1}}{A^{j-1}} \neq 0$. In Eq. (60), term 1 is the current parking price p^i and term 2 represents the future responsive quality to ΔC_{pay}^i . By multiplying both terms we transform the predicted responsive quality in term 2 to pricing units based on the current parking fee in term 1. The influence level of this predicted responsive quality term can be selected in our framework. Within term 2, y characterizes the level of responsiveness, i.e., it changes the level of influence of $\Delta \frac{N_s^{i+1}}{A^{i+1}}$ on the delta pricing value ΔC_{pay}^i . The sensitivity analysis in section 5.4.4 shows that changes to the parameter $y > 1$ only have a marginal influence on the total revenue results. This scale parameter, however, needs to be calibrated in future research such that it leads to reasonable pricing results over time that are acceptable for the drivers in the area. This parameter ensures the flexibility of our model for different pricing needs in an area. In the remainder of this chapter, we assume a square root dependency and set $y = 2$. An approximation for the predicted responsive quality in term 2 is computed by using term 3 and term 4. The idea of this approximation is to estimate the predicted responsive quality by the current quality term and past change effects regarding the ratios between the number of searchers and the number of available parking spaces over a limited amount of past time slices. This approximation has been validated by a data analysis from the case study in section 5.4, but the details are omitted in this chapter for brevity. Term 3 in Eq. (60) refers to the current responsive impact term. Term 4 is estimated by the total average of increases/decreases over the last fixed η_{pred} time slices, where $1 \leq \eta_{pred} \leq i - 1$ is an input parameter to the model. Thus, we consider all ratios $\Delta \frac{N_s^j}{A^j} \neq 0$ for $j \in \{i - \eta_{pred}, \dots, i\}$ to get the aggregated predictive estimate in term 4. For the input parameters $\eta_{pred} = 1$, the approximation term 4 in Eq. (60) only considers the increase/decrease of the ratio $\Delta \frac{N_s^j}{A^j}$ from the time slice $i - 1$

to the current slice i , while for $\eta_{pred} = i - 1$ this estimate covers the total average of increases/decreases of the ratio $\Delta \frac{N_s^j}{A^j}$ for all previous time slices $j \in \{2, \dots, i\}$. By properly setting this input parameter η_{pred} in Eq. (60), we can make sure that the ratios $\Delta \frac{N_s^j}{A^j}$ for initial time slices j have no impact on the predictive pricing for long simulations runs.

By using Eq. (60) we compute in Eq. (61) the actual predictive parking pricing fee C_{pay}^i for all available parking spaces in the next future time slices. Notice that this value is just a prediction and will not necessarily match the actual price set in future time slices.

$$C_{pay}^i = \begin{cases} p^i + \min\{\Delta C_{pay}^i, \Delta_{max}\}, & \text{if } \Delta \frac{N_s^{i+1}}{A^{i+1}} > 0 \\ p^i, & \text{if } \Delta \frac{N_s^{i+1}}{A^{i+1}} = 0 \\ p^i - \min\{\Delta C_{pay}^i, \Delta_{max}\}, & \text{if } \Delta \frac{N_s^{i+1}}{A^{i+1}} < 0 \end{cases} \quad (61)$$

For $\Delta \frac{N_s^{i+1}}{A^{i+1}} \geq 0$, we only consider ΔC_{pay}^i to increase or decrease p^i , if it is smaller than the maximum pricing change input parameter Δ_{max} . Otherwise this predicted pricing change is determined with Δ_{max} . For $\Delta \frac{N_s^{i+1}}{A^{i+1}} = 0$, no pricing change is made.

5.3.3.2 Predicted cost of traveling to next available parking space, $C_{dist}^{i,k}$

$C_{dist}^{i,k}$ represents the predicted cost of traveling from a given available parking space to the next parking possibility. This cost is associated with the driving distance and with the drivers' VOT depending on their user group $k \in K$.

Recall that L is the length of the network and v^i the average travel speed in time slice i . We do not know the exact location of the available parking spaces, as they are assumed to be randomly distributed on the network. However, even though at any given iteration or decision epoch the available parking spaces are randomly distributed in the network, in the long run, the locations of all the available parking spaces are expected to obey a uniform distribution. Hence, we define the road travel distance r^i in Eq. (62) as an expected average value.

$$r^i = \frac{L}{A^i} \quad (62)$$

With the aid of r^i we get the expected average travel time $\frac{r^i}{v^i}$ between available parking spaces that depends mostly on two factors: (1) the number of available parking spaces A^i , and (2) the average speed v^i in the traffic network. Both variables are updated in every time slice; v^i is a function of the traffic density. This traffic density is in turn a function of the through-traffic proportion β^i , the searching traffic and its ability to find parking (for details see section 2.4.1 based on [Cao and Menendez \(2015a\)](#)). We introduce the input variable p_a , the price per unit distance. Then, r^i and

$\frac{r^i}{v^i}$ are both used to model $C_{dist}^{i,k}$ in Eq. (63),

$$C_{dist}^{i,k} = \underbrace{r^i \cdot p_d}_{\text{term 1}} + \underbrace{\frac{r^i}{v^i} \cdot VOT^k}_{\text{term 2}}, \quad (63)$$

where term 1 is associated with the actual driving distance (i.e., external costs as petrol, wear and tear of vehicles) and term 2 refers to the cost of time with respect to drivers' VOT. Recall VOT^k is the input parameter showing the VOT costs for each user group k .

5.3.3.3 Penalty cost, $C_{pen}^{i,k}$

Now we consider as well the driving cost $C_{pen}^{i,k}$ in past iterations to account for the time drivers have already searched. We model this in Eq. (64) by using the average cruising time per vehicle at the network level. The longer the average cruising time on the network is, the higher will be the penalty cost $C_{pen}^{i,k}$, and thus the total costs of keep on searching $C_{tot}^{i,k}$. This leads to a higher likelihood of drivers accepting the available parking spaces. This penalty cost term is defined as

$$C_{pen}^{i,k} = ACT^i \cdot VOT^k, \quad (64)$$

where ACT^i is the average cruising time per vehicle at the beginning of time slice i , i.e., the average time a vehicle spends in the searching-state. For simplification purposes we assume that at any given time slice i , the average cruising time is the same for all user groups $k \in K$.

We now determine ACT^i by computing the maximum cruising time CT_{max}^i per vehicle at the beginning of time slice i . CT_{max}^i is estimated based on the queueing diagram in Fig. 5.2 showing the cumulative number of vehicles going through each transition event as a function of time. This diagram not only provides the basis for CT_{max}^i , it can also be used to estimate other interesting indicators for both the traffic and the parking systems, including the number of vehicles searching over time, and the total cruising time in the area at any given time slice.

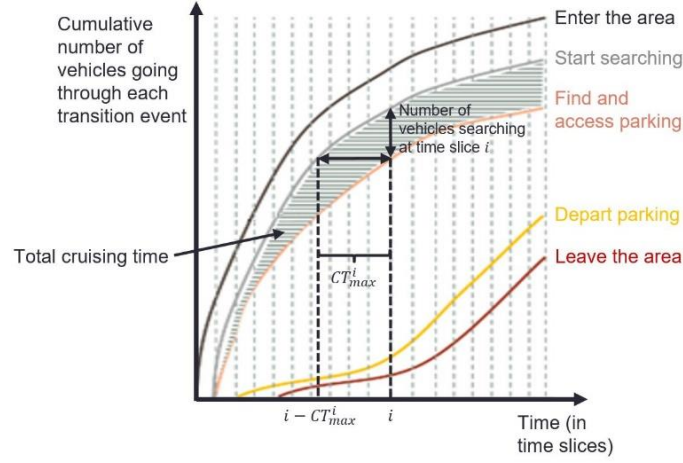


Fig. 5.2. Illustration of the maximum cruising time CT_{max}^i at the beginning of time slice i within the queuing diagram.

The maximum cruising time CT_{max}^i per vehicle can now be determined by using Eq. (65). As illustrated in Fig. 5.2, this equation sets the cumulative number of vehicles that have started searching before the beginning of time slice i equal to the cumulative number of vehicles that have found and accessed parking by the beginning of time slice i . In other words, Eq. (65) determines CT_{max}^i such that the cumulative number of $n_{ns/s}^j$ up to $i - CT_{max}^i$ equals to the cumulative number of vehicles that have found and accessed parking by the beginning of time slice i . Note that term 1 in Eq. (65) represents all vehicles for all user groups $k \in K$ having decided to park (as seen in Eq. (54a)). Eq. (65) can be interpreted by comparing the vehicles' time between the transition events "Start searching" and "Find and access parking" within the queuing diagram in Fig. 5.2.

$$\text{Find } CT_{max}^i, \text{ s. t. } \sum_{j=1}^{i-CT_{max}^i} n_{ns/s}^j = \sum_{j=1}^i \left(\underbrace{\frac{n_{s/p}^j}{N_s^j} \cdot \sum_{k=1}^K N_s^{j,k} \cdot \delta_{park}^{j,k}}_{\text{term 1}} \right) \quad (65)$$

Because all parking searchers are uniformly distributed on the network at the beginning of each time slice i , the average cruising time ACT^i is now computed in Eq. (66) as half of CT_{max}^i . Note that ACT^i only includes the cruising time of vehicles that are still cruising for parking and it does not include the cruised time for vehicles that already found parking. Recall that t is the length of a time slice.

$$ACT^i = \frac{CT_{max}^i}{2} \cdot t \quad (66)$$

Eq. (65) and (66) show an approximation for the average cruising time per vehicle ACT^i to determine $C_{pen}^{i,k}$ in Eq. (64).

5.4 Applications

In this section, a case study of an area within the city of Zurich, Switzerland, is provided to illustrate the interactions between a dynamic responsive parking pricing system and the traffic system. We use real data obtained by [Cao et al. \(2019\)](#) and present the results obtained from multiple simulation runs that are conducted with the aid of a simple numerical solver such as Matlab. Although the parking maneuvers themselves can also have a significant impact on traffic ([Cao and Menendez \(2015b\)](#); [Cao et al. \(2016\)](#)), here we focus on the cruising for parking phenomenon. We discuss the findings regarding parking pricing and the corresponding revenue in different pricing scenarios with its impact on the average/total searching time/distance in the network.

5.4.1 Case study of an area within the city of Zurich, Switzerland

We analyze the same study area as in section 3.4.1. It contains a total of $L = 7.7$ km of road. There are a total of 539 public parking spaces in the area, i.e., $A = 539$. We consider time slices of 1 min during a working day, i.e., $t = 1$ min and $T = 1440$ min. The traffic properties are modeled after the MFD of the city of Zurich (i.e., $v = 12.5$ km/h), based on ([Ortigosa et al. \(2014\)](#); [Loder et al. \(2017\)](#); [Dacic and Menendez \(2018\)](#)).

Fig. 5.3 shows the total traffic demand entering the network over all four user groups. Recall that 23% (618 trips) of the daily demand (i.e., $\beta^i = 0.23, \forall i$) does not search for parking and can be considered as through-traffic or having dedicated parking spaces in the center, while 77% (2069 trips) of the daily traffic searches for parking ([Cao et al. \(2019\)](#)). At the beginning of every working day 183 vehicles are already in the area, i.e., $N_p^0 = 183$ parking spaces are occupied. All other initial conditions are considered as zero, i.e., $N_{ns}^0 = N_s^0 = 0$.

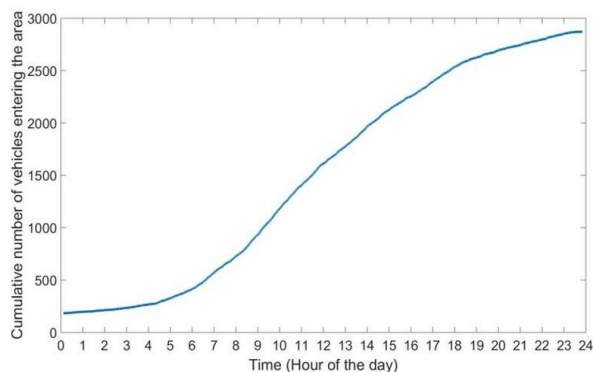


Fig. 5.3. Cumulative number of vehicles entering the area over one day (Source: [Cao et al. \(2019\)](#)).

The distribution of parking durations is determined as in Fig. 4.5 (section 4.4.1) using MATSim ([Waraich and Axhausen \(2012\)](#)). The initial parking fee is set to $p^0 = 2.50$ CHF for all parking spaces and the price per distance driven is $p_d = 0.3$ CHF/km. The

maximum pricing change per time slice is set to $\Delta_{max} = 0.1$ CHF/min and the predictive future parking fee is based on the past $\eta_{pred} = 10$ time slices (i.e., last 10 minutes).

In the following section, we analyze the outputs with a focus on the revenue that can be collected with the aid of responsive parking fees, and its effects on the total searching time in the area.

5.4.2 Parking pricing and traffic effects

Is it possible to implement parking pricing without having a significant negative effect on either traffic performance or environmental conditions in the short term? In other words, is it possible to keep the total time and the total driven distance the same in the short-term when introducing parking pricing on the network? These are relevant questions for city councils or private agencies that we would like to analyze in this section.

For this case study, we compare the following pricing scenarios in Table 5.3. All strategies result in a different parking pricing distribution over time with a different total revenue for the city. A total revenue of 5172 CHF is reached in the constant pricing scenario (b) after the period of one day compared to no revenue in the free parking scenario (a) (Table 5.4).

Table 5.3. Pricing scenarios and their pricing and optimization strategy.

Scenarios	Pricing and optimization strategy
Scenario (a): No parking pricing	Parking pricing set to 0 CHF for all time slices. No usage of the optimization problem in Eq. (58a-c), nor the parking fee prediction in Eq. (60)-(61).
Scenario (b): Constant parking pricing	Parking pricing set to initial parking fee from scenarios (c) and (d), i.e., 2.50 CHF for all time slices. No usage of the optimization problem in Eq. (58a-c), nor the parking fee prediction in Eq. (60)-(61).
Scenario (c): Occupancy-responsive parking pricing	Parking pricing set to change in response to the parking occupancy. Usage of the optimization problem in Eq. (58a-c), and the parking fee prediction in Eq. (60)-(61). However, since there is no dependency on the number of searching vehicles in the network, Eq. (5) becomes $\Delta(A^i)^{-1} = (A^i)^{-1} - (A^{i-1})^{-1}$ and $\Delta \frac{N_i^s}{A^i}$ is replaced by $\Delta(A^i)^{-1}$ in Eq. (58b), Eq. (60) and Eq. (61) for all time slices.
Scenario (d): Responsive parking pricing	Parking pricing set to change in response to the parking occupancy and the number of searching vehicles. Usage of the optimization problem in (58a-c), and the parking fee prediction in Eq. (60)-(61).

Table 5.4. Total daily revenue (in CHF) for all scenarios.

Scenarios	Cumulative revenue (in CHF)
Scenario (a): No parking pricing	0
Scenario (b): Constant parking pricing	5172
Scenario (c): Occupancy-responsive parking pricing	7018
Scenario (d): Responsive parking pricing	9742

The occupancy-responsive parking pricing strategy in scenario (c) uses the same methodology as our proposed pricing scheme in scenario (d). However, it is only dependent on the parking occupancy and there is no dependency on the number of searching vehicles on the network. Thus, Eq. (57) becomes $\Delta(A^i)^{-1} = (A^i)^{-1} - (A^{i-1})^{-1}$ and the variable $\Delta \frac{N_s^i}{A^i}$ is replaced by $\Delta(A^i)^{-1}$ in Eq. (58b), Eq. (60) and Eq. (61) for all time slices (Table 5.3). For our occupancy-responsive parking pricing scenario (c), we get the parking pricing output over time in Fig. 5.4(a). This plot is obtained by grouping the pricing fees over 5 consecutive time slices, i.e., the parking price is updated every 5 minutes. In addition, the parking fee is rounded to the next 0.5 CHF value to simplify the pricing structure¹. Recall that the parking fee cannot decrease below its initial value of 2.5 CHF. This pricing structure reflects the parking occupancy over time. This occupancy rate reaches its peak of 6.5 CHF at midday around the 12 hr and the 14 hr. Since we consider the shopping area Jelmoli within the city of Zurich, this might be explained by the shop opening time and the workers' lunch break, i.e., around this time most parking spaces are occupied. This rate decreases until the parking fee changes back to its initial value at approximately 16 hrs. The total revenue obtained with this pricing strategy amounts to 7018 CHF after the period of one day (Table 5.4).

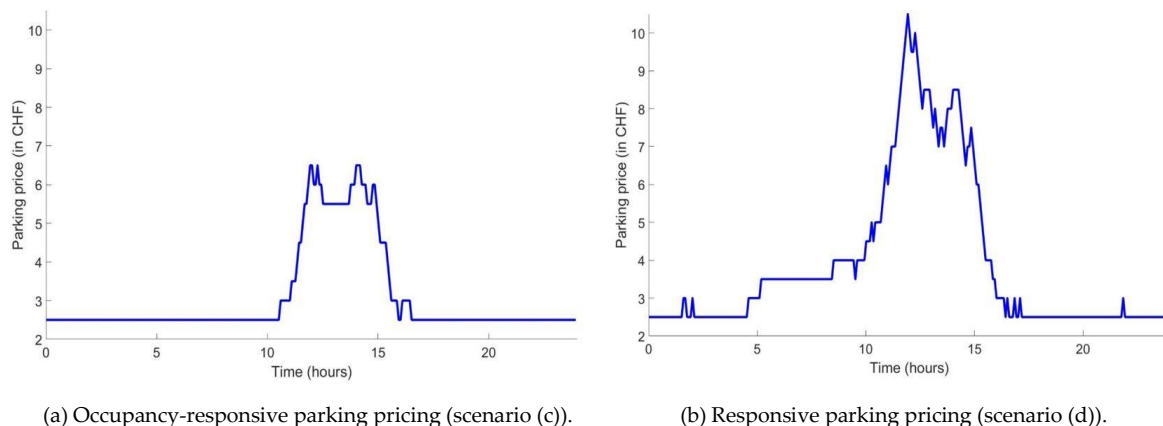


Fig. 5.4. Responsive parking pricing (in CHF) over time (in hours) in scenarios (c) and (d).

For our responsive parking pricing scenario (d), we get the parking pricing output over time in Fig. 5.4(b). As in the previous case, this output is obtained by grouping the pricing fees over 5 consecutive time slices and rounding it to the next 0.5 CHF value. Additionally, the parking fee must remain 2.5 CHF or higher. This parking pricing approach in Fig. 5.4(b) reflects the number of searching vehicles and available parking spaces on the network during the period of a working day. The pricing peak lasts approximately between the 10 hr and the 15:30 hr, i.e., around this time shops are open and, e.g., workers might drive there during their lunch break. The parking fee shows two peaks during this time period, the first peak reaches 10.5 CHF at midday and the second pricing peak reaches 8.5 CHF at approximately 14 hrs. During this period of time, there are more searching vehicles than available parking spaces

¹ For real-time pricing schemes it might be interesting to investigate a dampening mechanism to reduce oscillations, but this is considered out-of-scope for now and can be analyzed in future studies.

in the area (i.e., the real-time demand is higher than the real-time supply) (Cao et al. (2019)). Scenario (d) leads to a total revenue of 9742 CHF over the period of one working day (Table 5.4).

All parking pricing scenarios lead to different revenues for the city. However, coming back to our initial question, all scenarios result in the same time and distance costs on the network (Table 5.5). Due to the optimization algorithm in Eq. (58) no vehicles decide for extra cruising on the network. Thus, we have shown that it is possible to implement parking pricing without having a negative effect on traffic performance nor environmental conditions. The free or constant parking fee in scenarios (a) and (b) lead to the fact that Eq. (55) is always fulfilled, such that the drivers decide to park at the first possible parking location. The parking fees in scenarios (c) and (d) are chosen to minimize the total cruising time on the network, i.e., the parking pricing should not encourage drivers to keep on searching for a better future alternative in terms of cost. The average value for all VOT considering all user groups $\frac{1}{K} \cdot \sum_{k=1}^K VOT^k = 0.41$ CHF/min is used in Table 5.5 to determine the total time related costs.

Our responsive parking pricing strategy in scenario (d) not only provides a feasible model that minimizes the total cruising time on the network, but it also leads to financial revenues that significantly exceed the revenues obtained in the other pricing scenarios. Having a dependency on the number of searching vehicles results in much higher parking fee values over time compared to scenario (c), plus a slightly different pricing pattern throughout the day. The total revenue in scenario (d) increases by 38.8 % compared to scenario (c) and by 88.4 % compared to scenario (b), such that the pricing strategy leads to significant improvements for city councils or private agencies in the area. In addition, the responsive parking fee in Fig. 5.4(b) reflects the parking search phenomenon as well as the parking occupancy rate, and does not have negative influences on traffic performance nor environmental conditions in the short-term.

Table 5.5. Average/Total time and driven distance in the network (for all scenarios).

State	Average time per vehicle (min/veh)	Total time (min)	Total costs (converted through VOT)	Average driven distance (km/veh)	Total driven distance (km)
Searching state	3.14	7078	2902	0.65	1475
Non-searching state	4.43	9986	4094	0.92	2080
Total	7.57	17064	6996	1.57	3555

5.4.3 Impacts of traffic demand and parking supply

In this section, we investigate the impact of traffic demand and parking supply on our parking pricing model. Table 5.6 shows a comparison between the reference scenario (d) in section 5.4.2 and the responsive parking pricing scenarios with a 4 %

decrease or increase in the demand or the supply. As before, the average value for all VOT considering all user groups $\frac{1}{K} \cdot \sum_{k=1}^K VOT^k = 0.41$ CHF/min is used in Table 5.6 to determine the total time related costs.

Table 5.6. Comparison of reference scenario (d) to responsive parking pricing scenarios with a decrease/increase in demand and supply. Value within parenthesis represents the percentage change with respect to the reference scenario.

	Scenarios	Average time per vehicle (min/veh)	Total time (min)	Total costs (converted through VOT)	Average driven distance (km/veh)	Total driven distance (km)	Total revenue
Searching state	Scenario (d)	3.14	7078	2902	0.65	1475	
	Demand decrease (- 4 %)	1.47 (- 53.2 %)	3181 (- 55.1 %)	1304 (- 55.1 %)	0.31 (- 52.3 %)	663 (- 55.1 %)	
	Demand increase (+ 4 %)	7.02 (+ 123.6 %)	16395 (+ 131.6 %)	6722 (+ 131.6 %)	1.46 (+ 124.6 %)	3416 (+ 131.6 %)	
	Supply decrease (- 4 %)	7.26 (+ 131.2 %)	16348 (+ 131 %)	6703 (+ 131 %)	1.51 (+ 132.3 %)	3406 (+ 130.9 %)	
	Supply increase (+ 4 %)	1.47 (- 53.2 %)	3317 (- 53.1 %)	1360 (- 53.1 %)	0.31 (- 52.3 %)	691 (- 53.2 %)	
Non-searching state	Scenario (d)	4.43	9986	4094	0.92	2080	
	Demand decrease (- 4 %)	4.43 (+ 0 %)	9607 (- 3.8 %)	3939 (- 3.8 %)	0.92 (+ 0 %)	2001 (- 3.8 %)	
	Demand increase (+ 4 %)	4.44 (+ 0.2 %)	10362 (+ 3.8 %)	4248 (+ 3.8 %)	0.92 (+ 0 %)	2159 (+ 3.8 %)	
	Supply decrease (- 4 %)	4.43 (+ 0 %)	9980 (- 0.1 %)	4092 (- 0.1 %)	0.92 (+ 0 %)	2079 (- 0.05 %)	
	Supply increase (+ 4 %)	4.44 (+ 0.2 %)	9989 (+ 0.03 %)	4095 (+ 0.03 %)	0.92 (+ 0 %)	2081 (+ 0.05 %)	
Total	Scenario (d)	7.57	17064	6996	1.57	3555	9742
	Demand decrease (- 4 %)	5.9 (- 22.1 %)	12788 (- 25.1 %)	5243 (- 25.1 %)	1.23 (- 21.7 %)	2664 (- 25.1 %)	8084 (- 17 %)
	Demand increase (+ 4 %)	11.46 (+ 51.4 %)	26757 (+ 56.8 %)	10970 (+ 56.8 %)	2.38 (+ 51.6 %)	5575 (+ 56.8 %)	12581 (+ 29.1 %)
	Supply decrease (- 4 %)	11.69 (+ 54.4 %)	26328 (+ 54.3 %)	10795 (+ 54.3 %)	2.43 (+ 54.8 %)	5485 (+ 54.3 %)	12044 (+ 23.6 %)
	Supply increase (+ 4 %)	5.91 (- 21.9 %)	13306 (- 22 %)	5455 (- 22 %)	1.23 (- 21.7 %)	2772 (- 22 %)	8450 (- 13.3 %)

Table 5.6 illustrates that the total revenue increases as soon as the traffic system gets more congested, i.e., the demand increases or the supply decreases. However, the total revenue is more sensitive to an increase in demand (+29.1 %) compared to a decrease in supply (+23.6 %), while the traffic performance and the environmental conditions are more sensitive to a decrease in supply. The average time per vehicle and the average driven distance in the searching-state illustrate this behavior. The results for the non-searching-state do not show a high sensitivity towards an increase/decrease in supply nor in demand. This is not surprising, as the non-searching traffic is only indirectly affected by these changes. Both scenarios of

decreasing the demand and increasing the supply lead to less cruising vehicles in the area and a reduction on revenue for the city. The average time and the average driven distance per vehicle show similar results for both scenarios, such that the traffic performance and the environmental conditions have the same sensitivity towards a decrease in demand and an increase in supply. The total revenue, however, is more sensitive to a decrease in demand (−17 %) compared to an increase in supply (−13.3 %). Overall, the total revenue is more sensitive to changes in demand compared to changes in supply.

Future research could use more advanced sensitivity analysis methods ([Ge et al. \(2014, 2015\)](#); [Ge and Menendez \(2017\)](#)) to shed more light on the relation between these different variables. That being said, our macroscopic parking pricing model can be used to provide meaningful advice to the city, e.g., when considering inquiries for reducing or creating new parking spaces or when considering a population growth/decline with an effect on traffic demand. Additionally, the model allows city officials to explore changes in the parking pricing scheme while trying to optimize different criteria (e.g., maximize revenues such that the area is not significantly congested, or minimize travel distance) in the network.

5.4.4 Sensitivity analysis for influence factor of the responsiveness in the responsive parking pricing scheme

The parameter γ – used to determine the predicted future parking fee, C_{pay}^i , in section 5.3.3.1 – represents the influence factor of the responsiveness in the responsive parking pricing scheme, i.e., it reflects the influence of the number of searching vehicles and the parking occupancy on the parking fee. It is considered as a scale parameter that needs to be calibrated in future research such that it leads to reasonable pricing results over time that are acceptable for the drivers in the area. Table 5.7 shows a sensitivity analysis for parameter γ with respect to the responsive parking pricing scenario (scenario (d) in section 5.4.2) in the area within the city of Zurich. It illustrates the average/total time, the average/total distance in the network and the total revenue for different values of the parameter γ . All values within parentheses represent the percentage change with respect to parameter $\gamma = 2$ in the reference scenario (using scenario (d) in section 5.4.2). The average value for all VOT considering all user groups $\frac{1}{K} \cdot \sum_{k=1}^K VOT^k = 0.41$ CHF/min is used in this table to determine the total time related costs.

As shown in Table 5.7, changes to the parameter γ only have a marginal influence on the total revenue results if $\gamma > 1$, while the average/total time and distance stay constant in the network. These constant time and distance results can be explained by the parking fee optimization scheme that minimizes the total cruising time on the network. In general, reducing parameter γ leads to a higher total revenue. For $\gamma \geq 1.75$ an increase in parameter γ leads to a constant total revenue. Thus, the total revenue is only marginally sensitive to the parameter γ if we only consider parameter values $\gamma > 1$. Parameter $\gamma = 2$ is chosen in our reference scenario (section 5.3.3.1). This scale parameter, however, needs to be calibrated in future research for different

networks.

Table 5.7. Sensitivity analysis for parameter y , the influence factor of the responsivity in parking pricing. Value within parenthesis represents the percentage change with respect to parameter $y = 2$ in the reference scenario (scenario (d) in section 5.4.2).

Parameter y	Average time per vehicle (min/veh)	Total time (min)	Total costs (converted through VOT)	Average driven distance (km/veh)	Total driven distance (km)	Total revenue
0.25	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	49576 (+ 408.9 %)
0.5	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	38784 (+ 298.1 %)
0.75	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	31750 (+ 225.9 %)
1	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	18791 (+ 92.9 %)
1.25	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	11489 (+ 17.9 %)
1.5	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9848 (+ 1.1 %)
1.75	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9742 (+ 0 %)
2 - Reference scenario	7.57	17064	6996	1.57	3555	9742
2.25	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9742 (+ 0 %)
2.5	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9742 (+ 0 %)
2.75	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9742 (+ 0 %)
3	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9742 (+ 0 %)
3.25	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9742 (+ 0 %)
3.5	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9742 (+ 0 %)
3.75	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9742 (+ 0 %)
4	7.57 (+ 0 %)	17064 (+ 0 %)	6996 (+ 0 %)	1.57 (+ 0 %)	3555 (+ 0 %)	9742 (+ 0 %)

5.5 Summary of the chapter

In this study, we develop a dynamic macroscopic parking pricing model and analyze the interdependency between responsive parking pricing and searching-for-parking traffic. The model is integrated into an existing parking-state-based matrix to better model the real urban traffic and parking systems. The responsive pricing model is illustrated in a case study of an area within the city of Zurich, Switzerland. In addition, other three parking pricing scenarios are analyzed in this case study. These include a free, a constant, and an occupancy-responsive parking pricing scheme where the fee only changes in response to the parking occupancy.

The main contributions from this chapter are summarized below.

- Our responsive pricing scheme takes the parking search phenomenon into consideration, by changing in response to the number of searching vehicles, compared to previous studies that only focus on the parking occupancy. This means that the parking fee also changes in response to the parking demand, in addition to changes in response to the parking supply.
- An optimization model is formulated to maximize the parking pricing revenue to the highest level, yet minimize the negative impacts on the traffic system (i.e., minimize total cruising time on the network). This is achieved as the model tries to guarantee that the cost of paying the current parking fee remains smaller than the cost of keep on searching to obtain a lower parking fee across multiple user groups with different VOTs. The vehicles' decision to park depends on multiple factors, including the predicted parking cost at future time, the costs of traveling from the current parking space to another space associated with driving distance and VOT, and the penalty cost associated with the cruising time in past iterations.
- The model also provides a preliminary idea for city councils regarding an optimal parking pricing policy resulting in financial revenues while simultaneously minimizing the drivers' cruising time. The policy's impacts on the searching-for-parking traffic (cruising), the congestion in the network (traffic performance), the total driven distance (environmental conditions), and the revenue created by parking fees for the city are illustrated in a case study. In the short-term this parking pricing policy has neither significant negative influences on traffic performance nor environmental conditions, but it significantly increases the total revenue. This could lead to significant improvements for city councils or private agencies in the area. Notice that in the short-term the optimal parking fee might increase the revenue, but in the long-term it might deter drivers from driving into the city, potentially changing the demand. However, these long-term effects have not been studied here as they are considered out-of-scope in this chapter.
- In comparison to microscopic models or agent-based simulation tools which are typically used when analyzing the interdependency between parking pricing and parking-caused traffic issues, the macroscopic model proposed here has several advantages. The whole framework is based on very limited data inputs, while most of the tools used nowadays to analyze parking pricing and parking-related traffic require a lot of detailed data that is hard to get. Our model corresponds to aggregated values at the network level over time and only needs some general inputs, including probability distributions, i.e., it saves on data collection efforts and reduces the computational costs significantly. Such efficiencies are especially useful for real-time control algorithms or when the data is scarce. Moreover, the model can be easily solved with a simple numerical solver such as Excel or Matlab without the use of complex simulation software. This is in part possible because we only have a few parameters, and all of them have a physical interpretation. Moreover, they can all be obtained from field data. In addition, there is no

need to run the model many times in order to account for its stochasticity, as it is based on probability functions (i.e., the stochasticity is already implicit within the model formulations). Last but not least, the simpler form of the macroscopic model might provide additional insights that cannot be delivered by microscopic models (e.g., insights into the mathematical relation between traffic speeds and maximal parking pricing with respect to a minimal total cruising time on the network).

Overall, the potential of the proposed model is far beyond what we have illustrated in the case study. The pricing of off-street parking facilities can be modeled explicitly, such as the pricing of not uniformly distributed parking spaces over the network. In reality, vehicles could focus on parking possibilities in a central street or area of the network, while discarding other parking opportunities elsewhere. Future research could incorporate this non-homogeneous environment (e.g., where both, the parking demand and supply are inhomogeneously distributed) by modeling different adjacent subnetworks, where parking decisions are made using the proposed macroscopic model based on the conditions of more than one subnetwork. Each subnetwork can have a different distribution of parking spaces and parking prices. How to connect these subnetworks to each other should then be carefully studied. Additionally, it could be possible to introduce different pricing alternatives. For example, we could include a traffic demand split with a fixed (low subsidized) parking fee in all garages and/or some of the on-street parking spaces. This can be motivated by, e.g., the subsidy from a company or the city for its employees or residents, respectively. The remaining portion of the demand could then be treated responsively as in this chapter, reflecting the external costs for parking.

In summary, the proposed model, despite its simplicity, can be used to efficiently evaluate a dynamic responsive pricing scheme macroscopically. With the aid of limited aggregated data, this model can be used to investigate, how parking pricing can affect searching-for-parking traffic and traffic performance (e.g., average time searching for parking, and average distance driven); and how different traffic conditions (e.g., number of vehicles cruising for parking, and available parking spaces in the network) can affect the responsive parking pricing.

Part II

Parking Occupancy

Abstract

A very high parking occupancy can negatively influence the traffic performance of an area by causing very long cruising times. A very low parking occupancy, on the other hand, is inefficient from a space utilization perspective. Thus, the second part of this dissertation proposes a framework to compute the optimal parking occupancy rate over a given time horizon based on a macroscopic traffic and parking model. This rate is set high enough to ensure an efficient usage of the parking infrastructure. However, it should also guarantee a high likelihood of finding parking in order to eliminate the drivers' time wasted in cruising for parking and the added congestion it causes. The model outputs are based on small data collection efforts and low computational costs, and they can be generated without complex simulation software using a simple numerical solver. Multiple vehicle types are included into our methodology allowing us to generate insights about the optimal parking occupancy with or without differentiated parking (i.e., parking for specific vehicles, such as fuel and electric vehicles). In times of a modal shift towards electric vehicles, cities can use our model to evaluate how much parking supply (with battery charging opportunities) they would like to dedicate to electric vehicles in order to achieve optimal traffic and parking results, and whether a differentiated or hierarchical parking policy is desirable. We illustrate our framework in a case study of a central area within the city of Zurich, Switzerland, showing the traffic and parking impacts (e.g., average searching time for parking, total revenue created by parking fees, optimal parking occupancy rate) for different proportions of fuel and electric vehicles in the parking demand and/or supply. Our results confirm that optimal occupancy rates are between 80 % and 90 % for most realistic scenarios. We show that the non-differentiated parking policy leads to the lowest average cruising time and the highest optimal occupancy rate. However, it is the least ideal policy from the city's perspective. In the case of differentiated policies, equal proportions between electric vehicles in the demand and their parking spaces in the supply lead to the best traffic performance in the area. Moreover, hierarchical parking policies are more efficient than fully differentiated ones, by granting additional flexibility. These insights and the tools provided in this chapter are useful for cities to analyze their gain (or loss) in performance if they react (or not), e.g., to an increasing demand for electric vehicles over time.

Chapter 6:

Optimal Parking Occupancy with and without Differentiated Parking: A Macroscopic Analysis

This chapter is based on the results presented in:

Jakob, M., and M. Menendez. 2020. "Optimal Parking Occupancy with and without Differentiated Parking: A Macroscopic Analysis". Submitted to *Transport Policy*.

6.1 Introduction

Traffic congestion and its associated costs (i.e., loss in time, loss of productivity of workers sitting in traffic, increase in cost of transporting goods through congested areas, waste of fuel) often conflict with an efficient usage of the parking infrastructure. A very high parking occupancy rate can drastically reduce drivers' likelihood of finding parking, increasing cruising times and leading, in turn, to a worse traffic performance in the network. A low parking occupancy, on the other hand, is inefficient from a space utilization perspective. The problem becomes more complicated with differentiated parking (e.g., specific parking spaces for fuel and electric vehicles such that electric vehicles can charge their batteries while parking). Our study proposes a macroscopic model to determine the optimal parking occupancy rate to minimize the impacts on traffic and at the same time maximize the usage of the available parking spaces. Moreover, we analyze how the optimal parking occupancy might be affected by a modal shift towards a specific vehicle type such as electric vehicles, with and without differentiated parking.

In contrast to existing studies focusing on agent-based searching-for-parking traffic, our model does not require data for individual drivers or parking spaces as we focus only on average values and probability distributions across the network. This is especially useful for real-time control algorithms or when the data is scarce. Our framework follows an exogenous approach as the drivers' entry decision and their parking duration are independent of the different parking policies applied in the area. A city can estimate their target parking occupancy rate over, e.g., the peak hours of the day, to guarantee an optimal trade-off between an efficient usage of the parking infrastructure and a high likelihood of finding parking as to improve the traffic performance in a central area. The results can then be used to set the optimal parking occupancy rate *ex ante* and to establish measures (e.g., parking pricing policies (chapter 4)) in some areas in order to achieve this target rate in the future. These measures, however, are considered out-of-scope in this chapter. Our study defines the parking occupancy rate to be optimal by trying to minimize cruising time for all vehicles. At the same time, we aim to ensure an efficient usage of the parking infrastructure by having the highest possible parking occupancy rate. The model outputs can be generated with a simple numerical solver and without complex simulation software.

The contributions of this chapter are threefold. First, our research proposes a framework to compute the optimal parking occupancy rate based on a macroscopic traffic and parking model. We determine this single optimal rate over a given time horizon for an area within a city. Second, the extension of our macroscopic model to include multiple vehicle types provides us some insights about the parking occupancy's dependency on specific vehicle types (e.g., fuel and electric vehicles). We analyze a differentiated parking policy with exclusive parking spaces (e.g., fuel vehicles park at fuel vehicle parking spaces, and electric vehicles park at spaces with

battery chargers), and a hierarchical parking policy, considering no parking space restrictions for some vehicle types (e.g., electric vehicles can park at both parking spaces for fuel and electric vehicles). We then compare these two policies to a parking scheme without any parking differentiation. In all cases, our framework allows us to analyze the traffic and parking impacts (e.g., average searching time for parking, total revenue from parking pricing, optimal parking occupancy rates) of a modal shift towards a specific vehicle type, such as electric vehicles. Cities have the option to evaluate how to react towards a constantly varying parking demand and how much parking supply to dedicate to electric vehicles in order to have the best balance between traffic performance, optimal parking occupancies, and a high revenue for the city. Third, our methodology offers quick evaluation possibilities for the impacts on the optimal parking occupancy rate caused by a change in parking demand, supply, or parking duration in the network. We illustrate our proposed model using real data from a central area within the city of Zurich, Switzerland.

This chapter is organized as follows. Section 6.2 presents the strategy to determine the optimal parking occupancy rate based on a macroscopic traffic and parking model without and with parking differentiation using multiple vehicle types. Section 6.3 illustrates the use of the methodology to find the optimal parking occupancy for an area within the city of Zurich, and discusses the impact of different modeling inputs. Section 6.4 summarizes this chapter.

6.2 The optimal parking occupancy rate: A macroscopic model for multiple vehicle types

First, we explain our macroscopic traffic and parking framework differentiating multiple vehicle types (section 6.2.1). Second, we give insights into the mathematical model (section 6.2.2). Third, we present our optimization strategy to find the optimal parking occupancy rate in an area (section 6.2.3). Fourth, we show how to determine the average cruising time for parking and the parking revenue for the city over a defined time horizon (section 6.2.4). We have already introduced some relevant variables and parameters in chapters 2 and 3 (Table 2.1, 3.1, 3.2 and 3.3). The new variables and parameters used in this chapter are introduced in Table 6.1. We also indicate whether the variables in Table 6.1 are exogenous, policy variables, or drivers' responses to the applied policy.

6.2.1 A macroscopic traffic and parking framework for multiple vehicle types

6.2.1.1 Parking demand

Recall that the parking demand changes over time and it is homogeneously distributed on the network (section 2.2). The decision between different types of vehicles has been previously made for all drivers. E denotes the set of vehicle types

(e.g., electric vs. fuel), and K represents the set of user groups for the network's demand.

Table 6.1. List of main variables and parameters.

Notation	Definition	Type
E	Set of vehicle types indexed by e . This might include, e.g., fuel and electric vehicles.	Exogenous
A^e	Total number of public parking spaces for vehicles of type $e \in E$.	Policy variable
$A^{i,e}$	Number of available parking spaces for vehicles of type $e \in E$ at the beginning of time slice i .	Drivers' response to policy
$j_{ns}^{k,e}$	Average distance driven by a vehicle of type $e \in E$ from user group $k \in K$ before it starts to search for parking.	Exogenous
$j_p^{k,e}$	Average distance driven by a vehicle of type $e \in E$ from user group $k \in K$ before it leaves the area after it has parked.	Exogenous
$j_l^{k,e}$	Average distance driven by a vehicle of type $e \in E$ from user group $k \in K$ before it leaves the area without having parked.	Exogenous
p^e	Hourly parking fee for vehicles of type $e \in E$.	Exogenous
t_d^e	Parking duration of vehicles of type $e \in E$.	Exogenous
i_{cmax}	Time slice required to determine the expected maximum cruising time per vehicle for vehicles cruising at the beginning of time slice i .	Drivers' response to policy
ACT_{all}	Average cruising time across all vehicles over the whole time horizon T .	Drivers' response to policy
occ^i	Parking occupancy rate across all parking spaces at the beginning of time slice i .	Drivers' response to policy
$occ^{i,e}$	Parking occupancy rate of parking spaces for vehicles of type $e \in E$ at the beginning of time slice i .	Drivers' response to policy
I	Total revenue resulting from parking fees for all user groups K over time T .	Drivers' response to policy
S	Social impacts of introducing parking spaces for electric vehicles.	Drivers' response to policy
ϕ	Cost of establishing a parking space with charging facilities for an electric vehicle.	Exogenous
ε	Proportion of electric vehicles within the traffic demand entering the area for all time slices.	Exogenous
ζ	Proportion of parking spaces for electric vehicles with battery charging possibilities compared to the total parking supply.	Policy variable

6.2.1.2 Parking supply

Remember that our framework evaluates a compact urban area with a relatively homogeneous network of length L . This study evaluates three different parking supply schemes: a non-differentiated parking policy, a differentiated parking policy for vehicles of different vehicle types, and a hierarchical parking policy (section 6.2.2.3). Recall that we assume that all parking spaces (available or not) are homogeneously distributed in the network (section 2.2). This is valid for all available parking spaces independently on the vehicle type restrictions and the applied parking policy.

6.2.1.3 Dynamic macroscopic parking-state-based matrix

Our framework extends the parking-state-based matrix (section 2.4) in [Cao and Menendez \(2015a\)](#) for multiple vehicle types as they not only vary within the demand, but also have different parking needs, e.g., an electric vehicle might be charged while parking. Remember that the matrix shows the system dynamics of urban traffic, and aims to model macroscopically a dynamic urban parking system and its interactions

with the traffic system. It consists of different parking-related traffic states and the transition events between those states (Table 6.2). The traffic states slightly enhance the states presented in Table 2.2 and differentiate between non-searching vehicles with external and internal destinations. This modification results in more transition events in Table 6.2 compared to Table 2.2. Additionally, we highlight that all variables in Table 6.2 are modelled for all vehicle types $e \in E$ and user groups $k \in K$.

Table 6.2. Traffic state and transition event variables used in our traffic and parking framework

	Notation	Name	Definition
Traffic states	$N_{nse}^{i,k,e}$	Non-searching (external destination)	Number of vehicles of type $e \in E$ for user group $k \in K$ not searching for parking and with external destination (i.e., outside the area) at the beginning of time slice i .
	$N_{nsi}^{i,k,e}$	Non-searching (internal destination)	Number of vehicles of type $e \in E$ for user group $k \in K$ not searching for parking and with internal destination (i.e., within the area) at the beginning of time slice i .
	$N_s^{i,k,e}$	Searching for parking	Number of vehicles of type $e \in E$ for user group $k \in K$ searching for parking at the beginning of time slice i .
	$N_p^{i,k,e}$	Parking	Number of vehicles of type $e \in E$ for user group $k \in K$ parking at the beginning of time slice i .
Transition events	$n_{/ns}^{i,k,e}$	Enter the area	Number of vehicles of type $e \in E$ for user group $k \in K$ entering the area during time slice i .
	$n_{/nse}^{i,k,e}$	Enter the area (external destination)	Number of vehicles of type $e \in E$ for user group $k \in K$ entering and having their destination outside the area during time slice i .
	$n_{/nsi}^{i,k,e}$	Enter the area (internal destination)	Number of vehicles of type $e \in E$ for user group $k \in K$ entering and having their destination inside the area during time slice i .
	$n_{nst/s}^{i,k,e}$	Start to search for parking	Number of vehicles of type $e \in E$ for user group $k \in K$ starting to search for parking during time slice i .
	$n_{s/p}^{i,k,e}$	Access parking	Number of vehicles of type $e \in E$ for user group $k \in K$ accessing parking during time slice i .
	$n_{p/nse}^{i,k,e}$	Depart parking	Number of vehicles of type $e \in E$ for user group $k \in K$ departing from parking and moving towards a destination outside the area during time slice i .
	$n_{nse/}^{i,k}$	Leave the area	Number of vehicles of type $e \in E$ for user group $k \in K$ leaving the area during time slice i .

Using this matrix, we can model, e.g., the number of searching vehicles, more accurately than formulating them with other existing approximation methods that do not account for the dynamics of both the supply and the demand, including competition among drivers searching for parking. This might be important to capture differences throughout the day, and more nuances on the optimal parking occupancies.

The number of vehicles in each traffic state for vehicle type $e \in E$ and user group $k \in K$ are updated iteratively over time based on the number of vehicles in each transition event. These iterations finish when the whole time horizon is evaluated, or a defined criterion is reached (e.g., all the vehicles leave the area). The time horizon T (e.g., a day) is divided into small time slices t (e.g., 1 minute), such that the traffic and parking conditions are assumed to be steady within each time slice, but they can

change over multiple time slices. The traffic states and transition events are illustrated in Fig. 6.1 based on two different vehicle types ($E = \{1, 2\}$): fuel and electric vehicles.

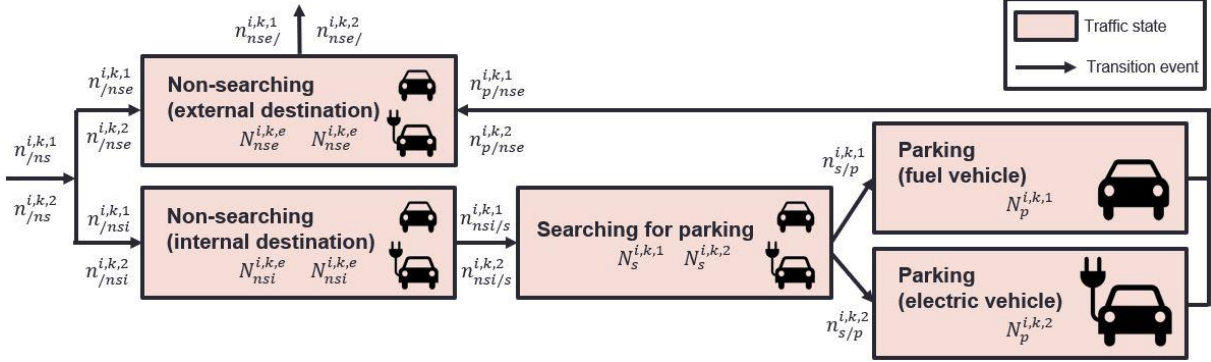


Fig. 6.1. Traffic and parking framework for two different vehicle types: Fuel and electric vehicles.

Vehicles enter the area with a destination outside (“non-searching (external destination)”) or inside the network (“non-searching (internal destination)”). The first group of vehicles represents the through-traffic or the drivers going to garage parking. The latter group (fuel or electric vehicles) searches for available on-street parking spaces (“searching for parking”) before parking (“parking”) at a parking space for fuel or electric vehicles. After having parked and paid the parking fee depending on their parking duration, the vehicles drive towards their next destination outside the network (“non-searching (external destination)”), and leave the area.

6.2.2 Mathematical formulations

6.2.2.1 Traffic states

Our model is based on four traffic states summarized in Table 6.2. Details about their mathematical formulations can be found in section 2.4 based on [Cao and Menendez \(2015a\)](#). The number of non-searching vehicles with external and internal destinations, $N_{nse}^{i+1,k,e}$ and $N_{nsi}^{i+1,k,e}$, are updated at the beginning of time slice $i + 1$ in Eq. (67) and Eq. (68) for all $k \in K$ and $e \in E$. Note that Eq. (67) and Eq. (68) enhance Eq. (1) by differentiating between non-searching cars with external and internal destinations. They are consistent with Eq. (42a-b), but are updated for all $k \in K$ and $e \in E$. Vehicles entering the area (i.e., $n_{nse}^{i,k,e}$ and $n_{nsi}^{i,k,e}$) and vehicles departing from parking (i.e., $n_{p/nse}^{i,k,e}$) join these states, and vehicles leaving the area (i.e., $n_{nse/}^{i,k,e}$) and starting to search for parking (i.e., $n_{nsi/s}^{i,k,e}$) leave these states.

$$N_{nse}^{i+1,k,e} = N_{nse}^{i,k,e} + n_{nse}^{i,k,e} + n_{p/nse}^{i,k,e} - n_{nse/}^{i,k,e} \quad (67)$$

$$N_{nsi}^{i+1,k,e} = N_{nsi}^{i,k,e} + n_{nsi/s}^{i,k,e} - n_{nsi/s}^{i,k,e} \quad (68)$$

The number of vehicles searching for parking at the beginning of time slice $i + 1$, $N_s^{i+1,k,e}$, is updated in Eq. (69) for all $k \in K$ and $e \in E$. Vehicles starting to search for

parking in the area (i.e., $n_{nsi/s}^{i,k,e}$) join this state, and vehicles accessing parking (i.e., $n_{s/p}^{i,k,e}$) leave this state.

$$N_s^{i+1,k,e} = N_s^{i,k,e} + n_{nsi/s}^{i,k,e} - n_{s/p}^{i,k,e} \quad (69)$$

We determine the number of vehicles parked at the beginning of time slice $i + 1$, $N_p^{i+1,k,e}$, in the area in Eq. (70) for all $k \in K$ and $e \in E$. Vehicles accessing an available parking space (i.e., $n_{s/p}^{i,k,e}$) join this traffic state, and vehicles departing from parking for an external destination (i.e., $n_{p/nse}^{i,k,e}$) leave this state.

$$N_p^{i+1,k,e} = N_p^{i,k,e} + n_{s/p}^{i,k,e} - n_{p/nse}^{i,k,e} \quad (70)$$

Note that Eq. (69) and Eq. (70) are consistent with Eq. (2) and Eq. (3), showing the vehicles searching and parking for each $k \in K$ and $e \in E$.

6.2.2.2 Transition events

All transition events are estimated macroscopically based on the size of the network, the likelihood of finding parking, and the distribution of parking durations, respectively ([Cao and Menendez \(2015a, 2018\)](#)). Enhancements to the framework presented in section 2.4 are shown here. Remember that we do not need to record the individual locations of each vehicle and parking space over time, i.e., only the average number of vehicles in each traffic state and transition event during each time slice is tracked.

The average travel speed, v^i , during time slice i is formulated in Eq. (4b) based on a triangular MFD ([Haddad and Geroliminis \(2012\)](#); [Haddad et al. \(2013\)](#); [Yang et al. \(2017\)](#); [Yang et al. \(2019\)](#)), and the average traffic density k^i (Eq. (71)) in the same time slice. Notice that k^i in Eq. (71) replaces the formulation in Eq. (4a) in this chapter. k^i is determined based on the total number of vehicles on the road network (consisting of non-searching, $\sum_{e=1}^E \sum_{k=1}^K N_{nse}^{i,k,e} + \sum_{e=1}^E \sum_{k=1}^K N_{nsi}^{i,k,e}$, and searching vehicles, $\sum_{e=1}^E \sum_{k=1}^K N_s^{i,k,e}$), and the network length, L_{lane} , in lane-km ([Cao and Menendez \(2015a\)](#); [Cao et al. \(2019\)](#)).

$$k^i = \frac{\sum_{e=1}^E \sum_{k=1}^K N_{nse}^{i,k,e} + \sum_{e=1}^E \sum_{k=1}^K N_{nsi}^{i,k,e} + \sum_{e=1}^E \sum_{k=1}^K N_s^{i,k,e}}{L_{lane}} \quad (71)$$

$n_{ns}^{i,k,e}$ describes the total number of vehicles entering the network for $k \in K$ and $e \in E$ during time slice i , which is a known demand input to the framework. Depending on the proportion of through-traffic, β^i , the vehicles enter the area for an external, $n_{nse}^{i,k,e}$ in Eq. (72), or internal destination, $n_{nsi}^{i,k,e}$ in Eq. (73). Eq. (72) is modelled consistently with Eq. (44a) for $k \in K$ and $e \in E$. Eq. (73) shows a simplified version of Eq. (44b) which includes no additional variables reflecting the drivers' decision.

$$n_{nse}^{i,k,e} = \beta^i \cdot n_{ns}^{i,k,e} \quad (72)$$

$$n_{/nsi}^{i,k,e} = (1 - \beta^i) \cdot n_{/ns}^{i,k,e} \quad (73)$$

The number of vehicles starting to search for parking, $n_{nsi/s}^{i,k,e}$, is determined in Eq. (74) depending on whether the vehicles' driven distance by time slice i has been long enough to cover a given distance $l_{ns/}^{k,e}$. Note that Eq. (74) and Eq. (45) are consistent and only differ with respect to the newly introduced dependency on $e \in E$. Remember that $l_{ns/}^{k,e}$ can be fixed or taken out of any given probability density function. The condition is then captured by $\gamma_{ns/}^{i',k,e}$ in Eq. (74). Recall that d^i is estimated based on the speed during that interval v^i (from Eq. (4b)) and the length of a time slice, t (i.e., $d^i = v^i \cdot t$).

$$n_{nsi/s}^{i,k,e} = \sum_{i'=1}^{i-1} n_{/nsi}^{i',k,e} \cdot \gamma_{ns/}^{i',k,e} \quad (74)$$

where

$$\gamma_{ns/}^{i',k,e} = \begin{cases} 1, & \text{if } l_{ns/}^{k,e} \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq l_{ns/}^{k,e} + d^{i-1} \\ 0, & \text{otherwise} \end{cases}$$

The likelihood formulations from [Cao and Menendez \(2015a\)](#) and [Cao and Menendez \(2018\)](#) are used to model the number of vehicles finding, accessing and paying for parking, $n_{s/p}^{i,k,e}$. We omit the mathematical formulation here as it is only slightly modified from Eq. (6) in section 2.4.2 – analogously to Eq. (46) – to include different vehicle types $e \in E$.

After departing from their parking spaces, the vehicles $n_{p/nse}^{i,k,e}$ (Eq. (75)) drive towards their external destinations during time slice i . Notice that Eq. (75) is consistent with Eq. (7) and modelled for each $k \in K$ and $e \in E$, analogously to Eq. (47). The likelihood that these vehicles depart from the parking spaces in time slice i is based on the distribution of parking durations $f(t_d^e)$ and the number of vehicles having accessed parking spaces, $n_{s/p}^{i',k,e}$, in a former time slice $i' \in [1, i - 1]$. The probability of their parking duration is then between $(i - i') \cdot t$ and $(i + 1 - i') \cdot t$, i.e., $\int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_d^e) dt_d^e$.

$$n_{p/nse}^{i,k,e} = \sum_{i'=1}^{i-1} n_{s/p}^{i',k,e} \cdot \int_{(i-i') \cdot t}^{(i+1-i') \cdot t} f(t_d^e) dt_d^e \quad (75)$$

Depending on whether the vehicles have parked or not, they leave the area, $n_{nse/}^{i,k,e}$ in Eq. (76), after having driven a given distance $l_{p/}^{k,e}$ or $l_{/}^{k,e}$, respectively. Remember that these distances are considered as fixed or taken out of any given probability density function, and they vary by the network size and the average trip lengths. Note that Eq. (76) is consistent with Eq. (50) and modelled for each vehicle type $e \in E$.

$$n_{nse/}^{i,k,e} = \sum_{i'=1}^{i-1} \left(n_{nse/}^{i',k,e} \cdot \gamma_{/}^{i',k,e} + n_{p/nse}^{i',k,e} \cdot \gamma_{p/}^{i',k,e} \right) \quad (76)$$

$\gamma_{/}^{i',k,e}$ and $\gamma_{p/}^{i',k,e}$ indicate whether the number of vehicles $n_{nse/}^{i',k}$ and $n_{p/nse}^{i',k}$ have driven long enough, $l_{/}^{k,e}$ and $l_{p/}^{k,e}$, respectively, in order to leave the area in time slice i . We omit their formulations here as they are modelled analogously to Eq. (35) and $\gamma_{ns/}^{i',k,e}$ in Eq. (74).

6.2.2.3 Parking policies

The non-differentiated parking scheme is presented in the first subsection. In case of differentiated parking, we consider two different levels of flexibility: differentiated parking and hierarchical parking. They are introduced in the second and third subsections, respectively.

Non-differentiated parking

The non-differentiated parking supply scheme assumes all parking spaces A to be identical and uniformly distributed in the area, i.e., either all or none of the parking spaces have battery charging facilities. The parking availability, A^i , is updated in Eq. (77) according to A and the number of vehicles parked, $N_p^{i,k}$, at the beginning of time slice i .

$$A^i = A - \sum_{k=1}^K N_p^{i,k} \quad \forall i \in \{1, \dots, T\} \quad (77)$$

As A^i is restricted by A , $0 \leq A^i \leq A$ is valid for all time slices i .

Differentiated parking policy

In our fully differentiated parking policy, we assume that vehicles are only allowed to park at their specific vehicle type parking spaces, i.e., fuel and electric vehicles are only allowed to access parking spaces for fuel and electric vehicles, respectively (Fig. 6.2(a)).

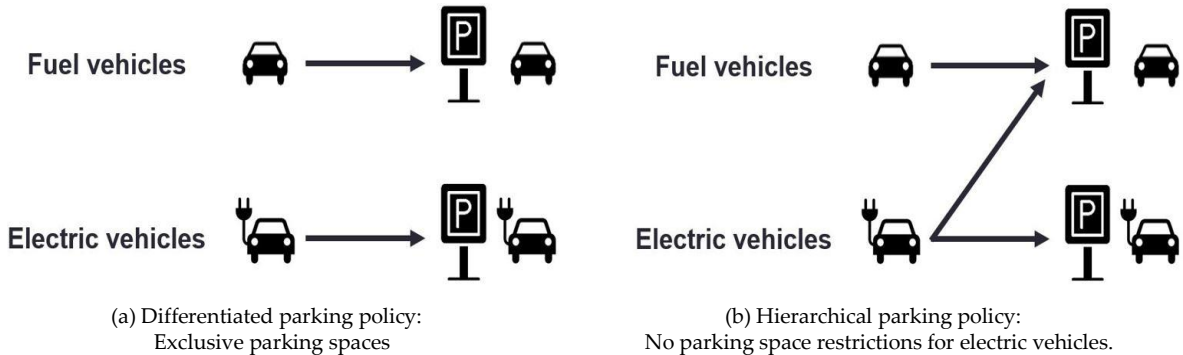


Fig. 6.2. A differentiated and a hierarchical parking policy for the access of parking spaces by fuel and electric vehicles.

The parking spaces A^e for each vehicle type $e \in E$ are assumed to be identical and uniformly distributed in the area. The parking availability, $A^{i,e}$, for $e \in E$ is updated

in Eq. (78) according to A^e and the number of vehicles parked, $N_p^{i,k,e}$, at the beginning of time slice i .

$$A^{i,e} = A^e - \sum_{k=1}^K N_p^{i,k,e} \quad \forall i \in \{1, \dots, T\}, \quad \forall e \in \{1, \dots, E\} \quad (78)$$

As $A^{i,e}$ is restricted by A^e , $0 \leq A^{i,e} \leq A^e$ is valid for all time slices i .

Hierarchical parking policy

The hierarchical parking policy assumes that no parking space restrictions are in place for vehicles of type $e = 2$, $e \in E$. On the other hand, vehicles of type $e = 1$, $e \in E$ can only access their dedicated parking spaces. Assuming electric vehicles are part of $e = 2$ and fuel vehicles belong to $e = 1$, the electric vehicles can access parking spaces for fuel and electric vehicles (Fig. 6.2(b)). However, it is reasonable to assume that they generally prefer parking spaces with battery charging options. In case these spaces are not available anymore, electric vehicles access parking spaces for fuel vehicles. Fuel vehicles can only access their dedicated parking spaces and get fined when parking at spaces with battery charging opportunities. Electric vehicle drivers have full contemporaneous information available, i.e., the drivers have access to real-time information about the availability of parking spaces for electric vehicles when deciding to search for a parking space with battery chargers or to search for a regular parking space instead. This parking usage information for electric vehicles can be made available to the drivers by providing real-time smartphone applications or information signs in the traffic network. The drivers do not have information about the exact location of the available parking spaces, but just the number of available parking spaces. They do not have information either about future electric parking availability. Evidently, this means there is still a chance they make the “wrong” decision as parking availability could change between the time they make the decision and the time they arrive at their destination. Both fuel and electric vehicles have the same chance to access an available fuel parking space in case all parking spaces with battery chargers are occupied.

The parking availabilities $A^{i,1}$ and $A^{i,2}$ are updated in Eq. (79) and Eq. (80) depending on whether there are enough parking spaces for vehicles of type $e = 2$ available in time slice i , i.e., we check whether the net number of electric vehicles moving to parking during time slice $i - 1$, $\sum_{k=1}^K (n_{s/p}^{i-1,k,2} - n_{p/nse}^{i-1,k,2})$, can access the available parking spaces, $A^{i-1,2}$, at the beginning of time slice $i - 1$. If this is the case, all vehicles of type $e = 2$ access their preferred parking spaces, and $A^{i,2}$ is updated to $A^{i-1,2} - \sum_{k=1}^K (n_{s/p}^{i-1,k,2} - n_{p/nse}^{i-1,k,2})$ (Eq. (80)). This leads to only vehicles of type $e = 1$ accessing their dedicated parking spaces, and $A^{i,1}$ is updated to $A^{i-1,1} - \sum_{k=1}^K (n_{s/p}^{i-1,k,1} - n_{p/nse}^{i-1,k,1})$ (Eq. (79)). If there are not enough preferred parking spaces for the vehicles of type $e = 2$ (i.e., $A^{i,2} = 0$ (Eq. (80))), all remaining vehicles move towards parking spaces for the vehicles of type $e = 1$, and $A^{i,1}$ is updated to $A^{i-1,1} + A^{i-1,2} - \sum_{k=1}^K (n_{s/p}^{i-1,k,1} + n_{s/p}^{i-1,k,2} - n_{p/nse}^{i-1,k,1} - n_{p/nse}^{i-1,k,2})$ (Eq. (79)).

$$A^{i,1} = \begin{cases} A^{i-1,1} - \sum_{k=1}^K (n_{s/p}^{i-1,k,1} - n_{p/nse}^{i-1,k,1}), & \text{if } \sum_{k=1}^K (n_{s/p}^{i-1,k,2} - n_{p/nse}^{i-1,k,2}) \leq A^{i-1,2} \\ A^{i-1,1} + A^{i-1,2} - \sum_{k=1}^K (n_{s/p}^{i-1,k,1} + n_{s/p}^{i-1,k,2} - n_{p/nse}^{i-1,k,1} - n_{p/nse}^{i-1,k,2}), & \text{if } \sum_{k=1}^K (n_{s/p}^{i-1,k,2} - n_{p/nse}^{i-1,k,2}) > A^{i-1,2} \end{cases} \quad (79)$$

$$A^{i,2} = \begin{cases} A^{i-1,2} - \sum_{k=1}^K (n_{s/p}^{i-1,k,2} - n_{p/nse}^{i-1,k,2}), & \text{if } \sum_{k=1}^K (n_{s/p}^{i-1,k,2} - n_{p/nse}^{i-1,k,2}) \leq A^{i-1,2} \\ 0, & \text{if } \sum_{k=1}^K (n_{s/p}^{i-1,k,2} - n_{p/nse}^{i-1,k,2}) > A^{i-1,2} \end{cases} \quad (80)$$

As $A^{i,1}$ and $A^{i,2}$ are restricted by A^1 and A^2 , respectively, $0 \leq A^{i,1} \leq A^1$ and $0 \leq A^{i,2} \leq A^2$ are valid for all time slices i .

6.2.3 Optimal parking occupancy rate

In this section, we determine the optimal parking occupancy rate based on our macroscopic traffic and parking model for different vehicle types $e \in E$. We formulate the parking occupancy rate $occ^{i,e}$ (section 6.2.3.1) for $e \in E$, and the average cruising time ACT^i (section 6.2.3.2) at the beginning of time slice i before we present the optimization framework (section 6.2.3.3).

6.2.3.1 Parking occupancy rate

We determine the parking occupancy rate, $occ^{i,e}$, for parking spaces for vehicles of type $e \in E$ (Eq. (81)) and, occ^i , for all parking spaces in the area independently of their vehicle type (Eq. (82)).

$$occ^{i,e} = 1 - \frac{A^{i,e}}{A^e} \quad (81)$$

$$occ^i = 1 - \frac{\sum_{e=1}^E A^{i,e}}{\sum_{e=1}^E A^e} \quad (82)$$

Both formulations depend on the relation between the parking availability $A^{i,e}$ in time slice i and the total parking supply A^e for $e \in E$. For the non-differentiated parking policy, Eq. (81) and Eq. (82) become equivalent as all vehicles behave similarly, so we drop the superscript e for vehicle type.

6.2.3.2 Average cruising time at the beginning of each time slice

The cumulative number of vehicles for all $k \in K$ and $e \in E$ going through each transition event in Fig. 6.1 are illustrated in Fig. 6.3 over time. The cumulative number of vehicles starting to search for parking, $\sum_{e=1}^E \sum_{k=1}^K n_{nsi/s'}^{i,k,e}$, is illustrated by the black curve, the cumulative number of vehicles accessing parking, $\sum_{e=1}^E \sum_{k=1}^K n_{s/p}^{i,k,e}$, by the blue curve, and the cumulative number of vehicles leaving parking, $\sum_{e=1}^E \sum_{k=1}^K n_{p/nse'}^{i,k,e}$, by the green curve over time. Fig. 6.3 allows us not only to visualize the number of

vehicles cruising for parking at time slice i (i.e., $\sum_{e=1}^E \sum_{k=1}^K N_s^{i,k,e}$), but also the expected maximum cruising time $i - i_{cmax}$ across those vehicles. Note that this is consistent with Fig. 5.2 in section 5.3.3.3. According to our framework in this chapter, Fig. 6.3 shows the cumulative number of vehicles for all $k \in K$ and $e \in E$ over time. As our model is meant to look for average values based on some probability distributions, we can compute the vehicles' expected maximum cruising time, i.e., after this period of time all drivers have on average found an available parking space.

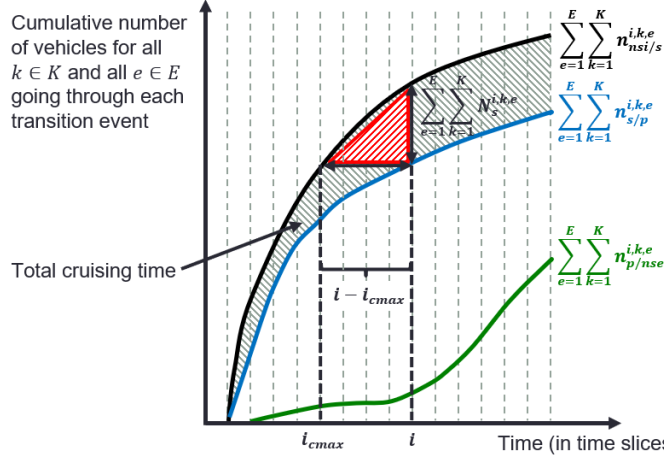


Fig. 6.3. The visualization of i_{cmax} at the beginning of time slice i within the queuing diagram.

We determine i_{cmax} in Eq. (83) based on the cumulative number of vehicles having accessed parking by time slice i (i.e., $\sum_{j=1}^i \sum_{e=1}^E \sum_{k=1}^K n_{s/p}^{j,k,e}$) across all $k \in K$ and $e \in E$. Then, we estimate the time at which the cumulative number of vehicles having started to search for parking (i.e., $\sum_{j=1}^{i_{cmax}} \sum_{e=1}^E \sum_{k=1}^K n_{nsi/s}^{j,k,e}$) is the same. Note that Eq. (83) is modelled analogously to Eq. (65), subject to the transition events $n_{nsi/s}^{j,k,e}$ and $n_{s/p}^{j,k,e}$ in this chapter.

$$\text{Find } i_{cmax}, \text{ s. t. } \sum_{j=1}^{i_{cmax}} \sum_{e=1}^E \sum_{k=1}^K n_{nsi/s}^{j,k,e} = \sum_{j=1}^i \sum_{e=1}^E \sum_{k=1}^K n_{s/p}^{j,k,e} \quad (83)$$

Approximating the area highlighted in Fig. 6.3 as a red triangle, we compute the average searching time across vehicles searching for parking during time slice i , ACT^i in Eq. (84), analogously to Eq. (66).

$$ACT^i = \frac{i - i_{cmax}}{2} \cdot t \quad (84)$$

ACT^i is required for our optimization framework in section 6.2.3.3 to propose the optimal parking occupancy rate which minimizes cruising time for all vehicles at all times. Notice that all non-searching vehicles including the through-traffic might affect the traffic performance in the area (see Eq. (4b) and Eq. (71)) and might thus impact ACT^i .

6.2.3.3 Optimization framework

Our framework combines ACT^i (Eq. (84)) with $occ^{i,e}$ (Eq. (81)) or occ^i (Eq. (82)), respectively. $m(ACT^i)$ denotes the moving average over the number of s values of ACT^i as a function of $occ^{i,e}$. The parameter s is considered as an input to the model. The optimization model to determine the optimal parking occupancy rate for parking spaces for vehicles of type $e \in E$ is formulated in Eq. (85). Note that we can replace $occ^{i,e}$ in Eq. (85) by occ^i to compute the rate for all parking spaces in the area.

$$\max \left\{ \arg \min_{0 \leq occ^{i,e} \leq 1} (m(ACT^i)) \right\} \quad (85)$$

Our optimization framework tries not only to minimize the average searching time for parking, but also to maximize the parking occupancy rate. This should lead to an efficient usage of the parking infrastructure and at the same time a high likelihood of finding parking in order to eliminate the drivers' time wasted in cruising for parking and the added congestion it causes. Fig. 6.4 visualizes this optimization strategy (Eq. (85)) for $m(ACT^i)$ as a function of $occ^{i,e}$ showing the valid solution set in green. We solve it using a simulation-based approach, such that $m(ACT^i)$ is determined depending on $occ^{i,e}$ or occ^i for all time slices i over T .

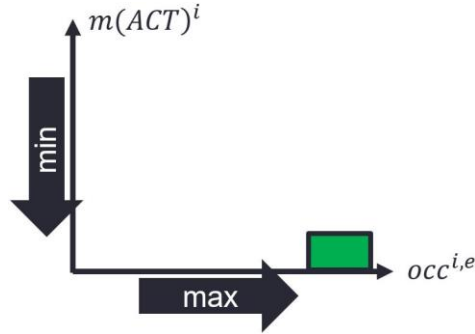


Fig. 6.4. Optimization strategy (Eq. (85)) for $m(ACT^i)$ as a function of $occ^{i,e}$.

6.2.4 Traffic performance, parking revenue, and social impacts

6.2.4.1 Traffic performance

The vehicles' average cruising time for parking, ACT_{all} , over the whole time horizon T is represented in Eq. (86), reflecting the traffic performance in the area. We determine the total cruising time (gray shaded area in Fig. 6.3), $t \cdot \sum_{i=1}^T \sum_{e=1}^E \sum_{k=1}^K N_s^{i,k,e}$, and divide it by the total number of vehicles accessing an available parking space over T , $\sum_{i=1}^T \sum_{e=1}^E \sum_{k=1}^K n_{s/p}^{i,k,e}$. Less available parking spaces might lead to more vehicles searching for parking, $N_s^{i,k,e}$, and thus to traffic congestion in the network.

$$ACT_{all} = \frac{t \cdot \sum_{i=1}^T \sum_{e=1}^E \sum_{k=1}^K N_s^{i,k,e}}{\sum_{i=1}^T \sum_{e=1}^E \sum_{k=1}^K n_{s/p}^{i,k,e}} \quad (86)$$

6.2.4.2 Parking revenue

Once the drivers depart from their parking spaces, $n_{p/nse}^{i,k,e}$, they pay their parking fee p^e subject to their individual parking duration. Note that the hourly parking fee, p^e , is considered as a time-invariant input to the model. This simplifies our framework as drivers' preferences on parking location, price, etc. can be avoided. However, this assumption can be relaxed in future research and the parking fees can be modelled using responsive pricing schemes in order to optimize the total revenue from parking pricing (chapter 5). The average parking duration across drivers is \bar{t}_d^e . Note that both p^e and \bar{t}_d^e can vary by $e \in E$ as some vehicle types might have different parking requirements (e.g., electric vehicles might need to park longer in parking spaces with charging possibilities for their batteries). The total revenue from parking pricing for the city is determined in Eq. (87).

$$I = \sum_{i=1}^T \sum_{e=1}^E \sum_{k=1}^K n_{p/nse}^{i,k,e} \cdot p^e \cdot \bar{t}_d^e \quad (87)$$

Recall that for non-differentiated parking we can drop the superscript e in Eq. (86) and Eq. (87).

6.2.4.3 Social impacts

In order to analyze the impacts of our parking policies on the society, we determine the social impacts of introducing parking spaces for electric vehicles ($e = 2, e \in E$) in Eq. (88). Similar as in section 6.2.2.3, fuel vehicles belong to $e = 1, e \in E$.

$$S = \underbrace{\sum_{i=1}^T \sum_{e=1}^2 \sum_{k=1}^K n_{p/nse}^{i,k,e} \cdot p^e \cdot \bar{t}_d^e}_{\text{term 1}} + \underbrace{\sum_{i=1}^T \sum_{e=1}^2 \sum_{k=1}^K n_{s/p}^{i,k,e} \cdot VOT^k}_{\text{term 2}} \cdot \left(\underbrace{\frac{2 \cdot AWD_{op}}{w}}_{\text{term 3}} + \underbrace{ACT_{all}}_{\text{term 4}} \right) + \underbrace{\phi \cdot A^2}_{\text{term 5}} \quad (88)$$

We add all cost variables for the drivers in the network (terms 1 – 4) and the cost for the city to establish an electric vehicle parking infrastructure (term 5). The cost terms 1 – 3 might impact the drivers' utility from parking ([Vrancken et al. \(2017\)](#)). Term 1 expresses the parking cost for all parking searchers based on p^e and \bar{t}_d^e for all $k \in K$, $e \in \{1, 2\}$ and $i \in T$. It is the same as the total revenue generated for the city (Eq. (87)). Term 2 uses the VOT^k to convert terms 3 and 4 into price units depending on the number of vehicles accessing parking $n_{s/p}^{i,k,e}$. Term 3 formulates the average walking distance AWD_{op} from the parking space to the final destination and back. Recall that AWD_{op} is determined in Eq. (13), as parking spaces are uniformly distributed throughout the area. Recall that our network can be abstracted as a square grid with its total road length, L , being equivalent to joining all blocks of average known length b together. Term 4 (Eq. (88)) shows the average cruising time for parking ACT_{all} . Term 5 estimates the costs of deploying electric vehicle parking, i.e., we multiply the cost ϕ per parking space by the number of parking spaces for electric vehicles A^2 . We do not account for the cost of operating a conventional parking space (i.e., a parking space for fuel vehicles), nor for any additional fees that might be paid by electric vehicles charging their batteries.

6.3 Applications

This section presents a case study of a central area within the city of Zurich, Switzerland, to determine the optimal parking occupancy rate for fuel and electric vehicles. As the interest in electric vehicles is continuously increasing, our findings evaluate the traffic performance and parking impacts of a modal shift towards electric vehicles with respect to the average searching time for parking, the total revenue from parking pricing, and the parking occupancy. Our methodology is implemented using a simple numerical solver such as Matlab based on real data obtained by [Cao et al. \(2019\)](#).

6.3.1 A case study for an area within the city of Zurich, Switzerland

The same study area ($L = 7.7$ km, and $b = 76$ m) within the city of Zurich is used as in section 3.4.1. The total network length is $L_{lane} = 15.4$ lane-km, as most of the streets have two lanes (either one lane per direction or two lanes in a one-way street). Remember that there are 539 public parking spaces with no parking time limit in the area ([Cao et al. \(2019\)](#)). We divide the working day into time slices of 1 minute, i.e., $t = 1$ min, so that $T = 1440$ min. All parking spaces have an hourly fee of $p^e = 2.25$ CHF approximating the average value in the city center of Zurich ([Cao et al. \(2019\)](#)). Recall that 77 % (2069 trips) of the daily traffic searches for parking, and the remaining 23 % (618 trips) does not search for parking (through-traffic), i.e., $\beta^i = 0.23, \forall i$. The parking durations are described by the probability density function (pdf) as in Fig. 4.5 (section 4.4.1). Notice that the application of the model is not limited to a specific distribution, and other distributions besides gamma could also be assumed for the parking duration ([Cao and Menendez \(2013\)](#)). We initially assume that the pdf of the parking durations is the same for all vehicle types. However, we relax this assumption in section 6.3.4. The traffic properties (i.e., $v = 12.5$ km/h, $Q_{max} = 250$ veh/hr/lane, $k_c = 20$ veh/km/lane, $k_j = 55$ veh/km/lane) are based on the MFD of the city of Zurich ([Ambühl et al. \(2017\)](#); [Dacic and Menendez \(2018\)](#); [Loder et al. \(2019\)](#); [Ortigosa et al. \(2014\)](#)). The travel distances $l_{ns}^{k,e}$, $l_p^{k,e}$ and $l_j^{k,e}$ follow a uniform distribution between 0.1 and 0.7 km for all $e \in \{1,2\}$ and all $k \in \{1, \dots, 4\}$. The initial conditions include $\sum_{e=1}^2 \sum_{k=1}^4 N_p^{0,k,e} = 183$ vehicles already parked in the area, and $\sum_{e=1}^2 \sum_{k=1}^4 N_s^{0,k,e} = 0$ vehicles searching for parking at the beginning of the working day. The average walking speed is assumed to be $w = 5$ km/h ([Browning et al. \(2006\)](#)). The cost of establishing a parking space with charging facilities for an electric vehicle is estimated as $\phi = 10,000$ CHF per year ([Huang and Kockelman \(2020\)](#); [Idaho National Laboratory \(2015\)](#); [Smith and Castellano \(2015\)](#) assuming 1 USD \approx 1 CHF), and includes the station maintenance costs.

6.3.2 Optimal parking occupancy rate, and traffic performance impacts

This section shows the optimal parking occupancy rate, and the resulting traffic performance when considering the differentiated and hierarchical parking space policies in comparison with a non-differentiated parking scheme (section 6.2.2.3). We first assume that the proportion of parking spaces for electric vehicles with battery charging possibilities, ζ (Eq. (89)), matches the proportion of electric vehicles entering the area, ε (Eq. (90)). This assumption, $\zeta = \varepsilon$, will be relaxed in section 6.3.3 when we analyze the trade-offs between different demand and supply proportions of electric vehicles. Note that ε is assumed to be equal for all time slices over one working day.

$$\zeta = \frac{A^2}{A^1 + A^2} \quad (89)$$

$$\varepsilon = \frac{\sum_{i=1}^T \sum_{k=1}^K n_{/ns}^{i,k,2}}{\sum_{i=1}^T \sum_{k=1}^K (n_{/ns}^{i,k,1} + n_{/ns}^{i,k,2})} \quad (90)$$

First, we evaluate our reference scenario with non-differentiated parking (scenario (a)), i.e., we do not distinguish between vehicles or parking spaces (section 6.2.2.3). We compare this scenario to the assumed scenarios (b) differentiated parking policy, and (c) hierarchical parking policy, reflecting two vehicle types, fuel ($e = 1$) and electric ($e = 2$) vehicles, with $\zeta = \varepsilon = 10\%$. Table 6.3 presents the results for these scenarios.

Table 6.3. Comparison of different scenarios considering non-differentiated, differentiated and hierarchical parking policies with $\zeta = \varepsilon = 10\%$ focusing on traffic and parking impacts. Value within parenthesis represents the percentage change with respect to the reference scenario.

Scenarios	(a)	(b)	(c)
	Reference scenario: Non-differentiated parking	Differentiated parking policy	Hierarchical parking policy
Optimal parking occupancy rate (single value for all parking spaces)	93.43 %	87.37 % (-6.5 %)	93.43 % (+0 %)
Optimal parking occupancy rate (parking spaces for fuel vehicles)	-	85.62 %	93.43 %
Optimal parking occupancy rate (parking spaces for electric vehicles)	-	87.6 %	93.63 %
Average time for vehicles searching for parking (min/veh)	3.14	3.77 (+20.1 %)	3.27 (+4.1 %)
Social impacts of introducing parking spaces for electric vehicles, S	27,145 CHF	566,660 CHF	566,250 CHF

Not surprisingly, scenario (a) with a non-differentiated parking scheme leads to the lowest average searching time (3.14 min/veh) over one working day. It also shows a high optimal parking occupancy rate (93.4 %). Note that we assume an optimistic case with all drivers going through all parking spaces in order to find the next available parking space in the area. This leads to slightly higher optimal parking

occupancy rates than the 85 % suggested by [Shoup \(1999, 2005, 2006\)](#). Fig. 6.5 shows the average searching time as a function of the parking occupancy rate. It can be used to visualize the computation of the optimal parking occupancy rate using our optimization framework from section 6.2.3.3.

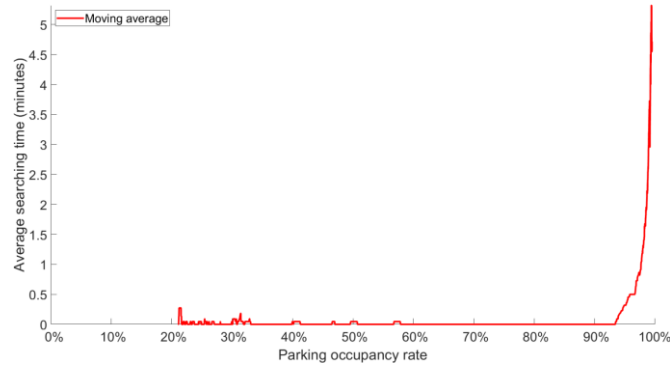


Fig. 6.5. Average searching time for different parking occupancy rates during a typical working day (scenario (a)).

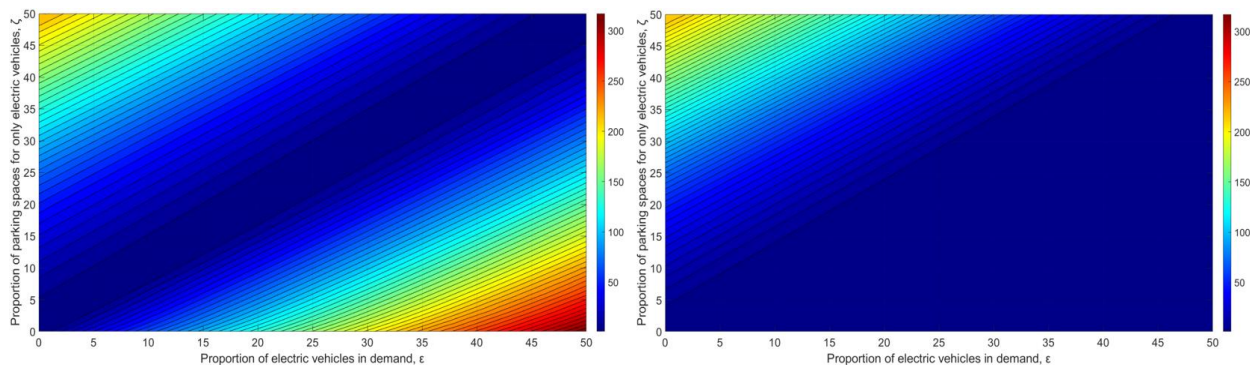
The differentiated parking policy (scenario (b)) leads to an average searching time increase of 20.1 % compared to the reference scenario (a), despite an optimal parking occupancy rate reduction of 6.5 % on average. The optimal parking occupancy rate of parking spaces for fuel and electric vehicles are relatively similar to each other (85.6 % and 87.6 %, respectively). These lower occupancy rates can be explained by the increase in average searching time in scenario (b). As fuel and electric vehicles are only allowed to access their dedicated parking spaces, more vehicles require longer to find an available parking space. The optimal parking rate for scenario (b) should then be lower to still ensure a high likelihood of finding parking besides an efficient usage of the parking infrastructure. The hierarchical parking policy (scenario (c)) leads to an average searching time decrease of 13.3 % compared to scenario (b). The lower average searching time also leads to slightly lower social impacts of introducing parking spaces for electric vehicles in scenario (c) compared to scenario (b). Note that the social impacts (Eq. (88)) mainly depend on the cost of electric vehicle parking infrastructure ϕ , which is an input to our model. This explains the significant increase of the social impacts in scenario (b) and (c) in comparison to having no electric vehicle parking infrastructure in place in reference scenario (a). One would expect, however, that with time, ϕ will go down reducing such difference. Recall also that we do not account for the cost of operating parking spaces for fuel vehicles, nor for any additional fees that might be paid by electric vehicles charging their batteries.

The improvements in scenario (c) come with the same optimal parking occupancy rate as in scenario (a). The electric vehicles fill up their parking supply with battery charging options in the hierarchical parking policy before they decide to use fuel parking spaces in the area. Thus, they cause less cruising-for-parking traffic compared to the differentiated policy (scenario (b)), and this leads to a better traffic performance in the network. The average searching time for parking is only 4.1 % higher than in the reference scenario. This makes the hierarchical parking policy the preferred parking policy for most cities when facing a demand and supply change in terms of fuel and electric vehicles. Some drivers of electric vehicles might, however, require a

parking space with battery chargers as their battery is almost empty. Depending on their planned activities, these drivers might decide to cruise for parking even when there are parking spaces for fuel vehicles available, or to drive to a different area instead. The latter might cause a change in the total parking demand, which is, however, out-of-scope in this chapter.

6.3.3 Trade-offs between demand and supply for electric vehicles

Due to a modal shift towards electric vehicles, cities face the challenge of building new dedicated parking spaces or turning existing parking spaces for fuel vehicles into spaces with battery chargers. Then the question arises of how much parking supply shall be reserved for electric vehicles in order to react to a constantly varying parking demand over time. Compared to section 6.3.2 ($\zeta = \varepsilon$), we analyze in this section a mismatch between ζ and ε , and its effects on the traffic and parking model outputs. We run a simulation-based search algorithm to understand the impacts of all proportions ζ and ε on the traffic performance (Fig. 6.6(a)-(b)) analyzing the average searching time for the differentiated and hierarchical parking space policies in section 6.2.2.3. The following figures are created using a cubic interpolation method of the results (Hazewinkel (1994)).



(a) Average searching time (differentiated parking policy). (b) Average searching time (hierarchical parking policy).

Fig. 6.6. Traffic performance impacts according to different demand and supply proportions for electric vehicles.

As one would expect, Fig. 6.6(a) shows that the average searching time for the differentiated parking policy is minimized for $\zeta \approx \varepsilon$ (i.e., along the diagonal). This is reasonable as the absolute size of the parking demand and the available supply are balanced for both electric and fuel vehicles, i.e., the proportion of vehicles searching for parking is similar to the proportion of available parking spaces over time. In other words, cities should aim to provide a proportion of parking spaces for electric vehicles, ζ , similar to the proportion of electric vehicles in demand, ε , to reduce cruising-for-parking in the area. The average searching time increases faster for $\zeta < \varepsilon$ compared to $\zeta > \varepsilon$. This is reasonable as both ζ and ε are below 50%. The average searching time follows the opposite behavior when both ζ and ε are over 50%. Either fuel or electric vehicles find it more difficult to find an available parking space when $\zeta \neq \varepsilon$. However, when a mismatch between ζ and ε cannot be avoided, it is safer to

have a ζ higher than ε , i.e., an oversupply of parking spaces for electric vehicles rather than an undersupply, as long as $\varepsilon < 50\%$. Applying the hierarchical parking policy mitigates this problem (Fig. 6.6(b)) as electric vehicles can park everywhere. This leads to the same searching times for $\zeta \approx \varepsilon$ and $\zeta < \varepsilon$. In other words, as long as we do not oversupply parking spaces for electric vehicles, the traffic performance is acceptable in the area. Notice, however, that providing some parking with charging stations could potentially lead to a modal shift, and this could be desirable for the city. Such changes in the demand are considered out of the scope for this dissertation.

The total revenue from parking pricing (differentiated parking policy) over one working day (Fig. 6.7(a)) equals to 17,630 CHF for $0.7\varepsilon \leq \zeta \leq 0.7\varepsilon + 29$. An efficient usage of the available parking spaces leads to these high revenues. Beyond this ratio, $\zeta < 0.7\varepsilon$ and $\zeta > 0.7\varepsilon + 29$, the revenue decreases. The hierarchical parking policy (Fig. 6.7(b)) leads to a revenue of 17,628 CHF when $\zeta \leq 0.7\varepsilon + 29$. The low average searching times (Fig. 6.6(b)) facilitate a more efficient usage of the available parking supply compared to the differentiated parking policy. An oversupply of parking spaces for electric vehicles and an undersupply of parking spaces for fuel vehicles reduce the parking revenue. Thus, if we want to increase revenues, we need to make sure that we do not undersupply parking spaces for fuel vehicles, contrary to what we said when talking about traffic performance.

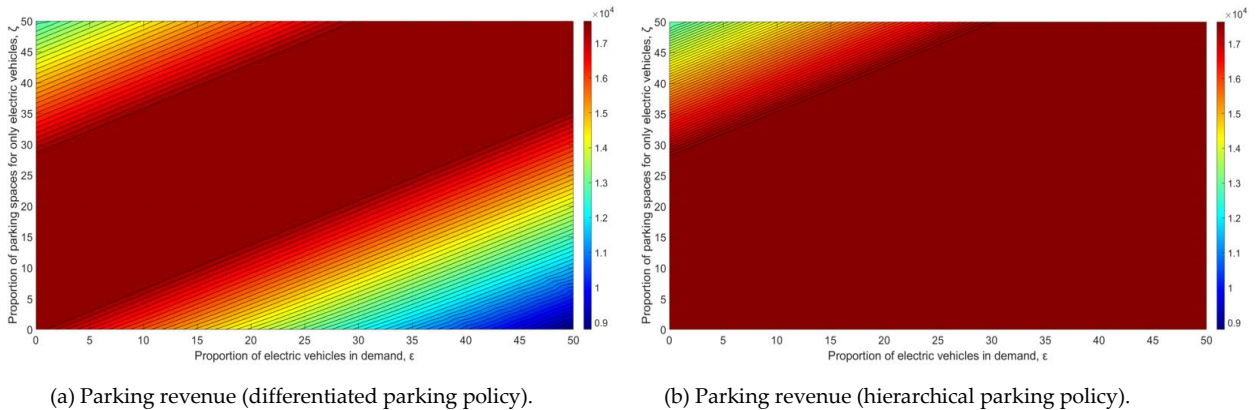


Fig. 6.7. Parking revenue impacts according to different demand and supply proportions for electric vehicles.

Fig. 6.8(a)-(b) analyze how the optimal parking occupancy rates of parking spaces for fuel and electric vehicles (differentiated parking policy) are affected by different proportions ζ and ε . The optimal occupancy rate is higher than 80% when $\zeta > \varepsilon$ for the parking spaces for fuel vehicles (Fig. 6.8(a)), and when $0.9\zeta < \varepsilon < 3\zeta$ for the parking spaces for electric vehicles (Fig. 6.8(b)). The former can be explained by an undersupply of parking spaces for fuel vehicles which leads to high optimal parking occupancies reflecting the high parking demand of fuel vehicles. The latter can be explained by an efficient parking space usage due to low searching times in the network. It is still possible to achieve a high likelihood of finding parking for drivers of electric vehicles, even if the parking occupancy rates in the area are high. Beyond this, the optimal occupancy rates of parking spaces decrease in order to compensate for the mismatch between the demand and the supply for one of the vehicle types. Therefore, and given that guaranteeing different occupancy rates for different types

of parking is rather complicated, it makes sense to set a single target value across all vehicle spaces. Such value should be around 80 % as long as there are similar proportions ζ and ε .

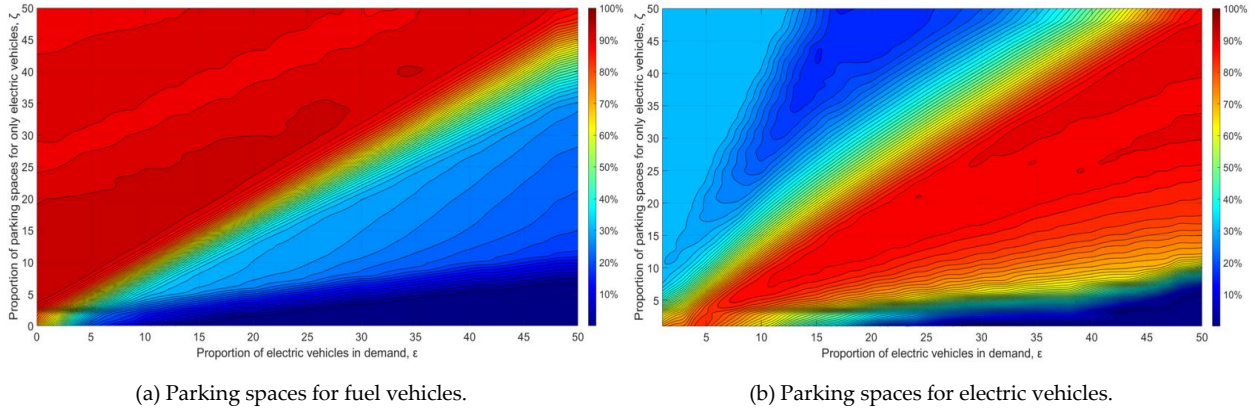


Fig. 6.8. Optimal parking occupancy rate for different demand and supply proportions for electric vehicles (differentiated parking policy).

This single target occupancy rate could be even higher, around 90 %, if we were to implement the hierarchical parking policy (see Fig. 6.9). Moreover, in this case, it would be applicable as long as $\zeta < \varepsilon$ which characterizes an undersupply of parking spaces for electric vehicles, as these vehicles can access both types of parking spaces. The hierarchical parking policy not only leads to a better traffic performance for $\zeta < \varepsilon$ (Fig. 6.6(b)) compared to the differentiated parking policy, but also to higher optimal parking occupancy rates for these proportions ζ and ε .

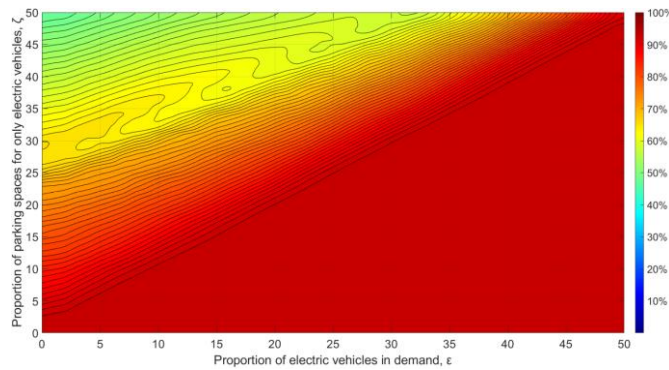


Fig. 6.9. Single optimal parking occupancy rate across all parking spaces in the area for different demand and supply proportions for electric vehicles (hierarchical parking policy).

In summary, achieving similar proportions, $\zeta \approx \varepsilon$, leads to the best traffic performance in the area for both the differentiated and the hierarchical parking policies. In the latter policy, the proportions $\zeta < \varepsilon$ can also lead to low searching times as drivers of electric vehicles can use fuel parking spaces instead of spaces with battery charging options. Equal proportions, $\zeta = \varepsilon$, come along with high revenues for the city and single optimal parking occupancy rates around 80 % (differentiated parking policy) and 90 % (hierarchical parking policy) across all parking spaces. Consequently, cities shall react towards a changing demand for electric vehicles over time by changing their supply accordingly. City councils can also use the results from this model to analyze the traffic performance loss when they do not react, e.g., to an

increasing demand for electric vehicles over time. These risks can be evaluated as a function of the parking policy in place.

6.3.4 Sensitivity to changes in parking demand, supply, or parking duration

Here we present a sensitivity analysis for the differentiated (section 6.3.4.1) and the hierarchical parking policy (section 6.3.4.2) quantitatively evaluating the impacts of a change in parking demand, supply, or the distribution (pdf) of parking durations on the optimal parking occupancy rate across all parking spaces. We use as a reference the total demand of 2687 trips entering the area, the total supply of 539 parking spaces in the network, and the pdf of parking durations described in section 6.3.1. A more in-depth sensitivity analysis considering dependency between inputs ([Ge and Menendez \(2017\)](#)) is considered out of the scope for this chapter.

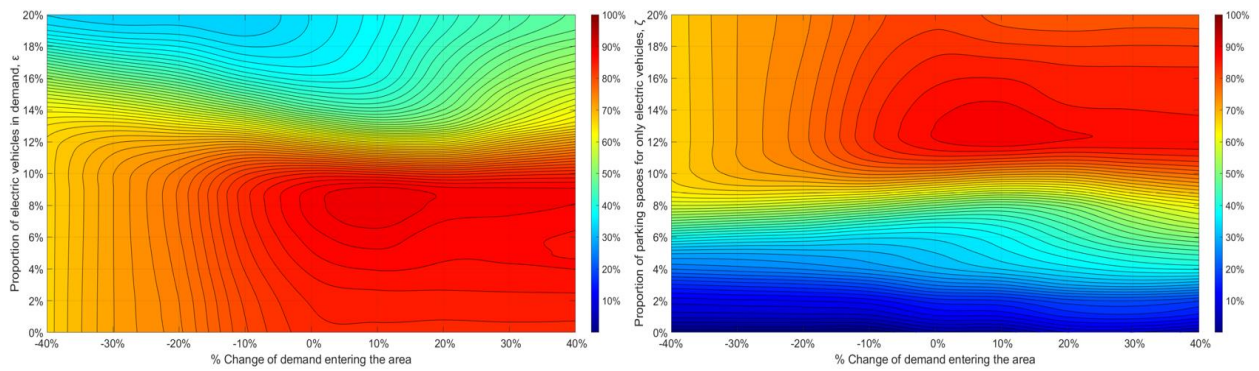
6.3.4.1 Sensitivity analysis for the differentiated parking policy

Fig. 6.10-6.12 show how a decrease or an increase in demand, supply, and the electric vehicles' average parking durations affect the single optimal parking occupancy rates across all parking spaces depending on different proportions of ε with $\zeta = 10\%$ (Fig. 6.10(a)-6.12(a)), and different proportions of ζ with $\varepsilon = 10\%$ (Fig. 6.10(b)-6.12(b)).

An increase in demand together with a low $\varepsilon \leq 10\%$ (Fig. 6.10(a)), or a high $\zeta \geq 10\%$ (Fig. 6.10(b)) leads to optimal occupancy rates above 80%. In these cases, electric vehicles do not cause additional searching for parking traffic as $\varepsilon < \zeta$. High proportions of electric vehicles in the demand, $\varepsilon > 10\%$, and low proportions of electric parking in the supply, $\zeta < 10\%$, lead to a decrease in optimal parking occupancy rates as the mismatch between the demand and the supply becomes more relevant. The low occupancy rates are needed to guarantee that despite the strong competition among electric vehicles looking for parking, cruising times are still minimized. For cases where $\varepsilon < \zeta$, as the demand entering the area decreases, the optimal occupancy rates do so as well. This can be explained by a decreasing absolute number of electric vehicles searching for parking compared to a constant parking supply with battery chargers, resulting in an increasing oversupply of parking spaces for electric vehicles as the total demand decreases.

Changes in parking supply (Fig. 6.11(a)-(b)) have a smaller impact on the optimal parking occupancy rates compared to changes in demand, mostly because the changes in absolute values are also much smaller. Recall that the total value of the supply is much smaller than the total value of the demand. However, the overall trends remain the same.

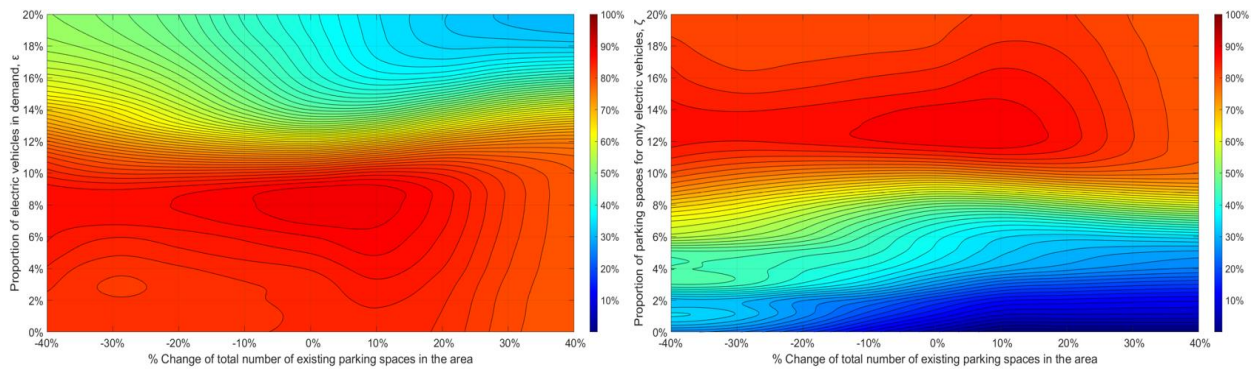
Last, changes in the electric vehicles' average parking durations have almost no impact on the optimal parking occupancy rates (Fig. 6.12(a)-(b)). Low $\varepsilon \leq 10\%$ (Fig. 6.12(a)), or high $\zeta \geq 10\%$ (Fig. 6.12(b)) lead to high optimal parking occupancy rates.



(a) By different proportions of ϵ with $\zeta = 10\%$.

(b) By different proportions of ζ with $\epsilon = 10\%$.

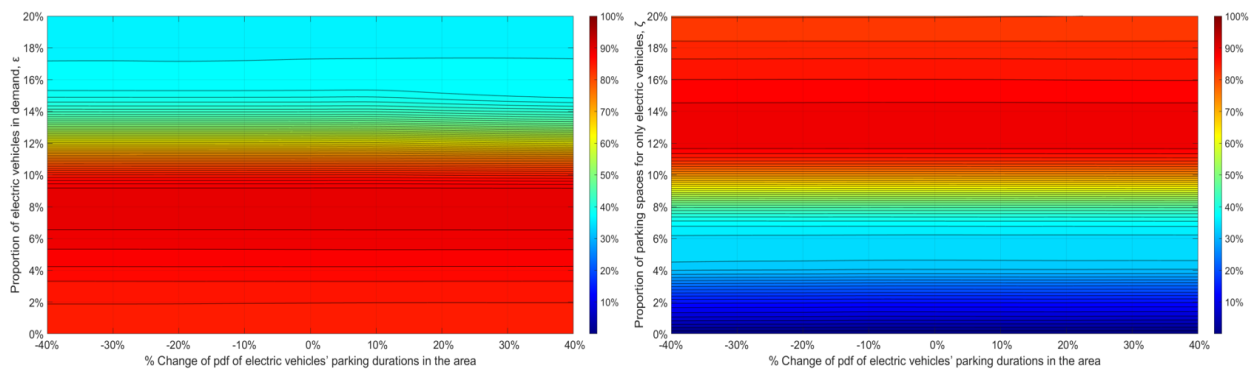
Fig. 6.10. Sensitivity analysis of the optimal parking occupancy rate across all parking spaces with respect to changes in the demand entering the area (differentiated parking policy).



(a) By different proportions of ϵ with $\zeta = 10\%$.

(b) By different proportions of ζ with $\epsilon = 10\%$.

Fig. 6.11. Sensitivity analysis of the optimal parking occupancy rate across all parking spaces with respect to changes in the total parking supply in the area (differentiated parking policy).



(a) By different proportions of ϵ with $\zeta = 10\%$.

(b) By different proportions of ζ with $\epsilon = 10\%$.

Fig. 6.12. Sensitivity analysis of the optimal parking occupancy rate across all parking spaces with respect to changes in the pdf of electric vehicles' parking durations in the area (differentiated parking policy).

6.3.4.2 Sensitivity analysis for the hierarchical parking policy

The hierarchical parking policy leads to generally higher optimal parking occupancy rates across all parking spaces compared to the differentiated parking policy in section 6.3.4.1. In this case, an increase in demand leads to the highest optimal parking occupancy rate of approximately 94 % for high proportions $\varepsilon \geq 10$ % (Fig. 6.13(a)), or low proportions $\zeta \leq 10$ % (Fig. 6.13(b)).

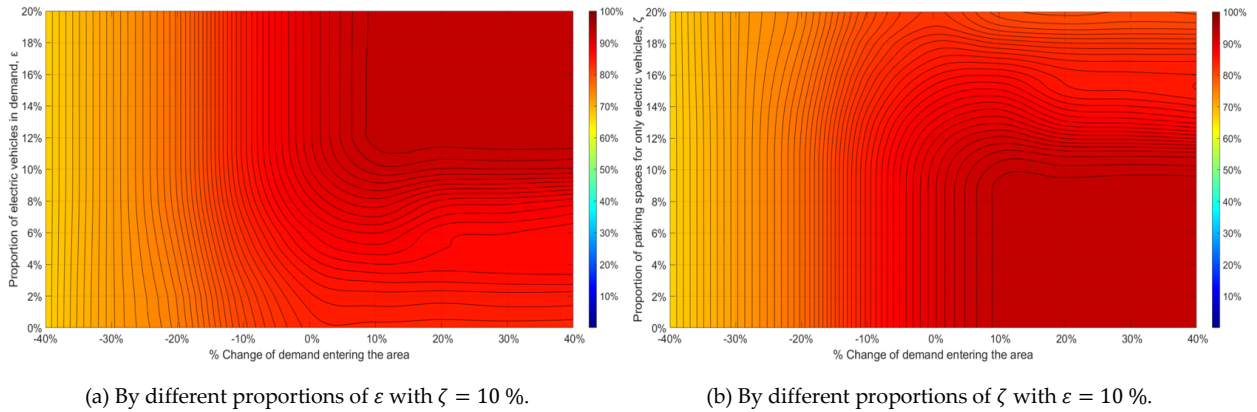


Fig. 6.13. Sensitivity analysis of the optimal parking occupancy rate across all parking spaces with respect to changes in the demand entering the area (hierarchical parking policy).

This is different than Fig. 6.10, as a high proportion of electric vehicles in the demand, ε , or a low proportion of parking spaces for only electric vehicles, ζ , do not necessarily increase the search times. Recall that in such cases electric vehicles will use a fuel parking space instead. Therefore, for any increases in demand, it is worth maintaining $\zeta \leq \varepsilon$. Note that we omit the figures showing the changes in supply and parking duration for the hierarchical parking policy as the variations in the optimal parking occupancy rates are hard to read due to their high values. As a matter of fact, there are no remarkable dependencies between changes in the total parking supply or the electric vehicles' average parking durations and the optimal parking occupancy rates. In the extreme case where the total supply were to be very limited with a hierarchical parking scheme, it is recommended to limit the supply for the non-differentiated vehicle class (here electric vehicles) compared to the differentiated vehicle class (here fuel vehicles) in order to achieve the best traffic performance in the network.

6.4 Summary of the chapter

In this chapter, we propose a model to determine the optimal parking occupancy rate for multiple vehicle types based on a macroscopic traffic and parking model over a given time horizon for an urban area. We demonstrate our methodology using real data from an area within the city of Zurich, Switzerland. Our findings confirm the optimal parking occupancy rates proposed by [Shoup \(1999, 2005, 2006\)](#), but we also discuss how these rates might change depending on various demand and supply relationships following different parking policies.

The usage of the proposed framework is far beyond the illustration presented here. Parking and/or congestion pricing measures (chapter 4) could be analyzed to achieve the optimal parking occupancy rate for some parking spaces in the network. A further consideration is to enhance the parking fees using responsive pricing schemes in order to optimize the total revenue from parking pricing (chapter 5). We could also enhance the model by including public transport and studying the multimodal demand effects on the parking occupancy ([Dakic et al. \(2020\)](#); [Loder et al. \(2017\)](#); [Paipuri and Leclercq \(2020\)](#); [Zheng et al. \(2014\)](#)). Future research could incorporate as well a differentiation between on- and off-street parking (chapter 3) and evaluate their impacts on the optimal occupancy rate. Our model does not explicitly account for delivery parking and assumes double parking does not cause any issues in the area. [Roca-Riu et al. \(2017\)](#) investigated the development of dynamic delivery parking spaces that could be integrated into the proposed framework in future studies. Additionally, vehicles could prefer parking possibilities in a central street or area of the network compared to parking spaces elsewhere. This non-homogeneous environment could lead to different optimal parking occupancy rates by modeling adjacent subnetworks that are connected to each other.

Below, we summarize the main contributions of this chapter and discuss their policy implications.

First, we propose a macroscopic model to determine the optimal parking occupancy rate in a central area that is based on small data collection efforts and has low computational costs. The model outputs can be generated with a simple numerical solver and without complex simulation software. Our study defines the optimal parking occupancy rate to minimize cruising time. The results help cities setting the optimal parking occupancy rate in order to guarantee an optimal trade-off between an efficient usage of the parking infrastructure and a high likelihood of finding parking such that the traffic performance is improved in the area. Multiple parking measures (e.g., parking pricing policies (chapter 4)) could then be used to obtain this target rate over time. However, they are considered out-of-scope in this study.

Second, a modal shift towards a specific vehicle type (e.g., electric vehicles) will lead to new challenges for cities as they try to establish the required parking supply (e.g., parking spaces with battery charging opportunities for electric vehicles). Our framework not only allows us to evaluate the impacts on the traffic performance and the society, but also on optimal parking occupancy rates for different proportions of fuel and electric vehicles both in the demand and the supply. We investigate a non-differentiated parking policy, a differentiated parking policy with exclusive parking spaces (e.g., fuel vehicles park at fuel vehicle parking spaces, and electric vehicles park at their dedicated parking spaces), and a hierarchical parking policy, considering no parking space restrictions for some vehicle types (e.g., electric vehicles can park at any parking space). Not surprisingly, the non-differentiated parking policy leads to the lowest average cruising time and the highest optimal occupancy rate. However, it is the least ideal policy from the city's perspective. Having all parking spaces equipped for electric vehicles is very expensive, and not providing any charging facilities for electric vehicles might deter drivers from switching to the more

sustainable technology. Notice that while the cost of deploying electric parking spaces seems quite high right now, it is expected to go down as the technology matures. Moreover, it could be at least partially recovered if drivers pay for the electricity consumed while charging their batteries. When it comes to differentiated parking policies, our results for the city center of Zurich not only show that equal proportions between electric vehicles in the demand and their parking spaces in the supply lead to the best traffic performance in the area, but they also allow city councils to analyze their loss in performance if they do not react, e.g., to an increasing demand for electric vehicles over time. These risks can be evaluated for both the differentiated and the hierarchical parking policies, such that our model can help cities to choose the right parking policy (in terms of, e.g., traffic performance, parking revenue, and social impacts), and apply it towards their needs (e.g., proportion of parking spaces for electric vehicles in the area). Overall, the hierarchical parking policy leads to better results in terms of traffic performance and parking revenues, as it provides higher flexibility.

Third, we can analyze the dependency of the optimal parking occupancy rate (for the differentiated and hierarchical policies) on changes in parking demand, supply, or parking duration. Cities can use the sensitivity analyses to react to these changes by modifying the supply of parking spaces with battery chargers, or by adapting the target occupancy rates.

In summary, our model combines the advantages of an easy to implement methodology to determine the optimal parking occupancy rate for different vehicle types with the opportunities of evaluating traffic and parking impacts (e.g., average searching time for parking, total revenue from parking pricing, optimal parking occupancy rates) of a modal shift towards a specific vehicle type, such as electric vehicles with differentiated and hierarchical parking policies.

Chapter 7:

Conclusions and Outlook

7.1 Summary

This doctoral research analyzes parking policies with respect to parking pricing and parking occupancy strategies and evaluate their impacts on the traffic performance. Based on a macroscopic methodology presented in **chapter 2** we generate insights into the interdependency between these parking policies and the traffic and parking systems using limited aggregated data at the network level. There is no data required for individual vehicles. One of the main advantages of a macroscopic approach is that it can model the dynamics of the urban parking and traffic systems without the need for tracking the location of individual parking spaces. Such efficiencies are especially useful for real-time control algorithms or when the data is scarce. Urban parking policies have always been discussed by many stakeholders with different interests and perspectives. In general, there are five types of stakeholders involved in the decision process regarding implementing parking policies. We highlight their perspectives in the following:

- **Drivers:** In order to achieve low travel times, drivers prefer a good traffic performance and no congestion near their parking destination in the area. They desire affordable parking and low parking occupancy rates in order to have an efficient commute into their area of interest. High parking fees, or longer times searching for parking might lead to traffic demand changes, with some drivers either changing their transportation mode or their desired destination (e.g., in case of shopping trips, or leisure activities).
- **Urban residents:** Residents would like to find available parking spaces when returning to their homes. As some residents have no private parking spaces, they must search for public parking near their houses or apartments. Thus, they desire low parking occupancy rates near their homes, and a general lower traffic demand in the area. They like to have a pleasant experience when commuting back from work or when returning from shopping trips and leisure activities. In case this is not feasible, residents might consider moving away or changing their transportation modes.
- **Retail, businesses and shops:** Parking might affect the economic development in the area which, in turn, has a direct influence on the number of customers for businesses and shops. Business and shop owners would like to have affordable parking pricing and low parking occupancy rates near their businesses such that they can be easily accessed by customers. In addition, logistics companies should not face any issues during delivery activities while short-term parking.
- **Non-retail companies:** Companies would like to ensure a good employee experience when commuting to their workplace. Employees who are stuck in traffic and cruise for parking cannot perform their jobs which might lead to loss of productivity. Additionally, the employee satisfaction might decrease

as their commute might make them feel stressed at the beginning and/or at the end of their workday. Thus, companies usually have private parking lots or private parking garages which allow employees to reserve parking spaces in order to avoid cruising for parking. Alternatively, companies might subsidize the employees' PT tickets trying to improve the traffic performance in the area.

- **City councils and local governments:** Parking can generate a considerable amount of revenue for city councils and local governments. Additionally, future parking usage and urban development might be of interest to the local authorities, in particular how the city area could be made more internationally attractive and sustainable. Example policies might consider to remove parking in an area in order to minimize the car usage, or to move existing on-street parking spaces into concentrated parking garages, such that the curb can be used for other activities (e.g., creating pedestrian zones or bicycle lanes).

This dissertation allows us to provide answers to different questions from these stakeholders using low data collection efforts and low computational costs. Some of these questions referring to chapters 3 to 6 are presented below together with a summary of each chapter.

Chapter 3: How are on-street and garage parking policies affecting the traffic performance in the network? Should real-time smartphone applications or garage information signs be provided in the traffic network such that all drivers have access to garage usage information? How many on-street parking spaces should be converted to garage parking spaces in order to reduce the average searching time for parking and increase the parking revenue?

These questions can be answered using our macroscopic modelling approach of on-street and garage parking. We model the drivers' decision between driving to a public parking garage or searching for an on-street parking space in the network, including the influences on the cruising-for-parking traffic, the traffic performance, the environmental impact, and the parking revenue for the city councils. Different parking fees might affect the drivers' decision and thus the cruising-for-parking traffic and the traffic performance, but they also influence the financial revenues. Therefore, our methodology allows cities to analyze the trade-off between the revenue and the average travel time. Furthermore, we show the changes to this trade-off when real-time garage usage information is provided to the drivers in the area. Overall, we provide tools to help local governments when deciding about converting on-street to garage parking spaces, and evaluate the short-term effects on the traffic and parking system. Here, using the case study of a central area within the city of Zurich, we consider also the perspectives from the local businesses and residents as these changes might lead to a higher average time driving to a parking garage, and a lower average searching time for on-street parking. As garage parking is usually more expensive than on-street parking, this conversion also comes along with an increase in the total parking revenue for the city council.

Chapter 4: Can static parking pricing strategies (in combination with P+R) lead to similar or even better traffic performance results compared to congestion pricing policies for a city with a high parking demand for public parking spaces? Can different VOTs have an impact on the drivers' decision between entering the area by car or switching to P+R instead? What is the best relation between the parking fee and the congestion toll in order to improve the traffic performance or the total revenue for a local government?

We show that parking pricing policies are indeed a viable option for drivers, residents and the local government compared to congestion pricing for a central area in Zurich which has a high demand for public parking spaces. Parking pricing strategies might not only lead to better traffic performance results, but they are also easier to implement and socially and politically more accepted than introducing a congestion toll in an area. Even stores and businesses might want to consider reimbursing customers' parking fee in order to attract more demand and at the same time to keep their spaces available for customers only. Our framework allows us to analyze the short-term impacts of P+R pricing, parking pricing and/or congestion pricing policies on the traffic and parking system, which, in turn, impacts the drivers' decision between entering the area by car or using P+R instead. Our decision methodology is based on a multimodal macroscopic traffic and parking framework using different VOTs for drivers entering the network. Besides the drivers' VOT, the P+R fare, the parking fee and the congestion toll impact this decision model. Thus, we developed a simulation-based search algorithm which improves the traffic performance or the total revenue for the city by finding the best trade-off between the parking fee and the congestion toll in the network. In case the share of drivers searching for public parking is large enough, parking pricing can be considered as a viable alternative to congestion pricing, and there is no need to introduce the more controversial congestion pricing schemes in an area.

Chapter 5: Can we establish a responsive pricing scheme not only changing in response to the the available parking supply (i.e., the parking occupancy rate), but also to parking demand (i.e., the number of vehicles cruising-for-parking), which maximizes the parking revenue for city councils and minimizes the traffic congestion in the area? Will drivers accept this parking fee, or will they continue cruising for a next available parking space hoping to find a cheaper parking spot in the area? How sensitive is our pricing framework when evaluating changes for the traffic demand and the parking supply with respect to their impacts on the parking revenue and the traffic performance?

Our dynamic macroscopic responsive pricing model actually takes the parking search phenomenon and the parking occupancy into consideration. It is based on an optimization framework maximizing the revenue and at the same time minimizing the total cruising time in the area. We achieve this by modelling the cost for drivers of paying the current parking fee which should be smaller than the cost of keep on searching for another available parking. These costs depend on several components including the drivers' VOTs and the predicted parking fee at the next available location. We show the short-term impacts on the searching time, the driven distance

and the revenue created by parking fees for the city of Zurich. Here, our scheme leads to no significant negative influences on the traffic performance and the environment conditions. However, it generates additional revenue for the local government in the short-term. In the long-term, it could potentially lead to demand changes as drivers might change their habits and not use their car anymore to drive into the area. As residents and businesses might be negatively affected by the application of this responsive pricing scheme to residents' parking or parking spaces near business locations, cities could potentially evaluate whether to apply this scheme to only a portion of the public parking spaces in a central area.

Chapter 6: How can an optimal parking occupancy rate be determined macroscopically in order to guarantee an optimal trade-off between an efficient usage of the parking infrastructure and a high likelihood of finding parking? How can a modal shift towards a specific vehicle type (e.g., electric vehicles) affect the traffic performance and the optimal parking occupancy rates in the area? Are differentiated or hierarchical parking space policies better than non-differentiated parking schemes when analyzing their impacts on the traffic and parking system, but also on the society? What is the best proportion of parking spaces with battery charging opportunities in the supply compared to the proportion of electric vehicles in the demand when evaluating the influences on the traffic performance?

We propose a macroscopic framework determining the optimal parking occupancy rate by having a minimal cruising time in a central area and at the same time a high parking usage. In different words, we basically focus on finding the highest possible occupancy rate that minimizes the total cruising time in order to ensure a good public parking experience for, e.g., customers at central businesses and also for urban residents when returning home from work. Additionally, we differentiate between specific vehicle types (e.g., electric and fuel vehicles) and different parking space policies, and evaluate their impacts on the traffic performance, the optimal parking occupancy rates and the society. Our methodology helps city councils analyzing their loss in performance for different parking space strategies if they do not react, e.g., to an increasing demand for electric vehicles over time. For the city center of Zurich, the hierarchical parking policy (i.e., no parking space restrictions for electric vehicles) leads to a better traffic performance and higher parking revenues than the differentiated parking policy (i.e., electric parking spaces are reserved only for electric vehicles, and fuel parking spaces for fuel vehicles). Moreover, equal proportions between electric vehicles in the demand and their parking spaces in the supply might lead to the best traffic performance for the city center of Zurich. Additionally, our model allows us to evaluate the sensitivity of the optimal parking occupancy rate depending on changes in parking demand, supply, or parking duration. Local governments can use this to analyze implications resulting from, e.g., modifications to the supply of parking spaces with battery chargers. This can include new policies by the city council controlling the demand, the supply, the parking duration, or the target occupancy rate over time.

7.2 Usage of our Methodology

Our macroscopic model allows us to study the interdependency between different parking policies and the traffic and parking system for an urban area. The methodology can be used to analyze parking policies with respect to parking pricing and parking occupancy strategies for different vehicle types or drivers with different VOTs associated to different user groups entering the area. Here, the vehicle types are not restricted to fuel and electric vehicles, and we could also investigate vehicles with and without a disabled parking permit, or different user groups of drivers corresponding to elderly drivers who prefer to park closer to their final destinations than younger drivers. The impacts of these different vehicle types or user groups on the traffic performance, the cruising-for-parking traffic, the environment and the revenue for the city can then be studied without the need of tracking data for individual vehicles and parking spaces in an area.

7.3 Thesis limitations, and Recommendations for Future Research

This dissertation evaluates different parking policies using a dynamic macroscopic traffic and parking model. The methodologies are validated with real data from the city of Zurich. However, given the complexity of traffic and parking systems, there are some limitations to our framework, and multiple improvements can be made. The following extensions to the parking demand, the supply, the traffic properties and the parking policies could be included in future studies.

Extension to the parking demand:

- In the long-term, drivers might change their behavior and avoid, for example, paying high on-street or garage parking fees and quit their journeys. Alternatively, they might get frustrated due to high searching costs and high parking occupancy, and change towards other transportation means, or they might even change their shopping behavior and focus on different businesses outside the area. This could affect the demand, but long-term effects are out-of-scope of this research, and we focus only on short-term changes in traffic conditions in response to a given time-dependent demand. This demand input is more realistic than fixed rate assumptions used in the existing literature. However, we could enhance it by reflecting the choice of travelers as a result of the parking policies over time. We could also add a dependency on the local conditions of the study area (i.e., residents' and commuters' preferences, culture, or travel behavior). This would make our demand input more realistic.

Extension to the parking supply:

- Our research focuses on homogeneously distributed parking supply and

demand in an urban area. The applicability of this model is limited to relatively small and compact networks. For such networks, it has been proven that the model represents a very good compromise between accuracy and efficiency. The network should not be too large such that the drivers' preference of parking location can be more or less neglected. It should not be too small either such that the traffic flow on it can be viewed macroscopically. Even though the scale of the network might sound restrictive in the current model, it allows us to analyze the problem with a new and comprehensive method, that, above all, has very limited data requirements and rather low computational costs. In other words, the current model can be seen as the first building block; with which further analysis can be developed later for more complex situations (e.g., where the parking spaces or the parking prices are not homogeneously distributed). As vehicles could prefer, in reality, parking spaces in a central street or area of the network, future research should incorporate non-homogeneous environments (e.g., where both, the parking demand and supply are inhomogeneously distributed) by modeling different adjacent subnetworks. Each subnetwork could be modelled as a building block, i.e., it would have, for example, identical parking prices but different subnetworks would have different prices. It should be carefully studied, how to connect these subnetworks to each other.

Extensions to the traffic properties:

- The traffic properties (i.e., free-flow speed, maximum traffic throughput, critical traffic density, jam density, coefficients capturing PT traffic properties) are considered as inputs to our research based on the MFD or the 3D-MFD of the city of Zurich, respectively. This MFD or 3D-MFD is assumed to be a fixed model input. In reality, these MFD properties might change with respect to the urban parking as the parking conditions might impact the traffic system. Future research can investigate this relationship, especially in areas with oversaturated parking conditions.
- We could incorporate parking maneuvers and their traffic disruptions into our macroscopic traffic and parking model. This will lead to more realistic influences on the traffic flow in an urban area.

Extensions to the parking policies:

- Future research can study the impacts of dynamic parking reservation systems for on-street and garage parking, especially during rush hour parking. This might reduce the cruising-for-parking times and improve the traffic performance in the area. Additionally, it can be analyzed how a reservation of a dedicated time slots entering a congestion pricing area by car can affect the traffic and parking system.
- Delivery parking and double parking are not explicitly accounted in our framework. We assume that these parking behaviors do not cause any issues in the area. Future research can incorporate the effects on traffic and parking,

and on our parking policies in an urban area.

- We could also split the traffic demand in future research. A portion of drivers pays a fixed (low subsidized) parking fee in all garages and/or some of the on-street parking spaces, which can be motivated by, e.g., the subsidy from a company or the city for its employees or residents, respectively. The remaining portions of demand could be priced responsively, reflecting the external costs for parking.
- Last but not least, our framework can be enhanced to study different parking pricing methodologies. Tiered parking pricing schemes for both on-street and garage parking, but also for P+R and congestion pricing can be included to the model. Drivers may pay a low parking/P+R rate for the first hours, and then the rate jumps up significantly to promote higher parking availability and to increase turnover. Alternatively, congestion pricing might be low when you enter the area for a limited amount of time, which guarantees that vehicles do not congest the central streets by staying there for a long time period. However, the congestion toll might also differ between the peak hours of the day compared to off-peak hours, and it might be free of charge for some days of the week (e.g., on Sundays in London, U.K.).

As we live in an ever more populated and connected world, the need to better manage traffic in urban areas is evident. At the same time, sustainable travel and transportation modes are gaining attention around the world. This dissertation shows that parking policies can reduce congestion and achieve traffic performance improvements, while simultaneously parking fees can lead to a significant revenue for city councils. Parking pricing strategies are also socially and politically more accepted and easier to implement than introducing a congestion pricing strategy in an urban area. The parking fees can then be used to improve or subsidize PT in order to facilitate a more sustainable form of traffic in the city. Alternatively, our parking occupancy policies can be used to evaluate how much parking supply with battery charging possibilities cities would like to dedicate to electric vehicles in order to achieve optimal traffic and parking results. This is especially relevant in times of a modal shift towards more sustainable electric vehicles.

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Appendix A

Input Data

A.1 Input data and implementation in Matlab

The data used to support the findings of this dissertation is available [here](#)². The frameworks are implemented with the aid of a simple numerical solver such as Matlab. That data includes the time stamps of all cars arriving to the area, and the times they leave the area after parking, as well as the parking occupancy in the area at the start of our simulation.

² <https://github.com/manueljakob1986/phd-thesis>.

Curriculum Vitae

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Research Interests

Traffic operations, urban parking management, multi-modal transportation, decision modelling, traffic and network optimization, mathematical modelling, mathematical optimization, big data analytics.

Professional Experience

- Aug 2012 – Today **Promerit AG – A Mercer Company,
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Managing Consultant, Senior Expert People Analytics,
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- Jun 2010 – Sep 2010 **Fraport AG, Traffic and Terminal Management - Corporate
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Three-month internship in the team Infrastructure Aviation

Education

- Oct 2013 – Dec 2020 **Swiss Federal Institute of Technology, ETH Zürich,
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Dissertation: "Parking policies and their impacts on urban networks",
Advisor: Prof. Dr. Kay W. Axhausen, Prof. Dr. Monica Menendez
- Apr 2007 – May 2012 **Darmstadt University of Technology, Darmstadt, Germany**
Diploma Program: Mathematics with Technology (Dipl.-Math.)
Overall Assessment: very good, GPA: 1.06 (Equivalent to A+)
- Oct 2011 – May 2012 **University of California, Berkeley, USA**
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Sep 2009 – May 2010

University of Saskatchewan, Saskatoon, Canada

Exchange student at the College of Arts and Science in Mathematics, Research Assistant at the Numerical Simulation Lab, Prof. Dr. Raymond J. Spiteri, Stipendiary of the German Academic Exchange Service (DAAD)

Jun 2006

Max-Planck-Gymnasium, Groß-Umstadt, Germany

A-levels, Overall Assessment: GPA 1.1 (Equivalent to A)

Languages

German: Mother tongue
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ScrumMaster, borisgloger consulting GmbH

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Design Thinking, Hasso Plattner Institute

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Engagement and Personal Interests

Feb 2011

ECRA European Cold Rolled Section Association Award 2011

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Member of the board "Intercultural exchange between the city Groß-Umstadt and St. Péray in France"

Publications

1. Jakob, M., M. Menendez, J. Cao. 2018. "A dynamic macroscopic parking pricing and parking decision model". *Transportmetrica B: Transport Dynamics*, Vol. 8 (2020), Issue 1, pp. 307–331, doi: 10.1080/21680566.2018.1488226.
2. Jakob, M., and M. Menendez. 2019. "Macroscopic Modeling of On-Street and Garage Parking: Impact on Traffic Performance". *Journal of Advanced Transportation*, Volume 2019, Article ID 5793027, 20 pages, doi: 10.1155/2019/5793027.
3. Jakob, M., and M. Menendez. 2020. "Parking pricing vs. congestion pricing: a macroscopic analysis of their impact on traffic". *Transportmetrica A: Transport Science*, doi: 10.1080/23249935.2020.1797924.
4. Jakob, M., and M. Menendez. 2020. "Optimal Parking Occupancy with and without Differentiated Parking: A Macroscopic Analysis". Submitted to *Transport Policy*.

Presented Papers and Reports:

1. Jakob, M., M. Menendez, J. Cao. 2016. "A dynamic macroscopic parking pricing model", *Transportation Research Procedia, Proceedings of the 14th World Conference on Transportation Research (WCTR 2016)*, Shanghai, China, July 2016.
2. Jakob, M., and M. Menendez. 2016. "A macroscopic off-street parking decision model". *Proceedings of the 16th Swiss Transport Research Conference (STRC 2016)*, Ascona, Switzerland, May 2016.
3. Bösch, P. M., M. Jakob, N. Zheng, G. Rérat. 2014. "NetCap: Intermodal capacity of links, segments and networks", Report, Institute for Transport Planning and System (IVT), ETH Zürich, Zürich 2014.

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